# BEAN LEAF DISEASE CLASSIFICATION USING MOBILE NET

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**Abstract— This paper aims to achieve accurate detection and classification of bean leaf disease using deep learning method. There are lot of diseases associated with bean leafs such as angular leaf spot disease, bean rust disease,... which hinder its production. Thus to solve these problems at an early stage, a deep learning approach is proposed to identify and classify bean leaf disease by using public dataset of leaf image and MobileNet model with the open source library TensorFlow. 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. This algorithm was tested on the bean leaf dataset and the results shows that our method detects the defects more accurately.**

**Index Terms—Dataset, MobileNet, Confusion matrix, TensorFlow**.

## 1. INTRODUCTION

In this paper, we have proposed a new method to classify bean leaf diseases into their classes by using MobileNet which is a convolutional neural network that provides efficient models for variousmobile applications. The proposed method was based on MobileNet with open source library TensorFlow. Based on an accurate comparison and evaluation of MobileNet architectures (hyper parameters and optimization methods) that defines smaller and more efficient MobileNet model, the effectiveness of different architectures were compared andevaluated in order build effective model that can easily classify disease into their classes. In the current study, we have used public datasets including two classes of beans leaf disease and one healthy class. The dataset 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 thispublic dataset, the data are separated into three classes such as Healthy class with 428 examples, Angular leaf spot with 432 examples 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 is to develop an automated model capable of classifying and identifying disease type using MoblieNet. The efficient network architecture in MobileNethelps us to build accurate models that can easily classify bean leaf disease with accuracy. The results that are evaluated with MobileNet architectures using single public datasetsare then compared with their results for classification of bean leaf disease. This finds the best usable architecture and optimum classification results. The effectiveness of different architectures are compared to get the best results such that all the parameters have to be controlled under the same conditions using the same datasets.

Furthermore, this paper proposes 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 results, 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 datasets 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 bean leaf diseases and give a clear idea about some problems of automating plant leaf disease classification using MobileNet model architectures and single public datasets. The performance of the model has been analyzed based on various parameters such as training accuracy, validation accuracy, loss and validation loss.

## II.RESEARCH MATERIALS AND METHODS

### A. DATASET AND SYSTEM CONFIGURATION

The dataset used in this study is a public dataset presented bytensorflow and was chosen 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.

Therefore, in this experiment the datasets are separated into three classes which are Angular leaf spot class, Healthy bean class and Bean rust class (as shown in Fig 1.) with 80% training and 10% testing and 10% validation. Samples of the leaf images according to the used classes are shown in Fig 2. 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.

The datasets will be trained using MobileNet architectures within the CNN model, and the results are evaluated according to different performance of evaluation criteria like Precision and Accuracy. The experimental results were tested using 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.

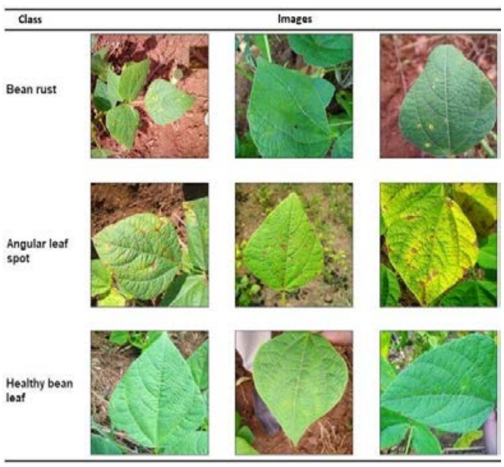



**Fig 1. Bean leaf disease classes**

### B.IMPLEMENTATION

The classification model is divided into different stages which examines 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, 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 to see if there is a class with significantly fewer samples than the other disease class.But in the current study, we used a public datasets 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 20.The classification results for this study were based oncomparing and evaluating different architectures (hyper parameters, optimization methods) under a similar condition work. Iin 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.

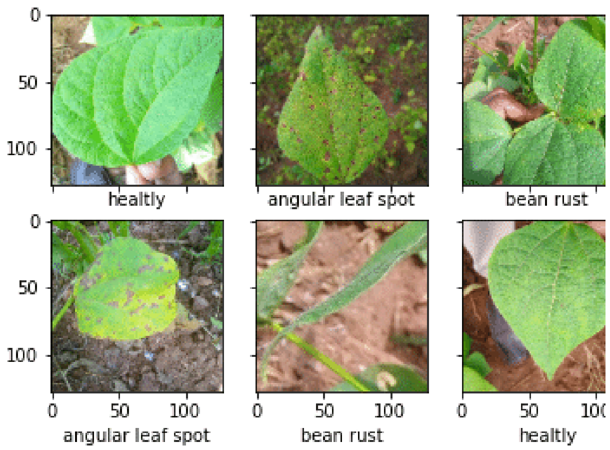



**Fig 2. Example of Labelled Dataset**

## 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 depth-wise 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 as 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.

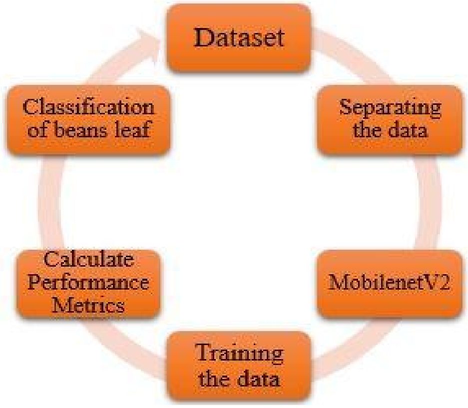
Actually, the size of the input to the network is also small, the output of the neural network is 3 classes labels of 1 crop. The architecture of MobileNets is trained and tested using Python language with TensorFlow CPU library. In other side we used other method called MobileNetV2 [23] which is a convolutional 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 [7] have shown a great result.

**Fig 3. Major Components of Bean Disease Classification**

Fig 3 shows the components of the system where the datasets is used to train and test the proposed MobileNetV2 based on beans disease screening algorithm.

## D. 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. On comparing the five optimizers, 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 do not suffer any decreases in accuracy. Therefore, we selected the both optimizers to be used in this experimental study based on MobileNet as shown.

Fig 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 91%. Fig 5. shows the trining accuracy and the validation accuracy.

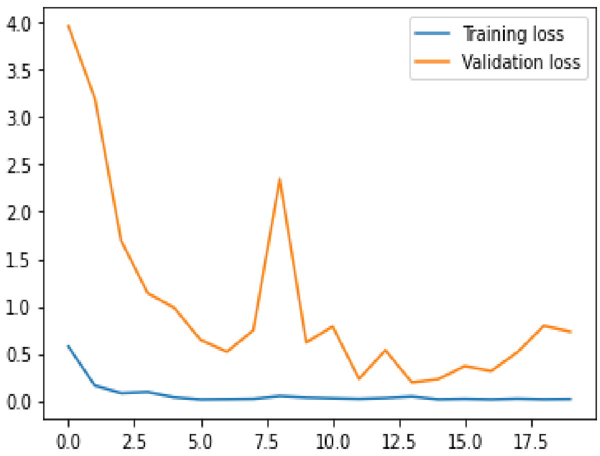



**Fig 4. Model Accuracy and Model Loss**

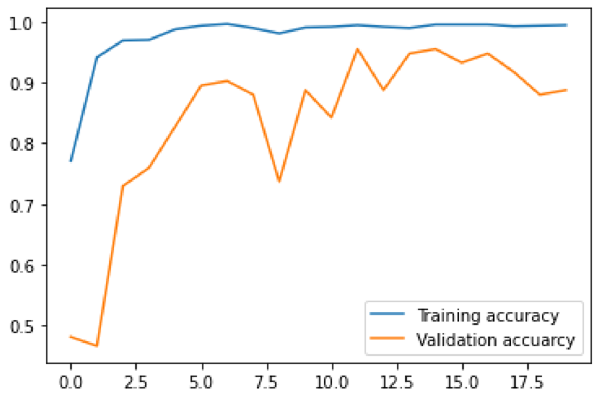



**Fig 5. Training Accuracy and Validation Accuracy**

## E. BATCHSIZE

Batch size is a hyperparameter that controls the number ofsamples images to the network for one training iteration. Inotherword,itreferstothenumberoftrainingexamplesusedin a single iteration in the model, and it is very importantwhile training.We used and testedbatch size of 32 to compare classificationaccuracy,andforthisexamplestudyweused20 epoch. During testing, we observed that minimal fluctuations intrainingerrorareobservedwhenusingthebatchsizemethod,butthebiggerbatchsizewilloutcometoovergeneralization.

Moreover, for the accuracy of classification we have usedbatch size of 32,we found that the high performance is obtained with anaccuracyvalueof91.4%.Inadditionally, thebatchsizenumbershouldnotbechosentoomuchandnottoolowandinsuchawaythatthenumberofimagesremains about almost the same at each step of an epoch,keepinginmindthatsmallbatchsizesrequiresmalllearningrates, and the batch size controls the accuracy of gradienterror estimation when training networks.

## I. USING MOBILENET AND MOBILEV2 STRUCTURE

The accurate classification of bean 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 experiment for bean 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 of 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. The small parameter number requirements allowed MobileNetV2 to obtain a highly accurate classification result for bean leaf disease compared with MobileNet. 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.

## II. CONFUSION MATRIX

The confusion matrix is an important tool to analyze how well the classifier can identify tuples of various classes. Fig 6 shows the general representation of a confusion matrix. The below code shows how to construct a confusion matrix using Tensorflow.

```
tf.Tensor(
[[40  3  0]
 [ 6 36  1]
 [ 1  0 41]], shape=(3, 3), dtype=int32)
```

| | Predicted class | | | |
|---|---|---|---|---|
| Actual class | | *yes* | *no* | Total |
| | *yes* | *TP* | *FN* | *P* |
| | *no* | *FP* | *TN* | *N* |
| | Total | *P′* | *N′* | *P* + *N* |

**Fig 6. General Representation of a Confusion Matrix**

The accuracy of a classifier on a given test set is the percentage of test tuples that are correctly classified by the classifier. The accuracy for our proposed model is calculated as follows:

$$accuracy = \frac{TP + TN}{P + N}$$

where TP – number of True Positives samples
TN – number of True Negatives samples
P – number of Positive samples
N – number of Negative samples

The accuracy for our proposed model is calculated as follows:
Accuracy =( (true positive + true negative) /(true positive +false positive + true negative + false negative) )* 100
= (40+36+41)/(40+3+6+36+1+1+41) = 0.914 *100 = 91.4% accuracy. Our proposed model for beans leaf diseases classificationwere successfully implemented, analyzed and a very satisfactory performance classification result were obtained. Themodel is computationally efficient but only evaluated forbean 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 ind ependently and inidentical fashion, then the mode lwould yield greater sults as well.

## V .CONCLUSION

In this paper we developed an automatic model to classify and identify the type of bean leaf image disease using MoblieNet based on an efficient network architecture, in order to build an accurate models that can easily classify 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, and it shows that the proposed method achieves higher performance in terms of classification of plant leaf diseases.The best experimental result is obtained when our model is trained using adam optimizer with a learning rate of 0.001 and a batch size of 32 .The model also achieved an accuracy of 91.4 % . Furthermore, it has been found that the classification training accuracy alue decreases as soon as the batch size increases and the learning rate decreases.

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