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Cassava leaf disease classification using Deep Learning

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Abstract

Cassava is an important crop that is cultivated in the tropics. The Food and Agriculture Organization of the United Nations (FAO) states that Cassava is a source of food and income for more than 800 million people around the globe. And it is reported that Africa accounts for more than 50% of the global production among the other cassava-producing regions of the world. But several pests and infections have been a menace to the production of this crop for a long while now since they periodically ruin the crop in some regions leading to famine and consequently leaving the farmers in peril. This dire situation entails new methods to identify cassava diseases at an early stage and thus help prevent this crisis. In this Research, a deep CNN model implementing EfficientNet-B3 has been developed that identifies five main classes: Cassava Mosaic Disease (CMD), Cassava Bacterial Blight (CBB), Cassava Green Mottle (CGM)), Cassava Brown Streak Disease (CBSD and a healthy specimen. This model makes use of the compound coefficient, a different scaling approach prescribed for EfficientNet, to scale up the model in a more structured way. This approach thus avoids brute force manual tuning and stagnating performance issues. The model achieved an overall accuracy of 96.74%.

Introduction

Cassava, also known as the ‘complete crop’, is an essential part of the diet of the people in Africa and provides a sustainable source of livelihood for millions of farmers [1]. The significance of the crop in the lives of African people is conspicuous from many documentaries. A famous novelist and poet from Nigeria commended the crop by calling it “Mother Cassava” in her book titled “Cassava Song and Rice Song “where she narrates how cassava sustained life in Nigeria (in a land where even rice is regarded as expensive and not affordable by the poor), even during the civil war in the late 1960s. It is also the second most important source of carbohydrates after maize. It is consumed by hundreds of millions of people every day on the mainland. The Democratic Republic of Congo is where the crop was first harvested. Later cassava became widely adopted as it was found to be more reliable than other crop varieties when struck by a drought or a locus attack. Cassava is a resilient crop as it grows in a wide range of ecological zones, even in agricultural lands where it is difficult for other crops to thrive. It is also found to produce higher yields compared to other crops such as rice, wheat, maize, and yams, in a given unit of land. All these reasons thus make it a befitting crop for poor farmers to cultivate under adverse weather conditions in the African mainland.

Viral diseases have wreaked havoc causing poor yields and a loss of around 12-23 million dollars yearly, given that more than 80% farms in Sub-Saharan Africa cultivate this crop [2][3][4][5].

Leaves of a healthy cassava plant. Credit: FAO/G. Napolitano

The shrunken and discoloured leaves of a plant infected with CMV. Credit: FAO/G. Napolitano

Figure 1: Source [6]

Harvesting healthy cassava. Credit: FAO/G. Napolitano

Root yield is dramatically reduced by CMV infection. Credit: FAO/C. Ferrand

Figure 2: Source [6]

CBSV disease symptoms on cassava plants - leaves and stem show limited symptoms. Credit: IITA

CBSV disease symptoms on tuberous roots - damaged and unusable. Credit: IITA

Figure 3: Source [6]

Research works have been carried out around the world to curb this situation. The preceding methods of disease detection requires manual inspection and diagnosis of the plants. Additionally, the work requires experts to annotate the plants after visually inspecting and diagnosing the plants. This method has its demerits as requires intensive manual labor and it is expensive in terms of both money, human effort and time. There is a need for effective solutions that ought to perform well under specific constraints like most African farmers only having access to mobile-quality cameras with low bandwidth.

We aim to classify each cassava image from the obtained dataset into four commonly found disease categories (Cassava Mosaic Disease (CMD), Cassava Bacterial Blight (CBB), Cassava Green Mottle (CGM)), Cassava Brown Streak Disease (CBSD) or a healthy specimen. This will allow farmers to swiftly diagnose the afflicted plants, conclusively saving their crops before they thrust permanent damage.

Model scaling is a predominant issue while designing neural networks because it requires manual tuning to get an accurate model which is both time and resource-consuming and not often promises optimal results. Thus, here we present the idea of implementing an unconventional CNN model to yield comparatively better results and an easier approach in making, which is to scale up the model in a more structured way using the compound coefficient method in the EfficientNet architecture. Our results show that this is a finer way to scale up the model because unlike in the traditional tuning where one dimension (width, depth, or image resolution) is tuned at a time or arbitrary scales are used, this approach uniformly scales all the dimensions with a fixed set of scaling coefficients. In addition to enhancing the predictive capacity of the network by replicating the underlying network structure and convolutional operations using the compound coefficient method suggested by Google Brain team [16], EfficientNet architecture comprises of the MBConv blocks which are accompanied by squeeze-and-excitation optimization.

2. Literature review

2.1. Disease categories

Four common classes of diseases that plague the cassava crop are discussed below [7]. Our end goal is to categorize these infections automatically by a deep learning model that interprets the signs and symptoms that arise due to these unique diseases.

Figure 4: Images representing a healthy leaf and four disease classes in our dataset. Source [8].

Cassava Bacterial Blight (CBB)

CBB as the name suggests is a bacterial disease that affects the crop. It is favoured by moist environmental conditions. Depending on the aggressiveness of the bacterial strains, the crop's location and season, etc, the severity of the disease's symptoms can vary. This causes leaves to wilt and fall prematurely when the infection becomes severe.

Main characteristics to leverage: **black and/or angular spots, dried up leaves.**

Figure 5: Cassava Bacterial Blight (CBB) affected plant

Cassava Brown Streak Disease (CBSD)

CBSD affects the cassava plant adversely. Whiteflies which are probably the most damaging insect pest, are vectors of the virus. CBSD is also transmitted through infected cuttings. During early stages of infection, the symptoms of CBSD shown are streaky patches of yellow amidst the usual green color. Over time, these yellow patches enlarge and merge forming larger yellow patches and the leaves become mottled. Another symptom is the development of brown streaks on the stem of the plant. If the infection becomes severe it may also lead to stunted growth and causes the plant to rot.

Main characteristics to leverage: **yellow patches, dark streaks on the stem, stunted leaves/roots.**

Figure 6: Cassava Brown Streak Disease (CBSD) affected plant

Cassava Green Mottle (CGM) :

CGM causes white spots to occur on the surface of the leaves, and on proliferating causes the leaf to lose chlorophyll. Reduced amounts of chlorophyll affect photosynthesis and thus reduces crop yield. Mottled symptoms are shown by CGM-affected leaves which are also shown by leaves affected with cassava mosaic disease (CMD). Based on the extremity of the infection leaves dry up, shrink and fall prematurely.

Main characteristics to leverage: **white spots, mottled leaves, and/or stunted leaves.**

Figure 7: Cassava Green Mottle (CGM) affected plant

Cassava Mosaic Disease (CMD) :

CMD is a predominantly found disease that plagues the Cassava crop. Symptoms of CMD are formation of mosaic like patterns, yellow-white patches on the leaves, discoloration and disfiguring of the leaves. The plants and leaves show stunted growth due to the infection.

Main characteristics to leverage: **mosaic patterns, severe shape distortion.**

Figure 8: Cassava Mosaic Disease (CMD) affected plant

At least two classes share the same patterns (CGM and CMD) in terms of spots and shape distortion up to some degree. Yellow spots are another common pattern across all the classes.

2.2. Related works :

In the paper [10], published in the year 2016, the authors have shown how computer vision can be used efficiently for identifying and classifying diseases in plant leaves. They have used digital image processing techniques such as color analysis and thresholding combining it with a deep learning framework called Caffe, to build a deep CNN network for detection and classification of plant diseases. The model was built for detecting the presence of leaves and classifying them as healthy and into 13 different types of diseases in case of getting identified as unhealthy. The model achieved an overall accuracy of 96.3%.

In the paper [11], published in the year 2018, the author, Konstantinos P. Ferentinos, has worked on plant disease detection and classification by training deep CNN models. He used simple images of healthy and diseased plants as the dataset to train the deep learning model. The database comprised 87,848 images, with 25 different plants in a set of 58 distinct classes of combinations of healthy and diseased plants. The model achieved a very high accuracy of 99.53% thus deeming it to be a very useful diagnostic tool for giving out early warnings in case of diseases in plants. But the dataset that was used to train the model contained unverified images causing inaccuracy in selected cases.

Both of the above-discussed papers have described models that were built for a generic domain of plant disease classification and were not pertinent to the cassava crop. But it helped to provide a solid platform for researchers to get started with similar domain-specific model building.

In the [12], published in the year 2017, researchers have trained deep convolutional neural network based on Inception v3 and have applied transfer learning on a dataset of cassava disease images. The model was able to identify three diseases and two pest damage varieties. They leveraged a TensorFlow application to deploy the model on mobile devices to detect cassava plant diseases in real-time. The model achieved an overall accuracy of 93%. Although their work fails to detect or classify cassava bacterial blight disease (CBB), their results have also shown that transfer learning can be an effective approach for early detection and diagnosis of plant diseases.

In the paper [13], published in the year 2019, the authors have developed and trained a total of 46 machine learning models to detect and classify cassava diseases. They have emphasized mainly two major classes of cassava diseases: Cassava Mosaic Disease (CMD) and Cassava Bacterial Blight disease (CBBD). They trained their model on 18,000 cassava leaf images in two different categories - one model (Cubic Support Vector Machine (CSVM) with 5-fold cross-validation) to detect the healthy leaf and the other model (Coarse Gaussian Support Vector Machine (CGSVM)) to detect the unhealthy leaf and classify the disease manifested on the leaf. The accuracies of 83.9% and 61.6% were yielded by the models respectively.

In the paper titled [14], published in the year 2020, the authors have built a deep learning model based on MobileNetV2 architecture for detecting and classifying cassava leaves into the above discussed categories of diseases. The model achieved an overall accuracy of 74.5% and 67.3%, for train and validation sets respectively.

In the paper titled [15], published in the year 2021, the authors have built deep convolutional neural networks from scratch to detect and classify Cassava diseases. They have utilized deep learning techniques such as Synthetic Minority Over-sampling Technique (SMOTE), focal loss to counter an imbalanced dataset so that the model can predict even the less represented classes accurately. The model achieved an accuracy score of 93%.

Our experiment extends on these previous works and we have explored an alternate deep learning convolutional neural network model - EfficientNet-B3, to detect and classify cassava diseases.

Proposed method

The model proposed here is deep learning CNN based on EfficientNet B3 architecture. This architecture was chosen for the following reasons:

1) EfficientNet is capable of a wide range of image classification tasks, thus rendering it a good model for transfer learning.

2) It also comes with a new scaling method that uses a simple and effective compound coefficient that uniformly scales all dimensions of depth/width/resolution.

3) It avoids brute force manual tuning and thus does not suffer from stagnating performance issues.

4) It has also been proven that the EfficientNet models score high on both accuracy and efficiency compared to existing CNNs, reducing parameter size and FLOPS to a considerate amount [16].

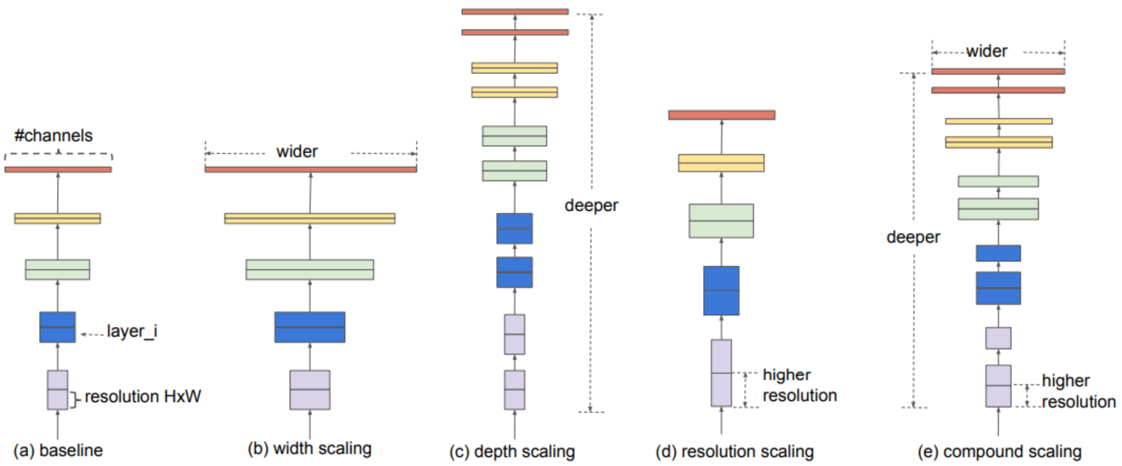

Figure 9: Sample image representing different model scaling approaches. Source [16].

In the above figure (b), (c), (d) represent traditional scaling methods while (e) represents compound scaling method. A swish activation function which tends to work progressively better for deeper networks has been used.

4. Experimental setup

4.1. Dataset

The dataset from Kaggle [9] comprises 21,367 expert annotated images from a survey in the farm lands of Uganda. The downloaded CSV file consists of an image Id and its respective disease label as ID code. Most images are photos from gardens taken by the farmers themselves thus the dataset represents real field scenarios. The annotations contain the above discussed classes of diseases including a class for healthy leaves. 95% of the dataset is used for training and the remaining 5% is used for validation and testing.

4.2. Data pre-processing

Data augmentation involves random transformations applied on original images. We have performed augmentation techniques like flips, rotations, shifts and a few others with the objective of improving the generalizability of the model.

4.3. Model architecture and training

The architecture of the baseline EfficientNet is shown below in Figure 10. The architecture is structured in a way that the convolutional layers do feature extraction from the images and the extracted features are passed on to the fully connected layers to classify images of cassava leaves into five different categories – 4 above discussed diseases and the healthy category.

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
1	Conv3x3	224 × 224	32	1
2	MBConv1, k3x3	112 × 112	16	1
3	MBConv6, k3x3	112 × 112	24	2
4	MBConv6, k5x5	56 × 56	40	2
5	MBConv6, k3x3	28 × 28	80	3
6	MBConv6, k5x5	14 × 14	112	3
7	MBConv6, k5x5	14 × 14	192	4
8	MBConv6, k3x3	7 × 7	320	1
9	Conv1x1 & Pooling & FC	7 × 7	1280	1

Figure 10: EfficientNet baseline architecture. Source [16].

MBConv block (inverted residual block)

The main building block of EfficientNet, as seen from the above diagram, is the MBConv block (aka inverted residual block). In normal residual blocks, skip connections connect the wide layers and the narrow layers are wedged in between the skip connections. On the contrast, the inverted residual blocks are where the narrow layers are connected by skip connections and the wide layers are wedged in between them. The main purpose for going for the inverted residual blocks is that, in the standard residual blocks, the in-between expansion block is a mere implementation detail. As conclusively information can also be pertained to the low dimension making the process computationally cheap.

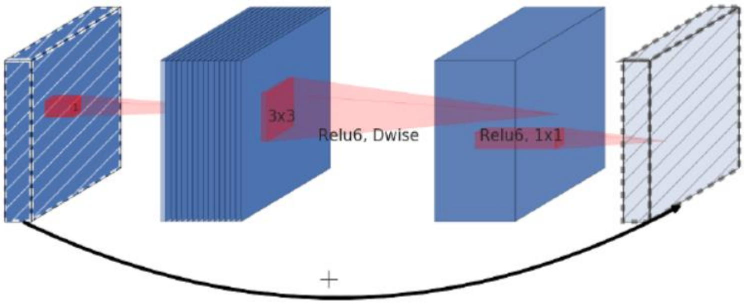

Figure 11. Inverted residual block

Starting from the baseline EfficientNet-B0, the compound scaling method is used to scale it up to higher architectures.

Compound scaling

The common ways of scaling up convolutional neural networks is shown in Figure 9. But traditional scaling requires manual tuning and at most times does not yield promising results. In the paper [16], the authors have shown that the compound scaling method can be used to scale the width, depth, and resolution of the network uniformly and in a more structured way. Results have also shown that compared to other scaling methods, compound scaling improves accuracy by up to 2.5%. EfficientNet architecture is also found to transfer well whilst reducing parameters by up to 21x than existing convolutional neural networks. Below given image shows how EfficientNets significantly outperform existing convolutional neural networks.

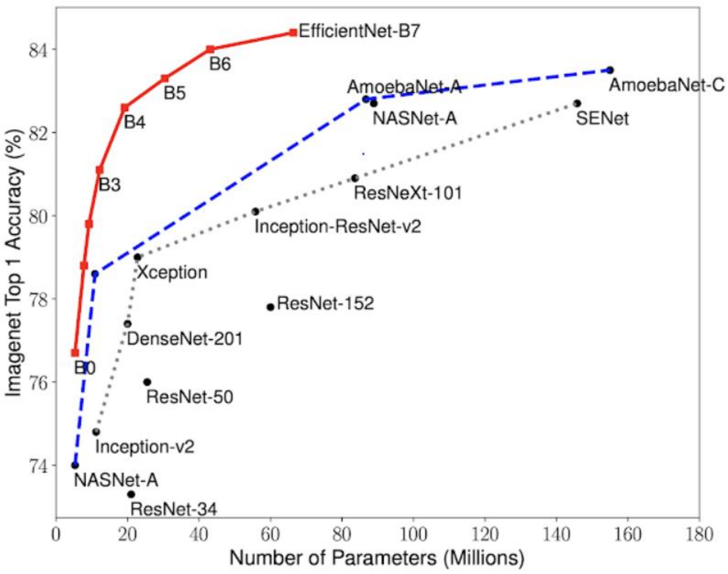

Figure 12: Model Size Vs ImageNet Accuracy. Source [16].

Swish Activation

The choice of activation functions in deep convolutional neural networks has a vital impact on the performance of the model. Rectified Linear Unit (ReLU) is susceptible to vanishing gradient problem, since for all negative values the derivatives obtained are zero. There are other possible substitute approaches to address this problem like: leaky ReLu, Elu, Selu, etc., but they have not been found to perform consistently.

Therefore we have used swish activation which is easy to use and has a propensity to work steadily and gradationally better for deep CNN networks across several challenging datasets [17]. Below given image of a graph, Figure 13, shows how Swish activation function outperforms ReLU on ImageNet.

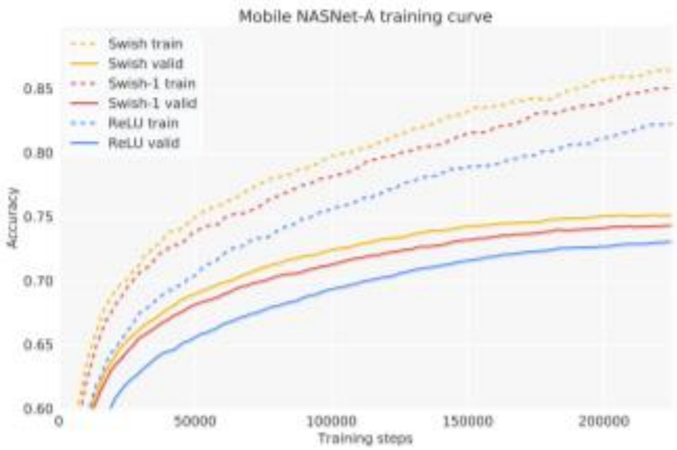

Figure 13: Training curves of Mobile NASNet-A on ImageNet. Source [17].

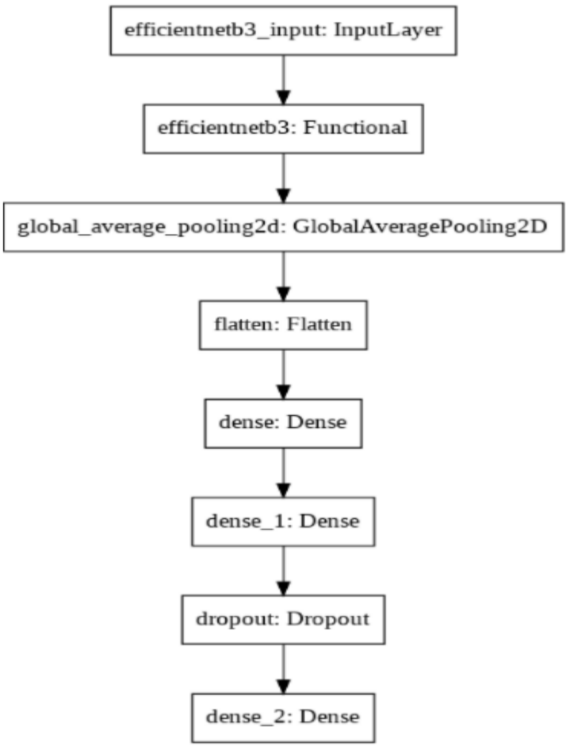

Figure 14: Model Architecture

The EfficientNet B3 model trained to classify cassava diseases is shown above in Figure 14. The target size of the images was set to 456 and the batch size for one epoch was set as 15. And we used free GPU from Google Colab to train the model.

Disease detection techniques	**Research Paper**	**Classification focussed on**	**Algorithm**	**Accuracy (%)**
Machine Learning	"**Detection and Classification of Cassava Diseases Using Machine Learning**" [13], 2019	1) Cassava Mosaic Disease (CMD). 2) Cassava Bacterial Blight disease (CBBD)	Cubic Support Vector Machine (CSVM) to detect the healthy leaf Coarse Gaussian Support Vector Machine (CGSVM) to detect the unhealthy leaf	83.9 61.6
Deep Learning	"**Deep learning for image-based cassava disease detection**" [12], 2017	1) Cassava Brown Streak Disease (CBSD), 2) Cassava Mosaic Disease (CMD) And three other diseases:	Inception V3 transfer learning	93

		Brown Leaf Spot (BLS), Red Mite Damage (RMD), Green Mite Damage (GMD)		
Deep Learning	“**Deep learning for detection cassava leaf disease**” [14], 2020	All five classes	MobileNetV2	74.5
Deep Learning	“**A predictive machine learning application in agriculture: Cassava disease detection and classification with imbalanced dataset using convolutional neural networks**” [15], 2021	All five classes	Deep CNN with SMOTE	93
Deep Learning (Proposed Method)		All five classes	EfficientNet	96.7

Table 1: Accuracy Comparison with existing methods for cassava leaf detection

5. Results and discussions

During model training, 95% of the dataset was used to train and 5% of the dataset was used to validate and test. The results also show that the model was not overfit to the datasets. The accuracy and loss metric comparison of the model is shown below in Figure 15. From the accuracy graph we can see that the train set accuracy has progressively increased within one epoch (15). Although there is a dip in the validation accuracy initially it shoots up and convenes together with the train accuracy. The loss graph, in agreement with the accuracy, shows progressive descent, as expected. The model achieved an accuracy of 96.53% and 96.95 % on the train and test sets respectively. Higher versions of EfficientNet architecture were not preferred because the accuracy had saturated with B3 architecture.

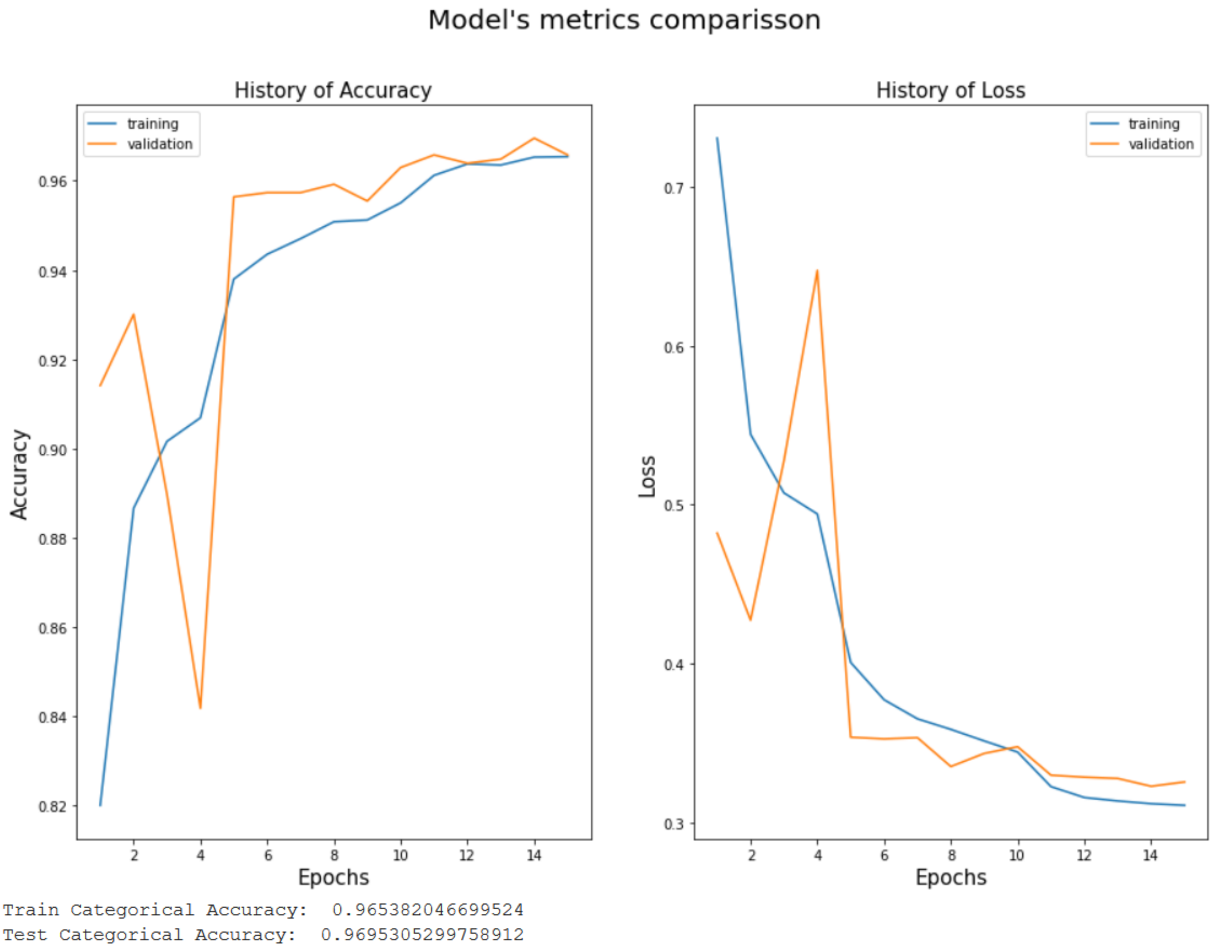

Figure 15: (On the left) Accuracy achieved by the model; (On the right) Loss incurred by the model

6. Conclusions and future work :

The trained EfficientNet deep learning model is thus able to detect and classify Cassava diseases into five categories: Cassava Mosaic Disease (CMD), Cassava Bacterial Blight (CBB), Cassava Green Mottle (CGM)), Cassava Brown Streak Disease (CBSD) and Healthy with an overall accuracy of 96.74%. This study therefore shows that the EfficientNet B3 architecture-based model can help detect cassava diseases with promising results.

The dataset is less reliable because the images were taken directly by farmers from their fields with their phones and also because the images will be prone to background noises. Robustness of the model can be further improved if the dataset comprised good quality images. Another major limitation to our work was the computational resources. Though we worked on the Google Colab platform, we ran out of allotted GPUs and were in need of more computational capacity to try and experiment with different model tuning parameters to improve the performance of the model.

By combining the model with a user interface, we can provide the farmers with a tool with which they can identify infected crops themselves and prevent the crops from further damage.

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