Kaggle competition: Classification of Cassava leaf diseases

Jérémie Mabaiala[1,†], **Tony Chisenga**[1] **and**
Team Name: KO[1]

[1] *African Institute for Mathematical Sciences, Senegal. E-mails: jeremie@aimsammi.org, tchisenga@aimsammi.org*
[†] *The authors contributed equally to this work. This manuscript was compiled on May 19, 2024*

Abstract

This document provides a brief report on the cassava leaf disease classification project, which stems from a Kaggle competition. Our methodology involves utilizing pre-trained models available in PyTorch and selecting the one that yields the highest test accuracy.

Keywords: Image classification, Deep neural network, Cassava leaf diseases, Kaggle competition.

1. Introduction

Cassava leaves are an important part of the diet in some regions of sub-Saharan Africa [1], but are frequently affected by diseases [4], which result from various factors such as climate and viruses, and can affect their qualities. Accurate identification and classification of these diseases are essential and crucial for effective management and food security. We utilize AI and Deep neural network models to train machines to perform this task.

2. Dataset

The dataset used consists of raw images of cassava leaves. It is provided by [2] and [4]. Below are randomly selected raw images.

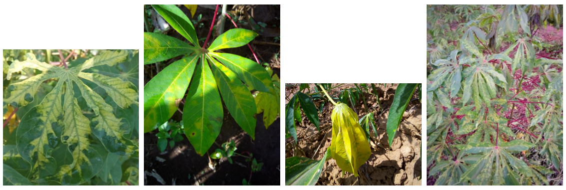
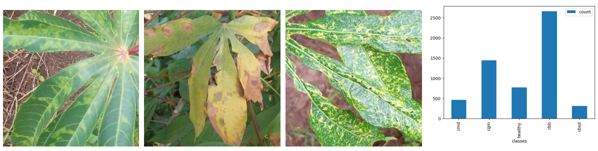


Figure 1. Four raw images of cassava leaves from the cassava disease dataset.

There are 4 disease categories in the dataset : Cassava Mosaic Disease (`cmd`), Cassava Brown Streak Disease (`cbsd`), `healthy`, `cbsb`, Cassava Bacterial Blight (`cbb`). The dataset is split in two: train dataset which consists of 5656 images and test data with 3774 images. We use 20% of the training set for validation. Before splitting, the training counts are as follow:



(a) Class `cbb` (b) Class `cgm` (c) Class `cmd` (d) Counts of each category in the training dataset

Figure 2. (a)-(c) preprocessed images for both training and test.

As it can be seen in fig. 1, the raw images vary in size. Therefore, we pre-process the dataset as follows: resize, crop, and transform. We employ center cropping and resize the images to a fixed size of 224×224 pixels. Additionally, we apply normalization to prevent common issues like exploding or vanishing gradients.

3. Model architecture

We experimented with several models, namely `ResNet19`, `ResNet34`, `DenseNet`, `ResNext`, `EfficientNet`. All these models, except the ResNet19 and DenseNet, achieved relatively good accuracies (16%, 84%, 83%, etc.). Among them, the ResNet34 yielded a higher accuracy of 84%, which was our initial submission. Our final submission, EfficientNet B4, gave an impressive result of 88%. This model is a family of Convolutional Neural Networks(ConvNets). Usually, ConvNets are scaled up for better accuracy. This is done by scaling either the network depth, width or image resolution [3]. EfficientNet is a result of scaling up the depth, width, and resolution of ConvNet using the compound scaling method. Additionally, we added an extra linear layer to the EfficientNet B4 to further improve the model's performance for this project.

4. Results

Below is the table summarizing our analysis:

Model	Train & valid. size	Val. split	Epochs	Test accuracy
RestNet19	(5656, 1131)	20%	5	16%
RestNet34	(5656, 1131)	20%	40	84%
DenseNet	(5656, 1131)	20%	35	48%
RestNext101	(5656, 1131)	20%	35	83%
EfficientNet	(5656, 1131)	20%	40	88%

Table 1. Results from the pre-trained models used for the cassava dataset.

5. Insights and Conclusion

We chose the EfficientNet [3] because it yielded the highest accuracy score. The performance of this model underscores the need to strike a balance between the depth, width and resolution of the ConvNet as opposed to focusing on scaling one component. Another insight is that techniques such as freezing some layers in training deep learning models are not effective in all cases. In our case, this technique did not work as we saw a decrease in the accuracy score when it was employed. For future works, we plan to find techniques to increase the accuracy of the models on the cassava dataset and try to deploy the results for large scale usage.

References

[1] A. Ufuan Achidi, O. A. Ajayi, M. Bokanga, and B. Maziya-Dixon, "The use of cassava leaves as food in africa", *Ecology of Food and Nutrition*, vol. 44, no. 6, pp. 423–435, 2005.

[2] E. Mwebaze, T. Gebru, A. Frome, S. Nsumba, and J. Tusubira, "Icassava 2019 fine-grained visual categorization challenge", *arXiv preprint arXiv:1908.02900*, 2019.

[3] M. Tan and Q. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks", in *International conference on machine learning*, PMLR, 2019, pp. 6105–6114.

[4] LvdM, *Cassava disease classification*, 2024. [Online]. Available: https://kaggle.com/competitions/ammi-2024-computer-vision.