Project: Cassava Disease Classification

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Abstract

This study proposes a cassava leaf disease detection system using convolutional neural networks (CNNs) with ResNets and EfficientNets architectures. A dataset of 9,436 labeled images of cassava leaves from Uganda was used for training and evaluation. The methodology includes data preprocessing, model training, quantization, and evaluation based on classification accuracy. The results aim to contribute to the development of an effective cassava Disease Classification system for protecting cassava production in Africa.

1 Introduction

Cassava is a very common plant in Africa and has many advantages. One of the advantages of cassava is that it can replace rice. According to statistical data from the Economic Community of West African States in 2018, cassava production in Africa amounted to 169 million tonnes per year . In addition to being a food ingredient, cassava can also be used as an industrial raw material and animal feed. Cassava contains about 60% water, 25-35% starch, protein, fiber, minerals, phosphate, and calcium. Cassava is also a more important source of energy than maize, sweet potato, rice, and sorghum . In addition, cassava is a staple food in many parts of sub-Saharan Africa. Africa produces about half of the world's cassava. Its production has declined due to a disease attacking cassava plants, resulting in a loss of about 12-23 million dollars. It is therefore important to identify cassava pests and diseases. Early detection and identification of plant diseases are therefore the main factors in preventing and reducing the spread of cassava plant diseases. This study will apply the convolutional neural network (CNN) method with the Resnets and EfficientsNets architecture and the Pythorch library to recognize images of cassava leaves, focusing on finding the best classification accuracy in cassava leaf disease detection.

1.1 Data and Methodology

1.2 Data

The dataset consisted of labeled images of cassava leaves, with a total of 9,436 images. These images were collected through a survey conducted in Uganda, with the participation of farmers who contributed images of their cassava gardens. The dataset included five fine-grained disease categories: cbb, cmd, CBS, cgm, and healthy. The images were annotated by experts from the National Crops Resources Research Institute (NaCRRI) in collaboration with the AI lab at Makerere University.

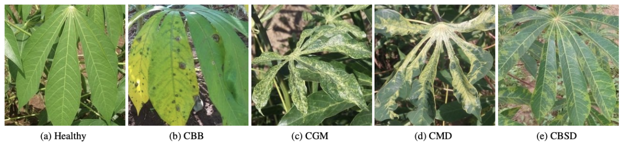

Figure 1: personal image.

1.3 Methodology

The methodology used in the cassava leaf disease detection study involves several steps to train and evaluate the classification models. Namely, Data Collection, Data Preprocessing or data augmentation, Model Architecture Selection, Model Training, Quantization, and Evaluation.

2 Results and Discussions

data train transforms	
Technique	Value
RandomRotation	30
RandomResizedCrop	500
RandomHorizontalFlip	0.3
RandomErasing	0.1
Normalize	True

Table 1: Different sets of transformations to perform data augmentation

data test transforms	
Resize	550
CenterCrop	500
Normalize	True

Table 2: Different sets of hyperparameters, used to train the model

Data Aumentation : Data augmentation techniques can help improve model performance by increasing the diversity of the training data and preventing overfitting.

Model	Resnet50	Efficientnet-b0
Criterion	CrossEntropy	CrossEntropy
Optimizer	SGD	SGD
epochs	10	10
Bach size	16	8
Test accuracy	0.52785	0.900

Table 3: Different sets of hyperparameters, used to train the model

Model	Resnet50	Efficientnet-b0
Criterion	CrossEntropy	CrossEntropy
Optimizer	Adam	Adam
epochs	10	10
Bach size	16	8
Test accuracy	0.52785	0.622458

Table 4: Different sets of transformations to use for data augmentation

Table 3 and Table 4 provide the results of the model training process for different models, criteria, optimizers, epochs, batch sizes, and test accuracies. Table 3 shows the results for the models trained using the SGD optimizer. The ResNet50 model achieved a test accuracy of 0.52785, while the test accuracy for EfficientNet-B0 model achieved a higher test accuracy of 0.900. Table 4 presents the results for the models trained using the Adam optimizer. The ResNet50 model achieved a test accuracy of 0.622458, while the test accuracy for EfficientNet-B0 model achieved a test accuracy of 0.52785.

Model Performance: The EfficientNet-B0 model consistently achieved higher test accuracies compared to ResNet50 in both optimizer settings (SGD and Adam). This suggests that EfficientNet-B0 may be a more suitable architecture for cassava leaf disease detection in this dataset.

Optimization Algorithms: The results indicate that the choice of optimizer (SGD or Adam) had a major impact on the test accuracies.

Therefore the results suggest that the EfficientNet-B0 model trained with SGD optimization achieved the highest test accuracy of 0.90.

3 Conclusion

The EfficientNet-B0 model consistently achieved higher test accuracies compared to the ResNet50 model in both SGD and Adam optimizer settings. This suggests that the EfficientNet-B0 architecture is better suited for cassava leaf disease detection in the given dataset. The choice of the optimizer (SGD or Adam) was found to significantly impact the test accuracies.
This research contributes to the field of cassava disease management by providing a reliable and accurate method for the early detection and identification of diseases, thereby assisting in the prevention and reduction of disease spread. The findings have implications for improving cassava production, supporting farmers in Africa, and minimizing economic losses caused by cassava leaf diseases.

References

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