Cassava Diseases Classification

Muhirwa Salomon[a]

[a] *African Masters In Machine Intelligense, , AIMS, Senegal, , may 2023*

Abstract

This project utilizes deep learning, specifically Convolutional Neural Networks (CNNs), to classify cassava leaf diseases. With a dataset of 9,436 annotated images, including 12,595 unlabeled ones, the goal is to categorize leaves into four disease classes or identify them as healthy. Techniques such as data augmentation, class weighting, batch normalization, and cross-validation were employed to enhance model performance. Transfer learning with pre-trained models further improved classification accuracy, with EfficientNet achieving 85 per cent accuracy in the validation set. Future work could include expanding the dataset and adding more disease classes for improved generalization.

Keywords: Cassaa leaf diseases, Convolutional Neural Network CNN, Machine learning, Classification, Deep learning

1. Introduction

Cassava is an important staple crop in many countries, providing food security and income to millions of people. However, cassava plants are susceptible to various diseases that can significantly reduce crop yield and quality. These viral diseases are major sources of poor yields for cassava, the 2nd largest provider of carbohydrates in Africa. Early detection and accurate classification of these diseases are crucial for implementing effective control measures and minimizing crop losses. In this project, we developed a deep learning-based approach to classify 5 fine-grained cassava leaf disease categories using Convolutional Neural Networks (CNNs).

2. Datasets

The dataset consists of leaf images of the cassava plant, with 9,436 annotated images and 12,595 unlabeled images of cassava leaves. The goal is to learn a model to classify a given image into these 4 disease categories or a 5th category indicating a healthy leaf. Our data set is divided into training testing and vali- dation sets. For data preprocessing we applied some geometric transformations to move some of the pixels around and then rotate the images a bit, we did hor- izontal flips, zoom in and out on all the images in the training set.

3. Methods

3.1. Data Preprocessing

We initiated the study by acquiring a dataset of cassava leaf images, which comprised 9,436 annotated images and 12,595 unlabeled images. The dataset was subsequently divided into training, testing, and validation subsets.

To enhance the diversity of the training data, we applied various geometric transformations to the training set, including random resizing, horizontal and vertical flips, random rotations, and color jitter. Additionally, we carried out mean and standard deviation normalization on the images, ensuring standardized data input.

3.2. Class Weight Computation

In order to address the class imbalance issue, we computed class weights based on the frequency of labels in the training dataset. This strategic calculation offered greater importance to underrepresented classes during the training process, thereby achieving balance in learning.

3.3. Model Architecture

Our approach incorporated a ResNet-based model designed for cassava disease classification. We employed the pre-trained ResNet50 model as the backbone and customized the final fully-connected layer to produce the requisite number of classes. In this instance, the model was configured to classify cassava leaf diseases into five distinct categories.

3.4. Training

The model training phase was executed employing the Adam optimizer with a learning rate of 0.0002 and weight decay (L2 regularization) for model parameters. Training continued for 15 epochs. To mitigate the risk of overfitting, we implemented an early stopping mechanism. The training process persisted until no improvement in the validation loss was observed within a predefined patience period.

4. Mathematical Formulas

4.1. Cross-Entropy Loss

The Cross-Entropy Loss (also known as Log Loss) is a common loss function used in classification problems. For a single training example with predicted class probabilities y_{pred} and true class label y_{true}, the formula for the loss is as follows:

$$L(y_{true}, y_{pred}) = -\sum_{i=1}^{N} y_{true,i} \cdot \log(y_{pred,i})$$

Where: L **is the Cross-Entropy Loss.**
N **is the number of classes.**
$y_{\mathbf{true},i} isabinaryindicator(0or1)ifclassi$
is the correct classification for this example.
$y_{\mathbf{pred},i} isthepredictedprobabilitythatclassi$
is the correct classification for this example.

4.2. Adam Optimizer

The Adam optimizer is a popular optimization algorithm used for training neural networks. It combines the advantages of two other optimization methods: RMSprop and Stochastic Gradient Descent (SGD). The update rule for the parameter θ in the Adam optimizer is defined as follows:

$$\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{v_t} + \epsilon} m_t$$

Where:
α**: is the learning rate**
v_t
ϵ **: is a small constant to prevent division by zero.**.
These mathematical formulas represent key components of the training process for deep learning models.

5. Results

The CNN-based approach demonstrated promising results in classifying com- mon diseases of cassava. The model effectively learned distinctive features from the input images, enabling accurate disease classification. The use of cross- validation allowed us to assess the model's performance robustly and mitigate overfitting concerns. The achieved accuracy on the validation set indicated the model's ability to generalize well to unseen data. In this work we just work on the labeled data, to improve our work in the future, the dataset could be expanded using the unlabeled data to include more samples and additional disease classes to improve the model's ability to generalize to different cassava diseases.

5.1. Related work

Prior research in the field of cassava disease classification has predominantly focused on traditional methods of disease identification, such as visual inspection and manual assessment by experts. These methods, while effective to some extent, suffer from subjectivity and limited scalability. Recent advancements in machine learning and computer vision have opened up new avenues for automating disease classification in crops, including cassava.

Several studies have utilized Convolutional Neural Networks (CNNs) for plant disease classification, demonstrating promising results in identifying various crop diseases. In particular, the application of CNNs to cassava leaf disease classification has gained traction. Researchers have developed deep learning models trained on labeled datasets to accurately distinguish between different cassava leaf diseases, including common and rare variants.

6. Conclusion

In this project, we addressed the critical issue of cassava disease classification using a deep learning-based approach. By employing Convolutional Neural Networks, we achieved notable success in classifying five fine-grained cassava leaf disease categories. The model effectively learned essential features from cassava leaf images, allowing for accurate disease identification. The use of cross-validation ensured the robustness of our model and helped mitigate overfitting concerns.

Although the achieved accuracy on the validation set was promising, there is room for further improvement in future work. Expanding the dataset to incorporate unlabeled data and additional disease classes could enhance the model's capacity to generalize to various cassava diseases. Moreover, the exploration of more advanced deep learning architectures and techniques, as well as fine-tuning hyperparameters, may yield even better results. This project lays a foundation for the development of efficient and scalable solutions to combat cassava diseases, which pose a significant threat to food security and livelihoods in many regions.

notebook Link: GitHub

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