

# Report on Cassava Disease Classification Project

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## Team Members

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## I. Introduction

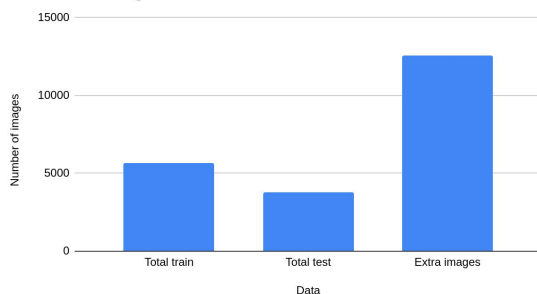
The project involved classifying pictures of cassava leaves into 1 of 4 disease categories (or healthy). The disease categories include Cassava Mosaic Disease(CMD), Cassava Brown Streak Disease(CBSD), Cassava Bacterial Blight(CBB), Cassava Green Mite(CGM).



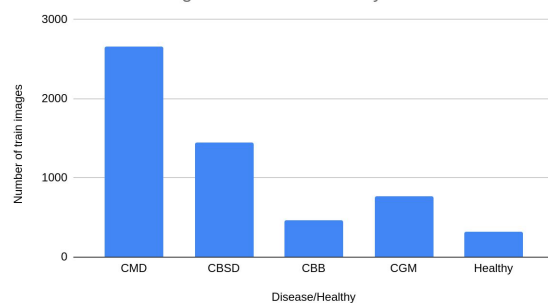
## Dataset

Dataset consists of **9,436** labeled and **12,595** unlabeled images of cassava plant leaves.

Number of images vs Data



Number of train images vs Disease/Healthy



Statistics of the Cassava Dataset. [Paper](#)

The graph shows training examples for CMD is twice more than every of the other classes. This creates a class imbalance.

**Project Assessment Criteria:** Top-1 Accuracy on test set.

## II. Approach

### Discussion on Research Paper

We read the paper to understand how the data was generated and annotated. The dataset was crowdsourced from approximately 200 farmers in Uganda with the same mobile devices. We also observed that different diseases have their unique symptoms while observing the training set.

### Data Preprocessing

- We split train data into 80% train and 20% validation using 5-fold stratified k-fold cross validation. The stratification was to cater for the imbalance in the dataset.
- Images were resized to 224px for small models and 500px for larger models.
- Different transforms such as centre cropping, rotation/affine transformation, horizontal and vertical flips.

### III. Results and Experiment

Table 1: Table Showing Different Experiments Performed.

| No | Model               | Train acc | Valid acc | Public LB      | Parameters |            |               |        |          |       |              |
|----|---------------------|-----------|-----------|----------------|------------|------------|---------------|--------|----------|-------|--------------|
|    |                     |           |           |                | optimizer  | Batch-size | Learning rate | Epochs | Drop-out | Folds | Extra-images |
| 1  | Resnet18            | 0.87      | 0.864     | 0.856          | SGD        | 16         | 0.0002        | 22     | No       | 5     | No           |
| 3  | Resnet34            | 0.8723    | 0.8736    | 0.8735         | Adam       | 16         | 0.0002        | 13     | No       | 2     | No           |
| 4  | Resnet50            | 0.8992    | 0.886     | 0.8741         | SGD        | 16         | 0.001         | 9      | No       | 5     | No           |
| 5  | Resnet50            | 0.9072    | 0.8993    | 0.90794        | SGD        | 16         | 0.001         | 20     | 0.5      | 5     | No           |
| 6  | Resnext101          | 0.9266    | 0.906     | 0.912          | SGD        | 16         | 0.0002        | 3      | 0.5      | 2     | No           |
| 7  | Resnext50           | 0.9651    | 0.909     | <b>0.91655</b> | Adam       | 8          | 0.001         | 10     | No       | 5     | No           |
| 8  | Ensemble of 5, 6, 7 |           |           | <b>0.92185</b> |            |            |               |        |          |       |              |
| 9  | Resnet50            | 0.9172    | 0.9108    | 0.910594       | SGD        | 16         | 0.001         | 20     | 0.5      | 5     | Yes          |
| 10 | Ensemble of 5, 6, 9 |           |           | <b>0.92384</b> |            |            |               |        |          |       | yes          |

### What we learnt

- Cross validation is important to understand how the model generalizes, especially for small datasets like this one.
- Dropout can help to prevent overfitting, especially in models with large capacity such as ResNet50.

### What did not work

- Extraimages did not significantly improve model performance during cross validation, when added to the training data.
- Some transforms like Random Erasing were not beneficial.

### Dealing with Extra Images

- We used our top-3 performing models to perform a pseudo-labelling of the examples.
- If the 3 models agree on a class, we add the example to our training data.

### Challenges

- Some images have more than one disease and could be classified into any of the classes. We tried label smoothing to cater for this.
- The large models took a lot of time to train, so difficult to iterate on ideas.