Deep Learning-Based Transfer Learning for Classification of Cassava Disease

Ademir G. da Costa Junior, Fábio S. da Silva, Ricardo Rios

Universidade do Estado do Amazonas (UEA)

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Introduction

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- In 30 years, world production of this tuber has more than doubled, with Brazil consolidating its position as a giant in the sector.
- Cassava has become a pillar of food security in vast regions of Africa, Asia and Central America, standing out for its resistance and hardiness.

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- Artificial Intelligence (AI) is emerging as a powerful tool in the field, revolutionizing the agricultural sector, especially in the early and accurate detection of diseases.
- Hypothesis: It is possible to train an effective Transfer Learning-based Convolutional Neural Network (CNN) model for this task.

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- Divided into five classes, four pathologies and the healthy category.

Class Distribution

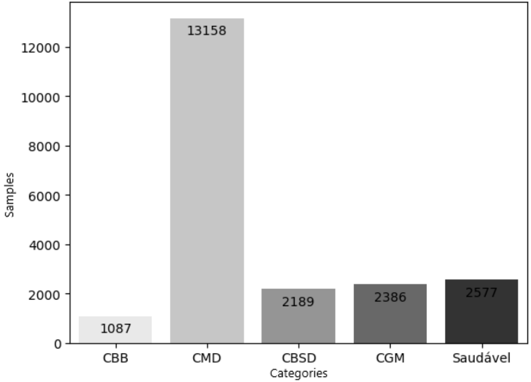

Figure 1: Graph of occurrences of each category in the data set.

Sample images

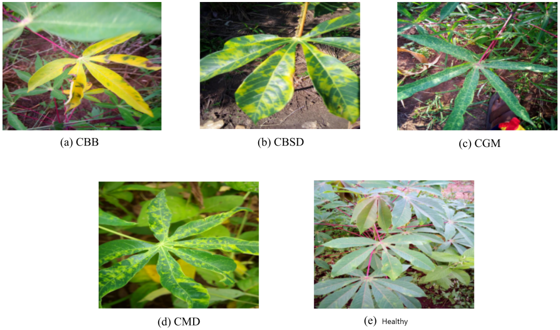

Figure 2: Images randomly selected from the dataset.

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- 20% for testing.

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- Evaluate the models in general and by class.

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- F-Score (F_1).

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- Batch size: 32

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- Rotation, random cropping, horizontal *flip* and brightness changes were used on the training images.

Results

Table 1: Results table

Models	Parameters (M)	Accuracy	Precision	Recall	F_1
EfficientNet-B3	12	0.877	0.878	0.877	0.877
InceptionV3	23.8	0.866	0.867	0.866	0.866
ResNet50	25.6	0.863	0.862	0.863	0.862
VGG16	138	0.615	0.378	0.615	0.468

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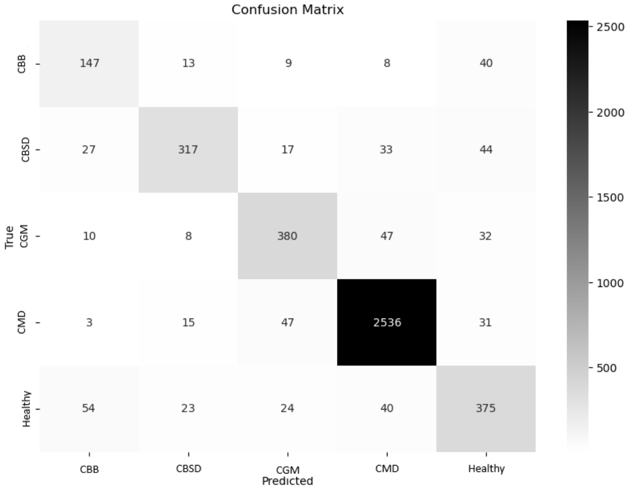
- InceptionV3 and ResNet50 presented results considered satisfactory, but were inferior to EffiecientNet-B3, with F_1 of 0.866 and 0.863, respectively.
- VGG16 struggled to generalize correctly on such an unbalanced dataset. All predictions tended to concentrate on the majority class. It is therefore considered a degenerate network.

EfficientNet-B3 Confusion Matrix



EfficientNet-B3 Classification Report

Table 2: Classification Report

class	precision	recall	f1-score	support
CBB	0.610	0.677	0.642	217
CBSD	0.843	0.724	0.779	438
CGM	0.797	0.797	0.797	477
CMD	0.952	0.964	0.958	2632
Healthy	0.718	0.727	0.723	516

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- **Most efficient model: EfficientNet-B3** with results considered satisfactory for the pathology classification task.
- Problem: VGG16 was unable to generalize the problem, perhaps it could be improved by varying the hyperparameters.

Future Work

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- Hyperparameter adjustment, especially for VGG16:
  - Optimizer
  - Initial Learning Rate
  - Other relevant parameters

Q&A