African Master's in Machine Intelligence

Course Tittle : Computer Vision

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Date : May, 2020.

1 Introduction

The Cassava Disease Classification is an in house kaggle competition, inspired by iCassava 2019Fine-Grained Visual Categorization Challenge. Cassava is known to be one of the key staples and food security crops in Africa, However, diseases that plague the crop are still a major challenge causing annual yield. The problem statement is therefore to device an automated tool could potentially guide experts to diagnose disease more reliably and enable farmers in remote places to monitor their crops without experts. The dataset consists of 9,436 labeled and 12,595 un-labeled images of cassava plant leaves. The annotations were 5 classes of images; healthy plant leaves (316/211train/val examples) and diseased plant leaves representing the 4 diseases; CMD (2658/1773 train/val), CBSD(1443/963 train/val), CBB (466/311 train/val), and CGM (773/516 train/val).

2 Methodology

The 3 main objectives of this project was to **(1)** have a robust model that could capture the different viewpoints and background of the image. To address that, we made did some data pre-processing i.e

- **Data Augmentation**: This strategy enabled us to significantly increase the diversity of data, with techniques such as cropping, padding, resizing, rotating, vertical and horizontal flipping were used
- **Data Normalization**: This technique were reduce redundancy and dependency of data. It was done separately for both the training and validation

(2) The model should be able to capture the different severity of disease as the diseases were very similar. To address this, we first stated with a simple 3 layer convolution Neural Network (A sample of what we had in CV 1, Lab 3), with that, we got an accuracy of 60%, it was observed that the model was too simple for the task, hence, we tried out different pretrained model (detailed would be given in the next section). With the use of pretrained models, vary severity of the diseases was captured and we had a much more better accuracy.

(3) Utilizing the unlabeled data was a very important task as in reality, there are much more unlabeled images than those annotated by experts. Thus, algorithms that utilize an abundance of un-labeled images and minimal labeled ones are preferred. To address this we tried out different models, and when we had gotten a "*good*" one, we then tried predicting with it on the unlabeled images (using a certain threshold), so we can add this pseudo labeled images to the training data, bu unfortunately due to the cross validation, it took so much time to train (more than 15 hours) hence, we were unable to finish up before the deadline for submission.

3 Summary of Models and Results

To begin with, we did some exploratory data analysis to visualize to see the distribution of the data. We got the know that the distribution of the classes was imbalance, to address this, we did what is called weighted loss (taking the count of the maximum class divided by the count of each class). The table below shows some of the models we experimented with.

Model	**Hyper Parameters** **learning rate, epoch, optimizer**	**Accuracy**
3 layers Convolution (baseline)	0.001 , 30, SGD + momentum	0.60
Resnet50	0.001, 20 , SGD + momentum	0.86
DenseNet169	0.0001 , 20 , Adam	0.88
Efficientnet-b5	0.001 , 10 , Adam	0.89
Efficientnet-b5 + One Cycle Policy Learning	0.001 , 10 , Adam	0.89
se_resnext 101 + CV + mix up	0.0004 , 5 , Adam	0.90
se_resnext 101 + CV+mix up + One Cycle Policy learning + TTA	0.0002 , 5 , Adam	0.92

Figure 1: ***The table above shows some of the different model we experimented with (space won't permit us write out all the models experimented), it contains the pretrained weights used, the learning rate, number of epoch and the optimizer used***

Training time:

• The training data set was further divided into training and validation set.

• Data preprocessing (data augmentation e.g flipping, random cropping, resizing)

• After trying out different models as seen above, it was observed that the **se_resnext 101 + CV+ mix up** 5. This model gave almost the same accuracy both on our personal computer and on the leader-board (compared to other models whose accuracy drops on the leader board, probability they were overfitting), hence, we decided to work more on this model. The next step was to have **se_resnext 101 + cross validation + One cycle policy learning + TTA**, the TTA involves creating multiple augmented copies of each image in the test set, having the model make a prediction for each, then returning an average of those predictions 5. (this was done at test time)

Inference Time:

• Resizing, centre cropping of the Image

• The TTA mentioned above.

4 Conclusion and Future work

This report is a step towards helping small-holder farmers monitor their plants and increase yields. This was an exploratory and eye opening exercise as we experimented and explored several techniques. To combat overfitting since we only had access to 40% of the text set, we took advantage of cross validation, data augmentations and mix-up. However, we had the challenge of training for longer hours with GPU. The future work would be to take advantage of model compression techniques like Quantization to creating a more lighter-weight model with minimal access to the cloud (an app), that would enable our solution to be easily accessible on farmers phones for easy diagnostic of plant diseases.

5 Reference

• https://arxiv.org/pdf/1803.09820.pdf : A discipline Approach to Neural network hyper-parameter.

• https://arxiv.org/abs/1710.09412 mix up: Beyond Empirical Risk Minimization