Cassava Disease Classification

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1 Introduction

This report summarises the findings and experiments of the in-class project for computer vision course.

2 Abstract

The objective is to provide a model to classify images of the cassava plant into 4 disease categories and healthy, given 9,436 annotated images and 12,595 unlabeled images of cassava leaves [1]. After the data prepossessing step we tackle the problem with two phases, first we use the labeled images to find our best model, then we fine-tune our best model using both the labeled and unlabeled images.

3 Supervised learning

- We started by downloading and visualising the data with different tools, we realised that the data was not balanced, to address this problem we use stratified cross validation to ensure a balanced distribution of labels during training.
- A simple convolution network with three $conv\_relu\_maxPool$ blocks model was our starting point, the model achieved 81% on the training set and 83% in the evaluation set.
- Then we move to **RESNET50** pretrained with ImageNet dateset, at the same time we introduced a bunch of data augmentation methods (Random Resize Crop, Random horizontal/vertical Flip, Normalisation, .. etc) and drop out to avoid over-fitting. We also introduced learning rate scheduler that seeks to adjust the learning rate during training . we achieved 86.3% in training set and 87.1% or the validation set. (Note: we use different augmentations for training and validation).

- Then we move to **RESNEXT50**, that uses group convolution, which provided a slightly better results, 87.4% in training and 87.9% in the evaluation.
- Finally we used **RESNEXT101** as a deeper version of RESNEXT family, that provided a train accuracy of 89.98% and evaluation accuracy of 90.05%

4 Semi-supervised learning

With **RESNEXT101** as our base-model we tried different semi-supervised learning experiments as follow:

1. We used our trained model to predict the labels of the extra images with various augmentations, then we defined 0.9 as threshold and accepted all the samples above the threshold as pseudo labels. we added the pseudo labeled images to our labeled images and retrained our model. The results was slightly better than the precious one. In order to make the data more balanced we got rid of the extra pseudo labeled images of the dominant category and retrained the model again. We achieved 91.3% in the train set and 92.3% in the validation set.
2. We tried different pseudo labelling approach that unitises a weighted sum of the labeled and the unlabeled losses, the results was slightly worth that out baseline model.
3. Lastly we tried a custom implementation of FixMatch paper, we still experimenting with this method. [2]

5 Results

Model	Train Accuracy	Evaluation Accuracy	Public Leaderboard
RESNET50	86.3	87.1	88.01
RESNEXT50	87.4	87.9	88.3
RESNECT101	90.1	90.5	90.26
PSEUDO-LABELING	91.3	92.3	90.5

6 Conclusion

RESNEXT101 model with semi-supervised learning achieved the best result. The most important lesson we can point to after this project is that you have to do your work in systematic and organised manor. Also, we touch the absolute importance of data processing and perceiving the characteristics of the data in hand before tackling the problem (eg. unbalanced data). We also encountered the notion of drop out, learning rate scheduler, semi-supervised learning, augmentation, average/max pooling, .. etc.

References

[1] Ernest Mwebaze, Timnit Gebru, Andrea Frome, Solomon Nsumba, and Jeremy Tusubira. icassava 2019 fine-grained visual categorization challenge. *arXiv preprint arXiv:1908.02900*, 2019.

[2] Kihyuk Sohn, David Berthelot, Chun-Liang Li, Zizhao Zhang, Nicholas Carlini, Ekin D Cubuk, Alex Kurakin, Han Zhang, and Colin Raffel. Fixmatch: Simplifying semi-supervised learning with consistency and confidence. *arXiv preprint arXiv:2001.07685*, 2020.