African Master's of Machine Intelligence

AIMS Senegal

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Course: Bootcamp
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1 Problem statement

Rice (Oryza sativa) is one of the staple foods worldwide. Paddy, the raw grain before removal of the husk, is cultivated in tropical climates, mainly in Asian countries. Paddy cultivation requires consistent supervision because several diseases and pests might affect the paddy crops, leading to up to 70 percent yield loss. Expert supervision is usually necessary to mitigate these diseases and prevent crop loss. With the limited availability of crop protection experts, manual disease diagnosis is tedious and expensive. Thus, it is becoming increasingly important to automate the disease identification process by leveraging computer vision-based techniques that have achieved promising results in various domains.

2 Objective

The main objective of this competition is to develop a machine or deep learning-based model to classify the given paddy leaf images accurately.

3 Hypothesis

For this task, our main objective is to build a robust model that is able to capture all patterns in the data and generalize well. The hypothesis we are looking forward to are;

- **Build a convolutional neural network from scratch** - this technique enables us to build a CNN model by choosing specific number of layers and activation functions. However this method may not yield great accuracy and also given the time frame, we might not have enough time to complete the project
- **Use of a pre-trained model** - this technique will enable us to use a state-of-the-art network in computer vision as a backbone model to train our network. Some of the models we are considering are the Resnet and Densenet variants. We also experiment with Convnext, which is developed entirely from the Convnets family.

4 Data exploration and methodology

We are provided a training dataset of 10,407 (75%) labeled images across ten classes (nine disease categories and normal leaf). Moreover, we are also provided additional metadata for each image, such as the paddy variety and age. The task is to classify each paddy image in the given test dataset of 3,469 (25 percent) images into one of the nine disease categories or a normal leaf.

- **CNN architecture** - the goal is to predict the disease categories with high accuracy so that this model can be applied in real life. To do this, first we started with a four-layer convolution network and obtained 62% accuracy. With this score, the model was not able to predict well. We also changed the learning rate, added momentum and batch normalization, and obtained an accuracy of 65%, which was still low. Hence, to get a better score, we tried different pretrained models. Using them, the accuracy improved significantly, and the models have a better capacity to predict the disease categories.
- **Pre-trained models** - we started training with **convnext_small_384_in22ft1k**. This model is from the Convnets variant which has been modified to improve accuracy, efficiency and scalability. We train this model on the training set of data for 40 epochs to achieve an accuracy of 96%. We experiment again with another variant of this model which a higher number of parameters to achieve an accuracy of 98%.
- **Data augmentation** - we employed several techniques including; resizing, random horizontal flip, cropping and rotation. This was a technique we used to improve the data we had for training our models.

5 Related papers

To complete this task we relied on state of the art models implemented from various paper. EfficientNet B4 model architecture from *EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks* (6). We also experimented with pretrained Residual Networks (ResNets) model architecture from *Deep Residual Learning for Image Recognition* (4). Pretrained ConvNeXt models from *A ConvNet for the 2020s* (5) were also fine-tuned for this classification task.

6 Results and discussion

The table shows different models we experimented.

Model	**Hyper parameters**	**Accuracy (%)**
4 layers convolution	lr=0.001, optimizer=Adam	62
convnext_small_in22ft1k	lr=0.002, optimizer=AdamP	98
convnext_small_384_in22ft1k	lr=0.002, optimizer=Adam	96
resnet26d	lr=0.01, optimizer=Adam	96
efficientnet_b4	lr=0.001, optimizer=Adam	97

Table 1: different models

The dataset was divided into training and test set. The number of epoch was set to be between 5-10. The model **convnext_small_in22ft1k** registered the highest of accuracy of **98%** on the test set.

7 Conclusion

This Kaggle competition is a step toward developing a robust model that will aid farmers in monitoring paddy diseases. The competition has given us an opportunity to learn a lot and put into practice most of the things we saw in class. We obtained a good accuracy that can always be improved by experimenting with other techniques. We did not have the GPU to properly test several other models for this project, which prohibited us from training for a long time. Furthermore, the training was slow, and some of the models could run for hours at a time. Understanding which model to employ among the several available pretrained models was also difficult, and much of the work was done by trial and error.

References

[1] `https://timm.fast.ai`.

[2] `https://towardsdatascience.com/getting-started-with-pytorch-image-models-timm-a-prac`

[3] We adopted a code from Kaggle, which can be found at `https://www.kaggle.com/code/peterpetrov826/saving-paddy-with-fastai-0-982-on-lb`.

[4] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016.

[5] Zhuang Liu, Hanzi Mao, Chao-Yuan Wu, Christoph Feichtenhofer, Trevor Darrell, and Saining Xie. A convnet for the 2020s. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11976–11986, 2022.

[6] Mingxing Tan and Quoc Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning*, pages 6105–6114. PMLR, 2019.