Potchara Wongyai
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potchara.wongyai@gmail.com

Plant Images Classification

How can we help farmers to work less and get better yields in their farms?

The answer is machine learning! Many areas of agricultural work can be automated, and better decisions can be made using machine learning. In this project, we focus on a computer vision problem, which is to classify different species of plant seedlings based on their images.

2 acres of farmland in Chiangrai, Thailand

Background:

The purpose of this project is to develop an image classification model, which will serve as a starting tool for an intelligence farming system that will be prototyped in a family-owned farm in Chiangrai, Thailand, in 2023.

The system will utilize machine learning in the following areas:

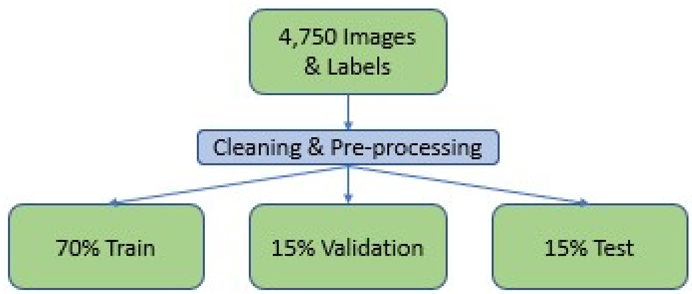
- Identify optimized water and fertilization mixtures that maximize growth for each plant type
- From aerial images taken by a camera drone:
    - **Classify plant types**
    - Monitor growth based on plant types
    - Detect disease or condition based on plant types

Therefore, the ability to classify plant types is essential to the success of this prototype farm.

Dataset

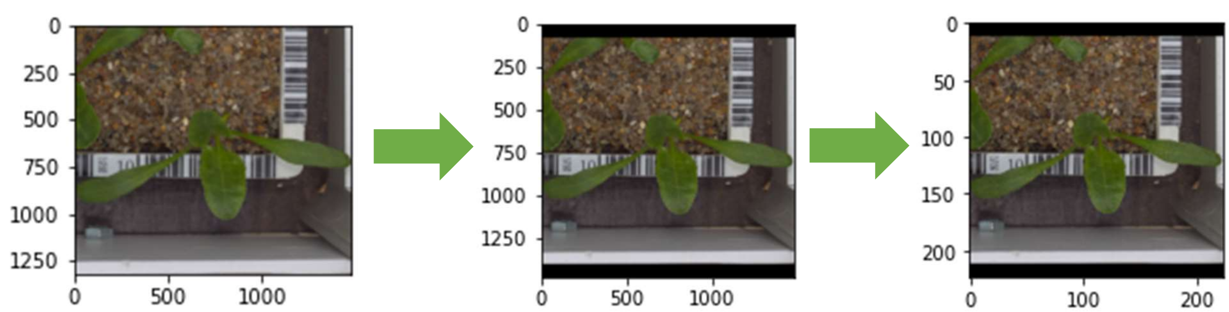
The dataset originated from the Aarhus University Signal Processing group in collaboration with University of Southern Denmark, and it was also used in a Kaggle competition in 2017. The dataset was downloaded from Kaggle. It contains 4,750 training images of plant seedlings in 12 different species with labels, and 974 testing images without labels. Only the images with labels were used in this project since their prediction accuracy can be measured. The training images were cleaned and split into 3 datasets including: 70% train, 15% validation, and 15% validation. Note, the stratify method was used to ensure that images in all 12 classes were split evenly into each dataset.

List of classes: Black-grass, Charlock, Cleavers, Common Chickweed, Common wheat, Fat Hen, Loose, Silky-bent, Maize, Scentless Mayweed, Shepherds Purse, Small-flowered Cranesbill, and Sugar beet.



Cleaning & Pre-processing

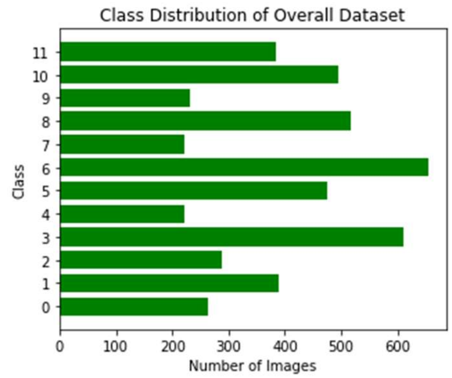
Cleaning: The raw images came in different sizes and shapes, so the first step of cleaning is to make them the same size. To avoid distortion, a black background was added to each image to maintain the aspect ratio of 1. The images were then resized to 224 x 244 pixels. After this step, the images were organized into an array with a shape of 4750, 224, 224, 3 (number of images, height, width, RGB channels). No missing value was found (meaning that every pixel contains a number). However, there were 3 duplicated images, which were removed.



Pre-processing: The pixel values were converted from the range between 0 to 255 to the range between 0 and 1 in order to reduce the magnitude of the variance and help the model perform more efficiently. The labels associated with each class were converted to class numbers (Class 0 to Class 11) as required by the loss function during modelling. In addition, various filters and image dimensional reduction were experimented at the pre-processing stage, but they did not yield any improvement in modelling.

Insights, Modelling, and Results

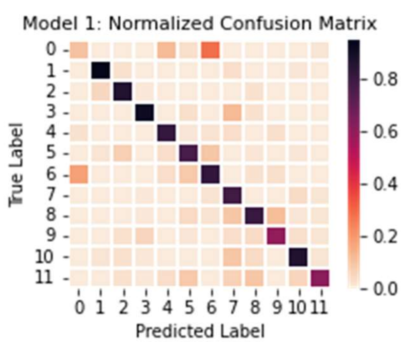
Insights: It was found during EDA that the number of images per class was not well balanced, which can lead to modelling bias of a certain class. From reviewing the images, some plants look similar. For example, Class 0 (Black-grass), Class 4 (Common wheat), and Class 6 (Loose Silky-bent) all have thin leaves, so they can be difficult to distinguish. Other classes have more distinct features, but if they are in the early stage of growth, those features might not appear.

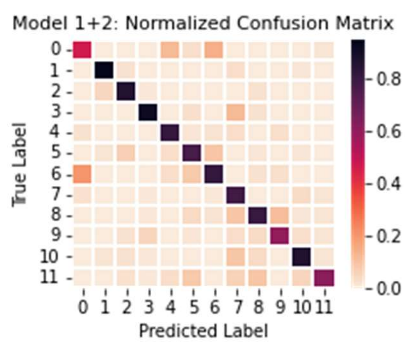


Modelling: Since this is an image classification problem, CNN models were selected. Various techniques such as ImageDataGenerator, up-sampling, adding, or removing CNN layers, and transfer learning were investigated through trials and errors. The final models below provide reasonable prediction scores.

Model	Objective	Construction	Technique Applied	Cross Validation	Model Scores (Test Data)
1	Predict 12 classes	CNN with 11 layers	ImageDataGenerator	5 folds	Avg Precision: 77% Avg Recall: 78%
2	Predict only between Class 0 and Class 6	ResNet50V2 with 7 added layers	Up-sampling	5 folds	**(Combined Model 1 & 2)** Avg Precision: 80% Avg Recall: 80%

Results: Model 1 has high overall prediction scores (precision, recall); however, Class 0 only got 10% of recall largely due to the misclassifications with Class 6. This is reasonable since both plants have similar features as mentioned above. Model 2 was trained specifically for reclassify all the images that were predicted as Class 0 or Class 6. Using both models together, the prediction of Class 0 greatly improved (precision increased by 31%, and recall increased by 36%) as illustrated in the plots below, while the overall model scores also improved slightly. Note, the confusion matrices below are normalized based on the true number of images in each class. The diagonal line represents recall.





Findings & Conclusions

The combined model was able to achieve relatively high prediction scores, which is surprising since plant images are generally difficult to classify by human eyes. The initial model had a difficulty separating between the two classes with similar leaves. Nevertheless, we were able to mitigate this issue by introducing the second model, which was specifically trained to classify the two classes.

For the real use case, we can use the model developed as the starting tool for the prototype farm, or apply the methodology learned in this project to develop a new CNN model. However, new challenges are expected since drone images will be different from the images in this dataset, which seem to be under a controlled environment.

To further improve the model, we can experiment with more CNN layers and keep adjusting the hyperparameters. However, we should also investigate images that are wrongly predicted and understand the reason behind it.