Machine Learning Engineer Nanodegree

Capstone Project

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July 16th, 2018

I. Definition

Project Overview

Farmers have been spraying their fields with herbicides for decades to reduce weeds. So far one herbicide mixture was used to spray an entire field. This is not a very effective approach. Massive usage of herbicides are expensive, bad for the environment and may lead to resistance in the weeds. Also a herbicide mixture that is effective against one species of weed can have little or no effect on another species. Not to mention that the herbicide may be damaging to the crop it is supposed to protect. A better approach would be a system that can recognise weeds from crops and only spray at places where it is needed.

Aarhus University in Denmark is working on a project to create weedmaps of a field from a tractor to pinpoint where a certain species of weed resides on a field. They have released a dataset of images of 960 unique plants belonging to 12 species at several growth stages.

Kaggle is hosting this dataset as a Kaggle competition. in order to give it wider exposure and to give the community an opportunity to experiment with different image recognition techniques.

Problem Statement

For this project we have to detect which species of plant is in each image of the dataset described above. Each image contains one seedling which has to be classified into one of twelve species.
The solution to this problem is a model trained to predict the plant species for a given image.

- Input: An image of a plant.
- Output: The name of the plant species on the image.

Steps taken to complete this task

1. Imported the required data sets.
2. Displayed some sample images for each plant to get a visual idea of the problem.
3. Separate the data set into training, validation, and testing sets.
4. Do some preprocessing converting to tensors and normalization and so on.
5. Augmenting and oversampling the dataset by using horizontal flipping, rotation, zoom and so on.
6. Create a few models using the transfer learning approach with pre-trained network as well as a neural network started from scratch.
7. Fine tune the model(s) using different optimizers and adjusting multiple parameters.
8. The F1-score will be calculated as described in the section "Evaluation metrics" above.
9. Finally my score will be compared to the leaderboard on Kaggle.

The desired outcome of this project is to show that it is indeed possible to automatically detect weeds so the spraying of herbicides can be applied as sparingly and as effectively as possible.

Metrics

I used the mean multi-class F1 score as the metric to evaluate my solution.
See scikit-learn.org

> The F1 score can be interpreted as a weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recall to the F1 score are equal. The formula for the F1 score is:

$$F_1 = \frac{2 * precision * recall}{precision + recall}$$

> In the multi-class and multi-label case, this is the weighted average of the F1 score of each class.

Precision is the ability of the classifier not to label as positive a sample that is negative. In formula:

$$precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

Recall is the ability of the classifier to find all the positive samples. In formula:

$$recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

The F1 score is also used by Kaggle as the metric to evaluate the solutions for this problem.link

Loss Function: Categorical Cross Entropy

Cross-entropy loss measures the performance of a classification model whose output is a probability value between 0 and 1. The lower the value the better the predicted probability matches the label. A perfect model would have a log loss of 0.
The formula for Categorical Cross Entropy is:

$$\sum_{c=1}^{M} y_{o,c} ln(p_{o,c})$$

where …

- M - number of classes (dog, cat, fish)
- ln - the natural log
- y - binary indicator (0 or 1) if class label c is the correct classification for observation o
- p - predicted probability observation o is of class c

More information can be found here and here.

II. Analysis

Data Exploration

The train and test datasets can be found on kaggle. There are 4751 images for training and

794 images for testing. Each image has a filename that is its unique id. The dataset comprises 12 plant species. The list of species is as follows:

Danish	English	Latin	EPPO code
Majs	Maize	Zea mays L.	ZEAMX
Vinterhvede	Common wheat	Triticum aestivum L.	TRZAX
Sukkerroe	Sugar beet	Beta vulgaris var. altissima	BEAVA
Lugtløs kamille	Scentless Mayweed	Matricaria perforata Mérat	MATIN
Fuglegræs	Common Chickweed	Stellaria media	STEME
Hyrdetaske	Shepherd’s Purse	Capsella bursa-pastoris	CAPBP
Burresnerre	Cleavers	Galium aparine L.	GALAP
Agersennep	Charlock	Sinapis arvensis L.	SINAR
Hvidmelet gåsefod	Fat Hen	Chenopodium album L.	CHEAL
Liden storkenæb	Small-flowered Cranesbill	Geranium pusillum	GERSS
Agerrævehale	Black-grass	Alopecurus myosuroides	ALOMY
Vindaks	Loose Silky-bent	Apera spica-venti	APESV
EPPO codes are computer codes			

developed for plants, pests (including pathogens) which are important in agriculture and plant protection.			

The images are of different sizes. The smallest 49 X 49 the largest 3991 X 3457. In order to use a Convolutional Neural Network, images are rescaled to one size (224 px by 224 px).

Below is an image of each species.

black grass	charlock	chickweed	cleavers
			

common wheat	cranesbill	fat hen	loose silky bent
			

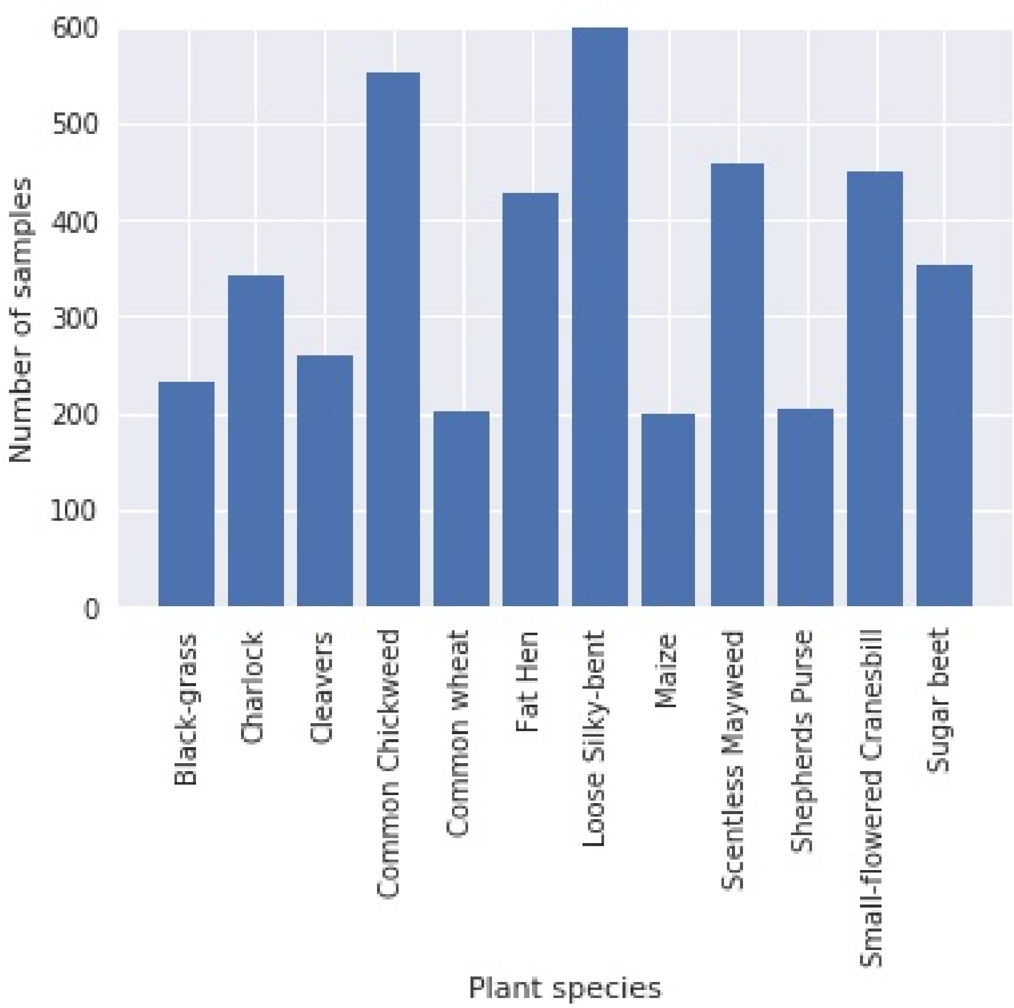
maize	scentless mayweed	shepherds purse	sugar beet
			

This is not a trivial problem Some species are very hard to to tell apart. Even for a human being!

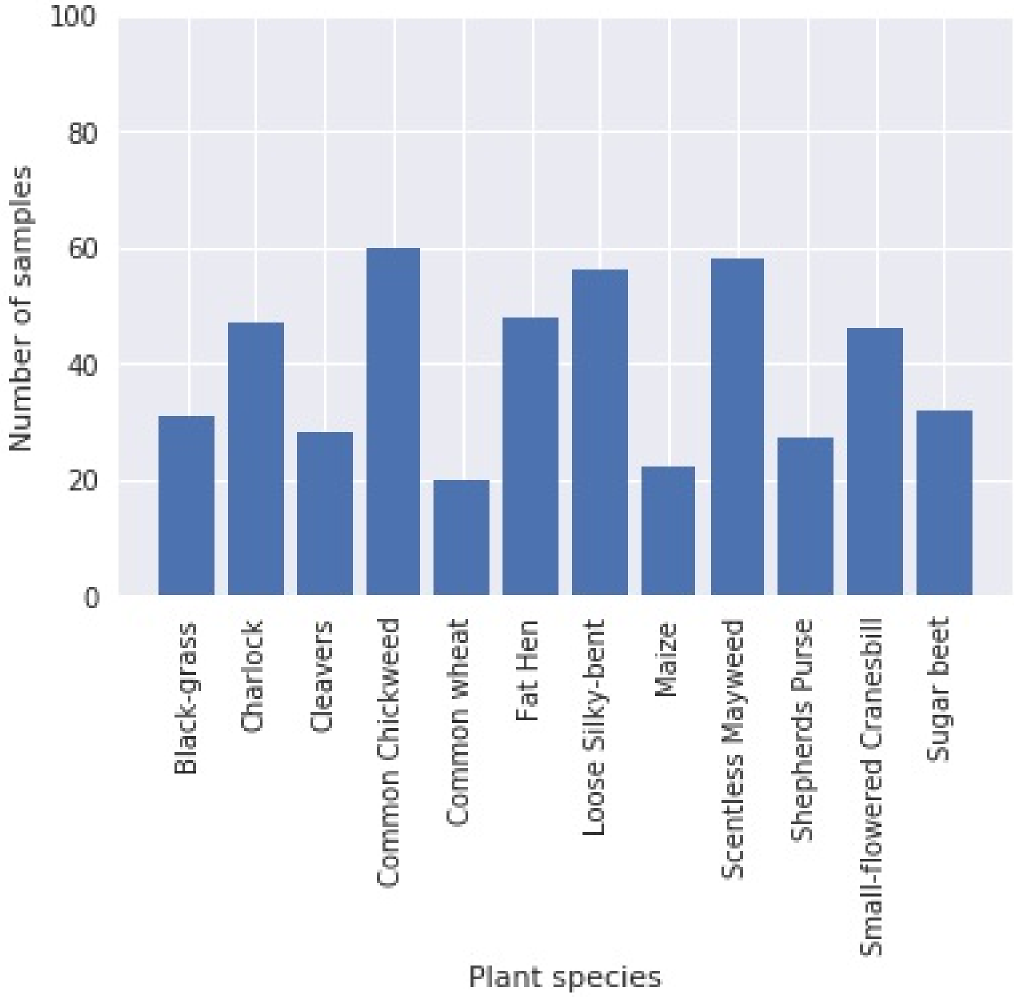
Exploratory Visualization

After loading the data in a jupyter notebook I split the data into a training set and a test set. Below are the distribution plots of these sets.

Training set



Testing set



There is a large mismatch in the set. For some species there are only 200 samples in the set and for others 600. A factor of 3. Also the complete data set could be larger. So I have augmented the data set using techniques shown here and here.

Algorithms and Techniques

CNN

A convolutional neural network (CNN) is a class of artificial deep neural networks. For image classifying problems (such as this project) this is a commonly used solution. CNN's consists of multiple layers. The layers I used are described below.

Convolutional layers

The convolutional layer is where the Convolutional Neural Network get it's name from. The layer has a set of learnable filters (or kernels), which have a small receptive window. Each filter moves across the width and height of the input volume during the forward pass. Each step the dot product between the entries of the filter and the input is calculated. This results in a 2-

dimensional activation map of that filter.
In the code a convolutional layer is added in the following manner.
`Conv2D(filters=32, kernel_size=2,strides=1,activation='relu')`
This layer has the following parameters.

- filters: Integer, the dimensionality of the output space (i.e. the number of output filters in the convolution).
- kernel_size: Integer, specifying both the height and width of the (square) convolution window.
- strides: Step-size of the convolution.
- activation: Activation function to use. I use ReLu described in the hyperparameters section below.
  The first (and only the first) convolutional layer has also an input_shape parameter. This is a Tuple specifying the height, width, and depth of the input.

Max Pooling layers

The role of the pooling layer is to reduce the dimensionality of the CNN. The max pooling layer takes a stack of feature maps as input. The max pooling layer slides over each feature map and calculates the maximum value in the window. The result is a stack with the same number of feature maps but with each feature map reduced in width and height. In code a pooling layer is added as follows

`MaxPooling2D(pool_size=2,strides=2)`

- pool_size: Number specifying the height and width of the square pooling window.
- strides: The vertical and horizontal stride.

Global average Pooling layer

The global average pooling layer is different from the max pooling layer in that we don't give the window size or stride. It calculates the average for each feature map. The result is a stack where each feature map is reduced to a single value.

Dense layers

The dense layer is as the Keras documentation puts it "Just your regular densely-connected NN layer". In the code it is added as

`Dense(len(data['target_names']),activation='softmax')`

The first parameter is the number of classes. The activation is softmax is explained in the hyperparameters section below.

Optimizers

In this project I use Adam. Adam is an optimization algorithm to update network weights iterative based in training data. Adam is a very popular algorithm in deep learning because it achieves good results fast. I used Adam with the default options defined in Keras.

Hyperparameters

In tuning the CNN I used the following hyperparameters.

Learning rate

The learning rate controls how much to update the weight in the optimization algorithm.

Number of epochs

Number of epochs is the the number of times the entire training set pass through the neural network. The optimum number of epochs is where the gap between the test error and the training error is the smallest.

Batch size

The batch size defines number of samples that is going to be propagated through the network together. A small batch is usually preferable in the learning process of CNN. A range of 16 to 128 is a good choice to test with. I used a batch size of 20. This means that the algorithm takes first 20 samples (from 1st to 20th) from the training dataset and trains network. Next it takes second 20 samples (from 21st to 40th) and trains the network again, and so on.

Activation function

Every activation function takes a single number and performs a certain fixed mathematical operation on it. There are several activation functions available. In this project I used the ReLu (Rectified Linear Unit) activation function.
In Relu $a(x)=x$ for $x > 0$ and $a(x) = 0$ for $x <= 0$.

Softmax function

The softmax function is often used in the final layer of a neural network-based classifier. Softmax assigns decimal probabilities to each class in a multi-class problem. Naturally those decimal probabilities must add up to 1.0. This additional constraint helps training converge more quickly.

Transfer Learning

In transfer learning knowledge gained during training in one type of problem is used to expedite the training in another related type of problem.

For image recognition with deep learning, the first few of layers are trained to identify features such as edges and colors. The last layers are used to classify objects such as cars or cats. So, during transfer learning, you can remove the last few layers of the pre-trained network and retrain with fresh layers for the problem you want to classify.

There are quite a few pre-trained networks available. In this project I use three well known pre-trained networks VGG16, VGG19, and ResNet50.

Benchmark

As part of the Plant seedlings classification project Kaggle hosts a page were people can share their kernels. As a benchmark I took the most popular at this time, the kernel shared by Beluga. I downloaded his submission.csv and submitted it to Kaggle. A score of 0.84005 was returned. So this is the score I want to improve.

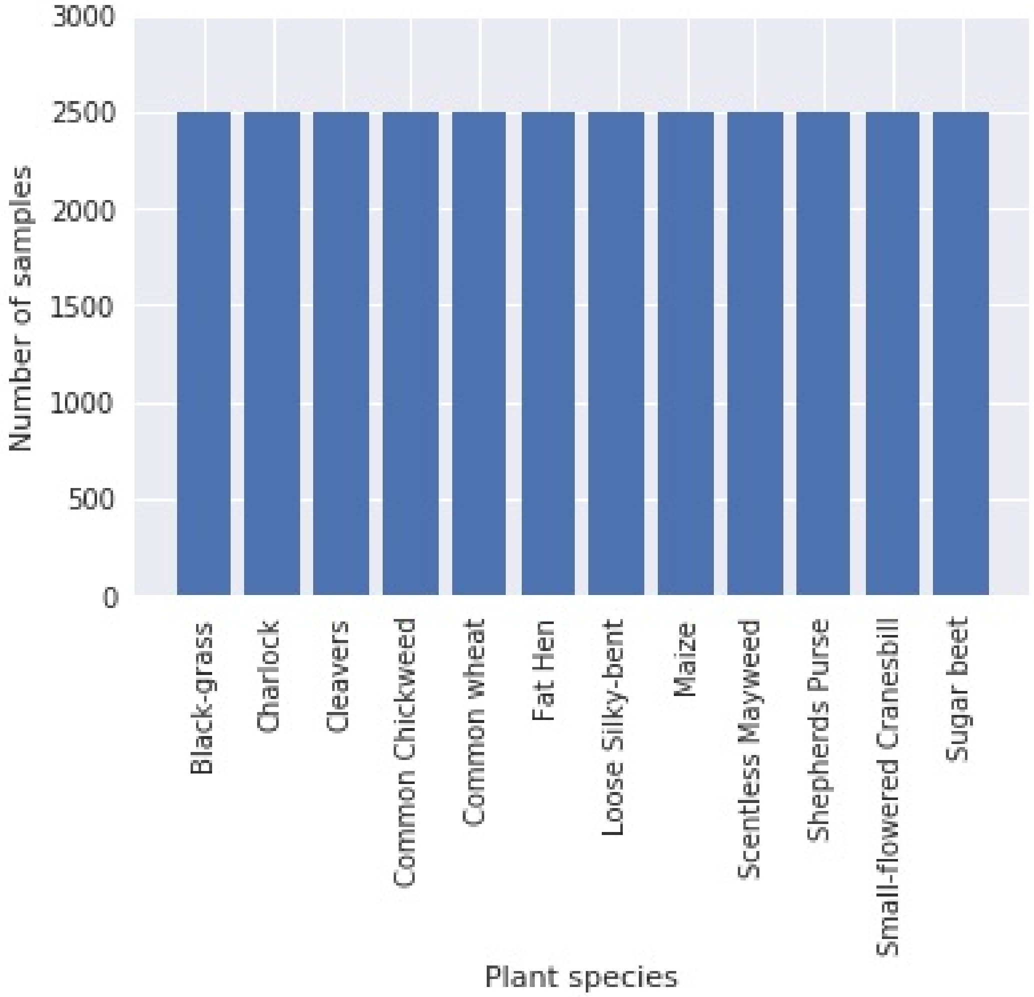
III. Methodology

Data Preprocessing

The data was split into a training set and a test set. Targets were one-hot-encoded, converting them from integers to vectors with length 12 (the number of plant species). The images were loaded into memory, resized to a resolution of 224 x 244 with 3 RGB channels, and converted to tensors.

As explained in the Data Exploration section above there was a large mismatch in the dataset were some species were represented by 600 images and other by only 200. Overall we could use more data. So data augmentation techniques were used to balance and enlarge the dataset. Using Keras ImageDataGenerator class I applied random rotations, zooms, and shifts in height and width.

This created a an even distribution with a lot more data as shown below.



Implementation

I created Convolutional Neural Networks to classify the images using the following approaches:
I used three approaches approaches to create a Convolutional Neural Network to classify images:

- Building a CNN from scratch.
- Transfer Learning on the VGG16 network.
- Transfer Learning on the VGG19 network.
- Transfer Learning on the ResNet50 network.

CNN from scratch

I started with the neural network I used in the dog classification project. However the results were not great. So after a lot of experimentation I ended up with the network below.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 223, 223, 16)      208
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 111, 111, 16)      0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 110, 110, 32)      2080
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 55, 55, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 54, 54, 64)        8256
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 27, 27, 64)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 26, 26, 128)       32896
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 13, 13, 128)       0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 12, 12, 256)       131328
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 6, 6, 256)         0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 12)                3084
=================================================================
Total params: 177,852
Trainable params: 177,852
Non-trainable params: 0
```

I also tried drop out layers but they had a negative impact on the result.

Transfer Learning

For the transfer learning experiments (VGG16, VGG19, and ResNet50) I followed the approach I learned in the CNN section of the Udacity course.

- I removed the toplayers, set the lower layers to non-trainable to keep features like edges and shapes.
- Added a new fully connected layer with 12 nodes. The 12 is the number of classes in the dataset.
- Train the network to update the weights of the new fully connected layer.
  The transfer learning models are to large to print here as I printed the basic CNN from scratch. Therefore I refer the interested reader to to the accompanying html exports. For example to find the VGG16 model I used look into the capstone_mlnd_vgg16_export.html file in section "Train and evaluate the models" you will find the VGG16 model I used printed.

Metrics

Keras does not offer a build in F1 metric so I used code I found on stackoverflow. This code can be found on the accompanying notebook in section "Calculating f1 score". Here follows an explanation of how the F1 metric is calculated. First some terminology:

True Positives are samples that are correctly identified as belonging to a certain class. This is calculated by

```
true_positives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
```

Here y_true is the class and y_pred is the predicted class.

False Positives are samples that are identified as belonging to a certain class, but was actually something else.

True Negatives are samples that are correctly marked as not belonging to a certain class. We don't need the true negatives to calculate the f1 score.

False Negatives are samples that should have been identified as a member of a class but mistakenly selected as not belonging to this class.

The predicted positives are the true positives plus the false positives. This is calculated by

```
predicted_positives = K.sum(K.round(K.clip(y_pred, 0, 1)))
```

The possible positives are the true positives plus the false negatives.
This is calculated by

```
possible_positives = K.sum(K.round(K.clip(y_true, 0, 1)))
```

Now we can calculate precision as

```
precision = true_positives / (predicted_positives + K.epsilon())
```

Here K.epsilon() is a numeric fuzzing constant used to avoid dividing by zero.

The recall is calculated as

```
recall = true_positives / (possible_positives + K.epsilon())
```

Finally we use precision and recall to calculate F1.

```
2*((precision*recall)/(precision+recall+K.epsilon()))
```

Evaluation methods

The confusion matrices were calculated using code I adapted from the scikit-learn documentation. This code can be found on the accompanying notebook in section "Evaluation functions".

The best model definition and weights for each were saved out to an hdf5 file with that model's name.

The F1 score and confusion matrix of each model was printed and an html export of the notebook was made for each model.

Predictions of the unlabeled set were made for each model and send to Kaggle.

Refinement

First models

Thinking an image is an image I started with the neural network I used for the dog-project. This gave a disappointing result. An F1 score of 0.09 ouch.

So I started from scratch with a simple model. I used a rather brute force method adding layers until more layers did no longer improve the results. After that I played with dropout layers but that had a negative effect. I ended up with the model I described in the "CNN from scratch" section and ended up with an F1 score of 0.882, not too bad.

using Augmented dataset

Second I augmented the data as described in "Data preprocessing" this resulted in an F1 score of 0.937. Better.

Transferred learning using VGG16 and VG19

Next I used transferred learning using VGG16 and VGG19 and ResNet50. This gave me the following F1 scores:

F1 scores

Network	Given dataset	Augmented dataset	Kaggle
CNN from scratch	0.882	0.937	0.92443
VGG16	0.878	0.886	0.88413
VGG19	0.882	0.930	0.92065
ResNet50	0.941	0.932	0.92569

As expected the VGG16 and VGG19 models performed better with the larger dataset. However the Resnet50 model did better with the smaller dataset.

IV. Results

Model Evaluation and Validation

The ResNet50 model gives the best results and is therefore the preferred model. Interestingly this Resnet50 model did not need a the larger augmented data set to perform well. It also had the greatest score at the unlabeled dataset send to Kaggle (Although the VGG19, and the home-made CNN were very close). This means that the performance of the Resnet50 does not vary greatly if it is exposed to a new dataset it never saw before. Let's look at the normalized confusion matrix of the ResNet50 model.

Here we can see that most plants are properly classified. Only the Black grass and the Loose Silky-bent are recognized less than 90% of the times.

Justification

All 4 models I tried did improve on the bench mark on the benchmark(0.84005). The highest score I received was 0.92569 for the ResNet50 prediction. However I also compared my score with the leaderboard.

I compared the scores I received from Kaggle with those on the leaderboard. There were 836 submissions to the leaderboard. The scores ranged from 1.000 for number 1 to 0.04534 for number 836. The score I received from Kaggle for the Resnet50 model is 0.92569. This would place me at rank 520. Clearly there is room for improvement, which I will discuss in the Improvement section below.

Is the solution good enough to solve the problem? I think it is. Weeds do not come alone and a farmer is not going to spray a field for one strand of grass. Even with the lowest recognition rate of 74% for black grass a patch of weed will be recognized. Even when the system misidentifies a strand of black grass the majority of the neighbours will be correctly recognized and the correct herbicide will be applied. That said other Kagglers have shown a better result is possible and we should strive for that, which will be discussed in the last section.

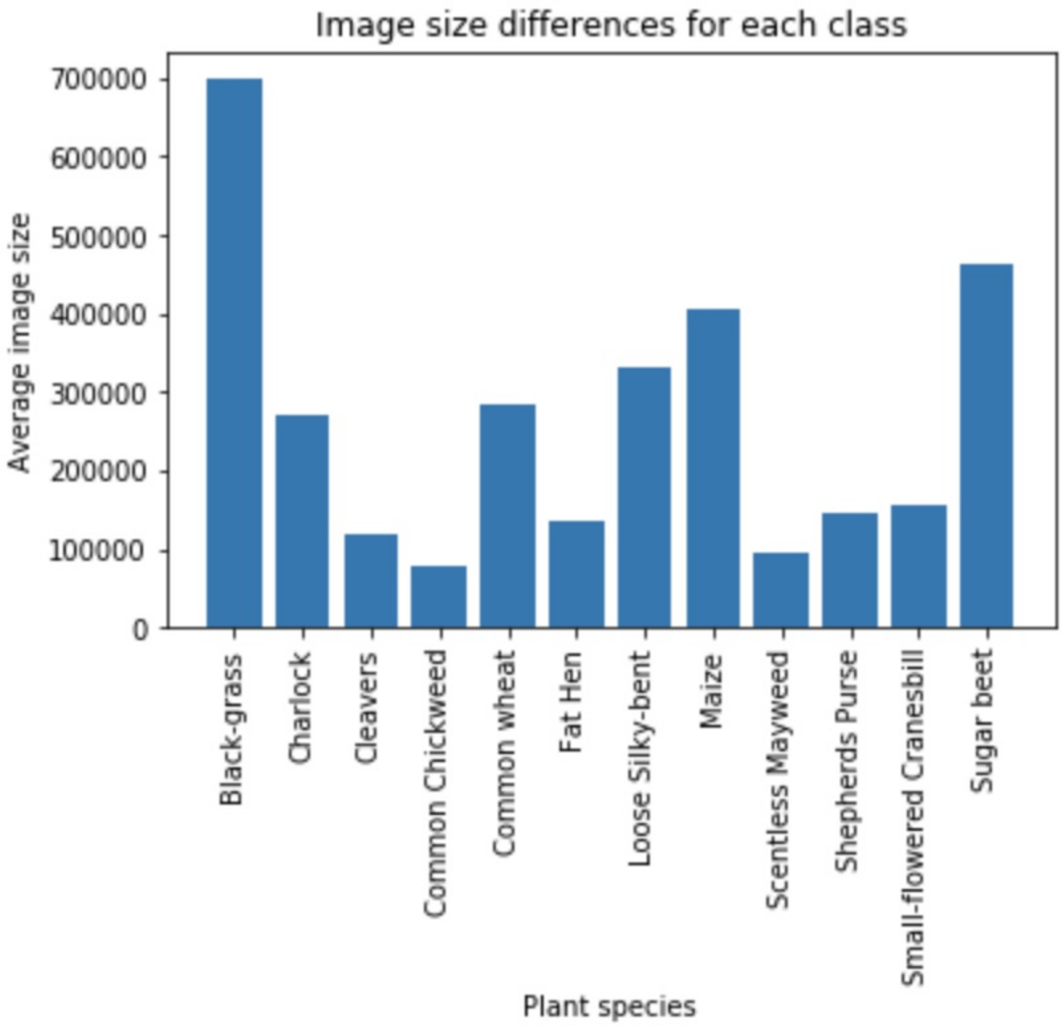
V. Conclusion

Free-Form Visualization

In resizing the image some information is lost namely the size of the plant. It was given that the images had a physical resolution of roughly 10 pixels per mm. By resizing the image we resize the appearance of the size of the plant. To investigate this further I created a second notebook with the name get_sizes.ipynb. Here I plotted the average size of the area of the images for each category. Naturally the area was calculated by

area = width * height

This resulted in the following plot:



We see a large difference in average image size between the species, ranging from less than 100.000 pixels to 700.000 pixels (width * height). For most species this is not a problem as the models classified them correctly anyway. But most importantly the images of Black grass are on average more than two times the size of the Loose Silky-bent. As the models struggled to separate these two species it may be needed to take the real sizes of the plants into account if the suggestions for improvements below do not give better results.

Reflection

This project was executed in the following steps.

- The labeled and unlabeled datasets was retrieved from Kaggle.
- I used Floydhub.com to get the GPU power I needed.
- Sample images were shown to get an idea about the data.
- The labeled data was split in a training set and a test set.
- The images in te training and test set were resized and converted to tensors.
- The training set was augmented by flipping, rotating, translating, and zooming.
- A CNN model was created from scratch.
- Transfer learning models were used VGG16, VGG19, and ResNet50
- The augmented set was used to train the models and the test set was used to evaluate.
- F1 scores were calculated using code found on stackoverflow
- Confusion matrices were created with code from the Scikit-learn documentation.
- The trained models used the unlabeled dataset from Kaggle to create predictions.
- The predictions were send to Kaggle for evaluation.

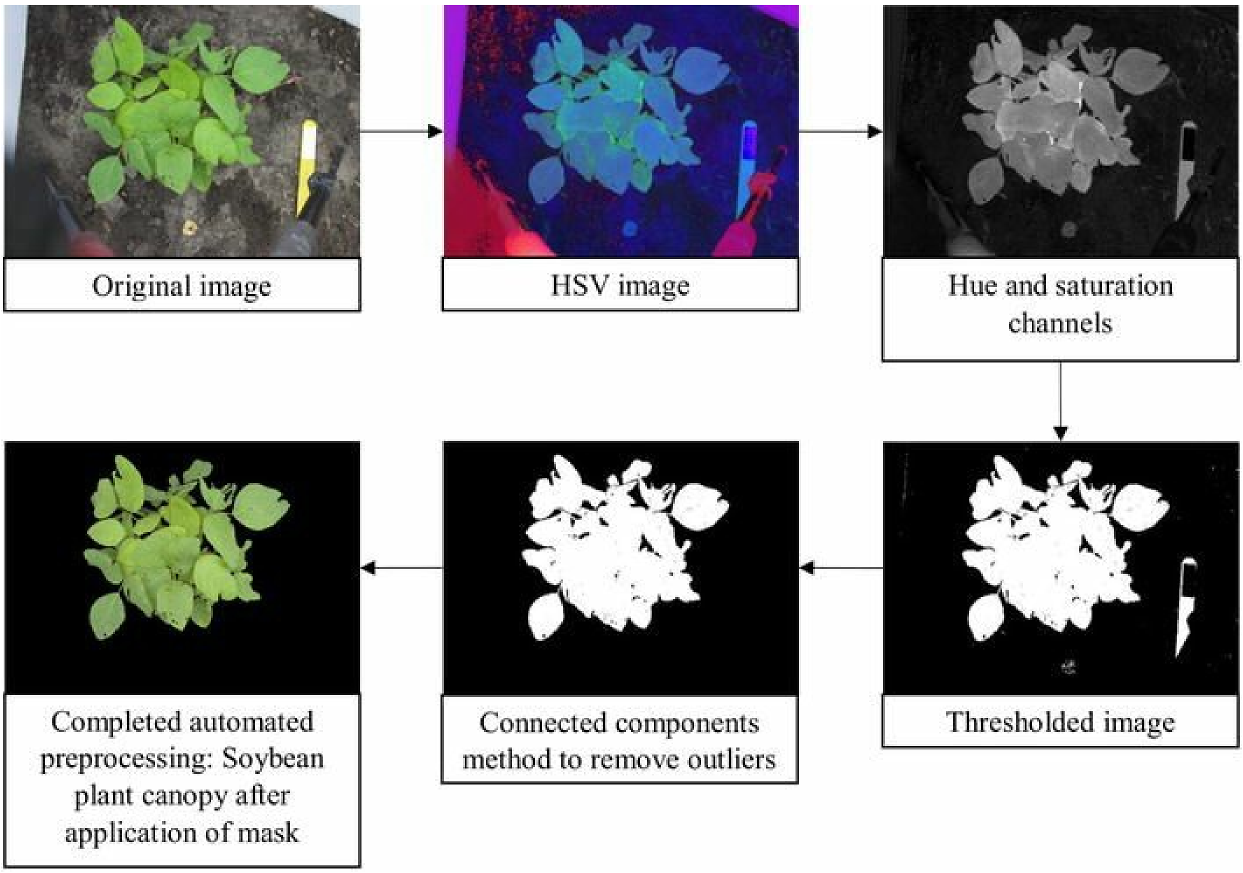
This project was much more difficult and time consuming than the classifying dog project. I was impressed by the power of Convolutional Neural Networks in classifying plant species that look very similar. It is satisfying to know that the models used could reduce the amount of herbicides used.
One thing I found particularly interesting is the influence of augmented dataset. The impact showed clearly that getting more data is often more important in deep learning than tweaking parameters.

Improvement

While the current results would already be helpful for the farmer to decide which parts of the field needs to be sprayed with herbicide some Kagglers proved that better results are possible. This section is about improvement. I see two possible avenues of improvements.

Additional hyper-parameter tuning or using other pre-trained models such as inception-V3 or xception could make a difference. However the model does already well for 10 out of 12 species so most of the improvement can be gained by better recognizing the remaining two, Black grass and Loose Silky-bent. A better approach would therefore be to build a separate model to better separate those two.

A second more promising avenue of improvement is to further improve the data. It is no surprise that the models we have seen so far have the most difficulty with Black grass and Loose Silky-bent. Black grass is a tiny grass blade surrounded by pebbles and markers and Loose silky-bent is a tiny grass blade surrounded by pebbles and markers. Those are easily confused. The small size could also lead the model to see the pebbles and markers as features. To solve this we could use image preprocessing techniques to remove the background pebbles and markers. These techniques are described by Petre Lameski who used this techniques for image detection of tobacco, carrots, and spinach and Mads Dyrmann. The figure below demonstrates the removal of the background.



Separating the plant from the background. From Mads Dyrmann.

After the removal of the background of all the images the model would no longer be distracted by pebbles and markers. This would possibly yield better results in the distinction between Black grass Loose Silky-bent.

References

- Kaggle seedlings evaluation

- Scikit-learn.org f1 score
- Roboweedmaps at Aarhus University in Denmark
- Kaggle competition
- Explanation loss function
- Explanation cross entropy loss
- Keras ImageDataGenerator class
- stackoverflow calculate F1
- scikit-learn documentation - confusion matrix
- Petre Lameski
- Mads Dyrmann
- Floydhub.com
- Kernel shared by Beluga
- Adam