Machine Learning Engineer Nanodegree
Capstone Project
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Aerial Cactus Identification (Determine whether an image contains a columnar cactus)

DEFINITION

Project Overview

VIGIA project [1] is a project based in Mexico developed to assist government led efforts to preserve natural areas. The traditional surveillance mechanisms have been insufficient to log and monitor the impacts of climate change and human activities on the flora and fauna. The goal of VIGIA project is to build an automatic surveillance of such protected areas.
To build such a system various tools and technologies are used such as unmanned aircrafts (drones) equipped with a camera or cameras to take aerial imagery of the protected areas. The imagery can then be fed into a computer vision recognition system to distinguish flora/fauna, log the number of a certain protected species, etc.
Specifically in this project/competition [2], the task of computer vision recognition system is to detect a certain species of cactus. To lead the way in protecting the flora (specifically columnar cactus) in protected natural areas, aerial imagery taken from unmanned aircraft can be fed into a system which utilizes state-of-the-art computer vision and machine learning methods to assist in the recognition task.

Problem Statement

Climate change and human encroachment to natural areas especially spread across a vast area of land (often remote) is difficult to be surveyed manually. Such threats in these areas can be recognized and monitored in an efficient and resourceful manner with imagery obtained from unmanned air vehicles and analyzing them.
The problem statement of this competition is to predict whether an image captured from the unmanned aircraft is a columnar cactus species (*Neobuxbaumia tetetz*o) or not. This is a two class problem where the predictions will be whether an image contains the columnar cactus or not.
This is a binary classification problem where if an image contains a columnar cactus it is predicted to have a probability closer to 1 else closer to 0. It can also be set as 1 or 0 based on a threshold such as 0.5, i.e if probabilities are greater than 0.5 then set to 1 else 0.

The strategy to solve this problem can be outlined in the following bullet points.

1. Read the train and test data images

2. Convert the JPEG images to RGB pixel information and convert to floating tensors for use in the neural network (specifically CNN)
3. Re-scale the pixel information from 0-255 to a [0, 1] interval.
4. Apply a simple CNN-based model on the data to get the benchmark model to compare against future improved CNN models.
5. Improved models will optimize on this benchmark model using various measures such as image data augmentation, using batch normalization, regularization techniques, etc.
6. Further well-established image classification models such as VGG16/19, InceptionV3, MobileNet, etc. whichever appropriate will be used to get an even better model.
7. The result to be submitted will be in a *.csv* file and of the format as shown below:
    a. **Id -** *name of the image file in the test folder*
    b. **Has_cactus** - *the predicted probability of the image being a cactus*
8. Predict the probabilities in the validation set images and check the validation accuracy.
9. Predict probability of cactus for Kaggle submissions.

Metrics

The final evaluation metric used for Kaggle submission (for test data) is Area Under Receiver Operating Characteristics (ROC) curve. ROC curve is a plot of true positive rate (TPR) against false positive rate (FPR). TPR is the ratio of true positives over all positives. FPR is the ratio of false positives over all negatives.
TPR = TP/P ; FPR = FP/N.
All positives is the sum of true positive and false negative.
All negatives is the sum of true negative and false positive.

As for the training dataset, the evaluation metric used is accuracy which is a ratio of the sum of true positives and sum of true negatives over the total dataset.
Accuracy = (TP + TN)/total dataset size

ANALYSIS

Data Exploration

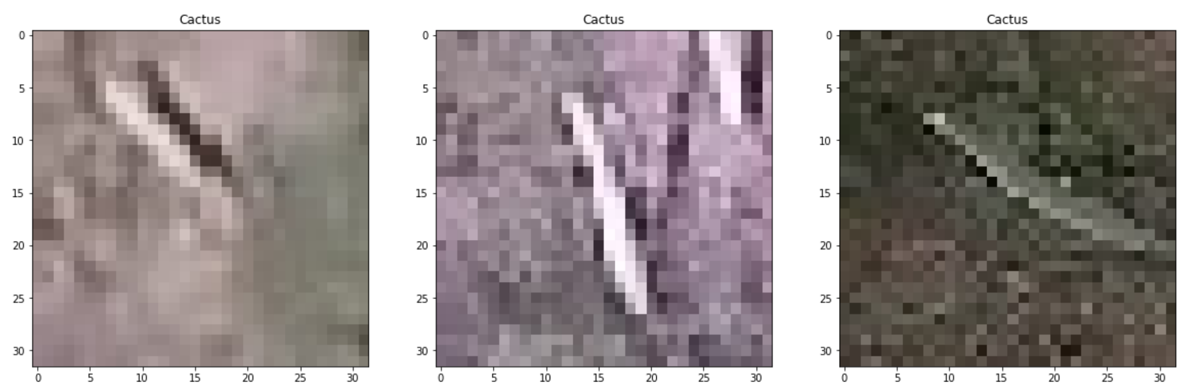
The dataset can be downloaded from the link in [3].
The aerial cactus identification competition [2] contains dataset with large number of 32x32 thumbnail images of aerial photos of cacti. The image dataset has been resized for uniformity. The dataset consists of train and test images in **train** and **test** folders respectively. **Train.csv** contains two columns **id** and **has_cactus**. The **id** column has the image name which can be fetched from the **train** folder. The **has_cactus** column is training image label, 1 if it has a cactus

else 0. There are 17500 training images and 4000 testing images in the train and test folder respectively.
The dataset in file **train.csv** looks like the following.

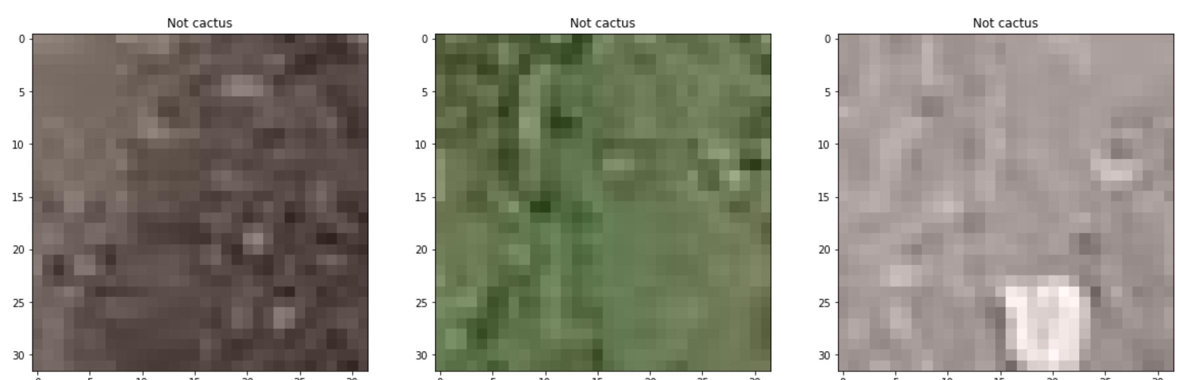
	id	has_cactus
0	0004be2cfeaba1c0361d39e2b000257b.jpg	1
1	000c8a36845c0208e833c79c1bffedd1.jpg	1
2	000d1e9a533f62e55c289303b072733d.jpg	1
3	0011485b40695e9138e92d0b3fb55128.jpg	1
4	0014d7a11e90b62848904c1418fc8cf2.jpg	1

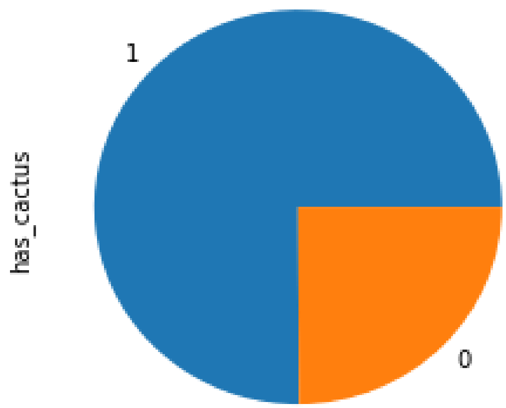
Exploratory Visualization

Some sample images of images having cactus are shown below:



Some sample images of images having no cactus are shown below:





We can see that there are a larger number of cactus images (13,136) than there are no cactus (4363) images in the dataset.

Algorithms and Techniques

CNN (convolutional neural network) classifier is a state-of-art classifier for image classification. It uses convolution kernel/filter to extract features from each dimension of images which can be represented as a matrix of RGB values. The convolution operation superimposes the filter onto the image matrix to obtain a feature map out of the image matrix. For example, the convolution of a 32x 32 input image matrix with a 3x3 filter is done by superpositioning the filter on the image, and then adding the product of the values from filter and the values from the image matrix. This is done over the image matrix to give an output feature map. Stride is a parameter which can be used to determine how the filter should shift.
Max pooling layer extracts features from input feature map in a certain window size, say 2x2 and outputs maximum value in this region.
Relu activation layer adds nonlinearity like tanh and sigmoid but relu helps solve the vanishing gradient problem which occurs especially when training a large network. Vanishing gradient problem is where the gradient decreases exponentially in the backpropagation algorithm while updating the weights resulting in slow to no update to the weights.
Dropout layers are used to reduce overfitting which is a technique where given a probability value such a 0.5, 50% of the neurons are randomly chosen and are not used in the training phase.

In the next run of the training, another set of 50% randomly chosen nodes will be skipped in the training and so on.
Above building blocks can be used to build a simple CNN model to train the images in the dataset.
To further improve the model, **data augmentation** can be done. Let's take a scenario where a classifier is being trained on perfectly centered images, despite good training accuracy, on not-so-perfectly centered images in the test dataset the model will underperform. To cater to diverse images with shift in their position from center, horizontal flip of the images, etc. data augmentation techniques can be employed in the training data.
Transfer learning takes a pre-trained model which has its own network architecture and weights, which can be frozen and only the lower layers can be trained for the problem dataset at hand. The high level features weights from the top layers are then fine-tuned to the problem at hand by connecting this top layers to a self-designed fully connected network architecture to obtain a final model. For this project, VGG16 model with weights from 'imagenet' dataset is used for transfer learning.
For the **loss function**, since it is a binary classification problem we use binary cross entropy or log loss function where y is the label and p(y) is the predicted probability of being y for all N points.

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

As for **optimizers,** adam optimization algorithm is used. Unlike stochastic gradient descent algorithm which maintains a single learning rate which doesn't change throughout the training, adam has a learning rate for each network weight or parameter and is adapted during the training phase.

Benchmark
A simple benchmark model comprises of three convolutional 2D layers (16, 32, 64) of kernel size 3x3. All of these layers use relu activation. Three max pooling layers (2x2) follow each of these convolutional 2D layers. And, later these are trained on 500 node fully connected layer with relu activation, and a 1 node layer since it is a binary classification problem. The final layer of single node is set with sigmoid activation to give probability estimates for each class.

```
model = Sequential()
model.add(Conv2D(16, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model.add(MaxPool2D(2, 2))
model.add(Conv2D(32, (3, 3), activation='relu'))
```

model.add(MaxPool2D(2, 2))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPool2D(2, 2))
model.add(Flatten())
model.add(Dense(500, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

This model gave a val_loss of 0.0478 and a validation accuracy of 98.40%.
Also, results from [4] show a very high recognition accuracy of 95% on the validation set of columnar cactus identification tas with an image dataset of more than 10, 000 images. These two models, this simple CNN and another benchmark of 95% accuracy will be used to assess the quality of the machine learning model.

METHODOLOGY

Data Preprocessing

In the data preprocessing step all the field values of train data column has_cactus was made into a string field. Also, all the images are scaled to be between 0 and 1 by dividing them by 255 value.
There is a class imbalance issue, since there are 13,136 images of cactus vs 4363 images of no cactus in the dataset. Using sklearn library's class_weight module, class weight were computed from the training data and used in the training.
In the image augmentation step, keras' ImageDataGenerator module is used to transform the training images. To maintain the nature of cactus and not distort its shape haphazardly, only width_shift_range, heigh_shift_range and horizontal_flip parameters were adjusted.
Width_shift_range does random horizontal shifts, **heigh_shift_range** does random vertical shifts and **horizontal_flip** flips the image horizontally.

Implementation

The training dataset was shuffled and 70% were used in training and 30% were used in validation.

Model 1: Benchmark model (as discussed above)

Model 2: Benchmark model with Dropout layers of 0.1 probability to reduce overfitting.
model = Sequential()
model.add(Conv2D(16, (3, 3), activation='relu', input_shape=(32, 32, 3)))

```
model.add(MaxPool2D(2, 2))
model.add(Dropout(0.1))
model.add(Conv2D(32, (3, 3), activation='relu'))
model.add(Dropout(0.1))
model.add(MaxPool2D(2, 2))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(Dropout(0.1))
model.add(MaxPool2D(2, 2))
model.add(Flatten())
model.add(Dense(500, activation='relu'))
model.add(Dropout(0.1))
model.add(Dense(1, activation='sigmoid'))
```

Refinement

In the refinement step, image augmentation techniques and pre-trained classifier VGG16 model was explored and these models result predictions on the test dataset were submitted to Kaggle.

Model 3. Model 3 but trained with augmented image data.

In the image augmentation step, the parameters were set as, **Width_shift_range**=0.1, **heigh_shift_range=0.1** and **horizontal_flip** was set to True.

Model 4. VGG16 model.

The VGG16 top layers were not included and for the lower layers, three dense layers of node size 500, 300 and 100 were used with activation function ‘relu’. BatchNormalization and Dropout layers with 0.5 probability of dropout were used following each dense layer. And for the final output layer a single node dense layer with ‘sigmoid’ activation was used.

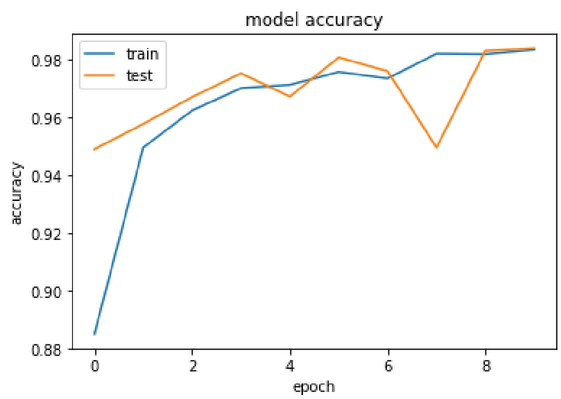
```
vgg_model = Sequential()
vgg_model.add(vgg16)
vgg_model.add(Flatten())
vgg_model.add(Dense(500, activation = 'relu'))
vgg_model.add(BatchNormalization())
vgg_model.add(Dropout(0.5))
vgg_model.add(Dense(300, activation = 'relu'))
vgg_model.add(BatchNormalization())
vgg_model.add(Dropout(0.5))
vgg_model.add(Dense(100, activation = 'relu'))
```

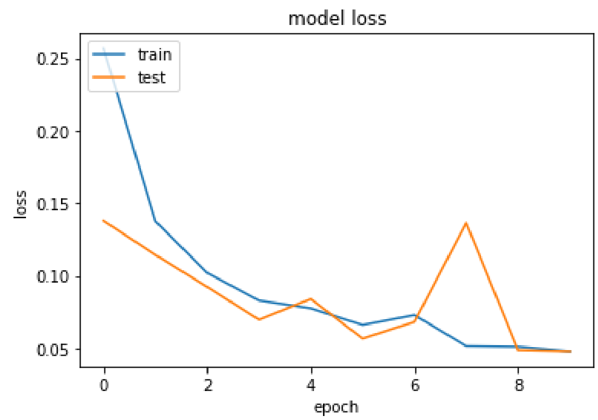
vgg_model.add(BatchNormalization())
vgg_model.add(Dropout(0.5))
vgg_model.add(Dense(1, activation = 'sigmoid'))

RESULTS

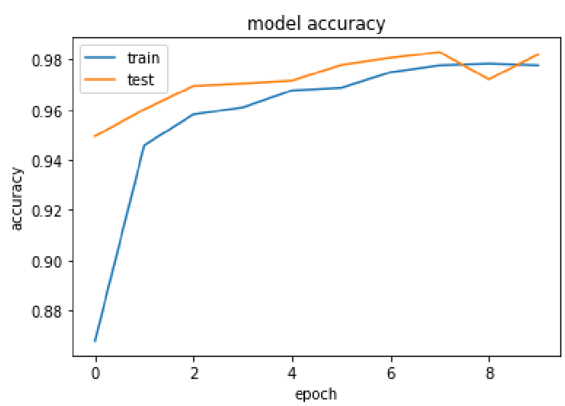
Model Evaluation and Validation

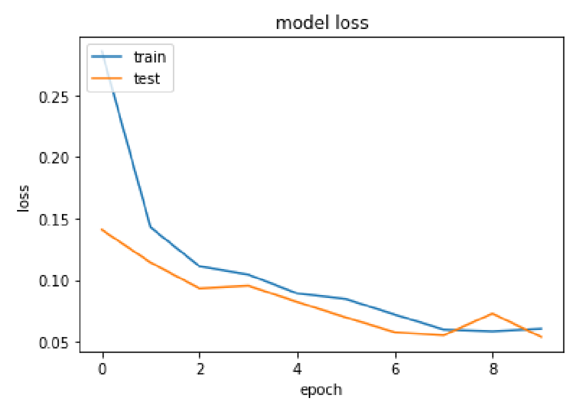
Model 1: This model gave a val_loss of 0.0478 and a validation accuracy of 98.40%.



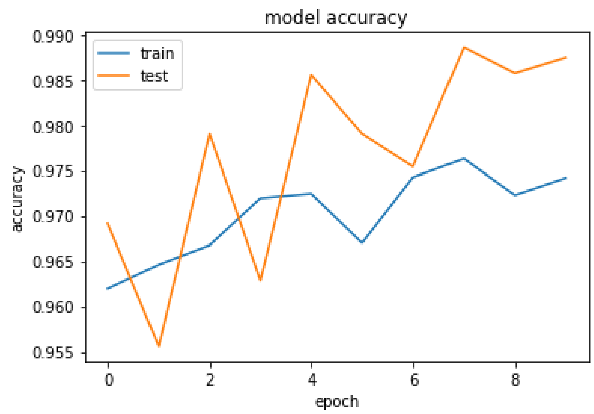


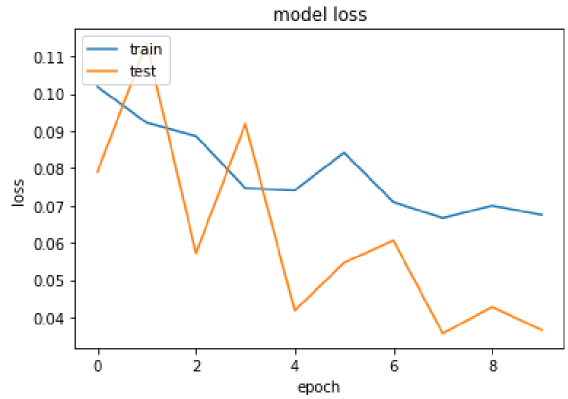
Model 2: This model gave a val_loss of 0.0539 and a validation accuracy of 98.21%.



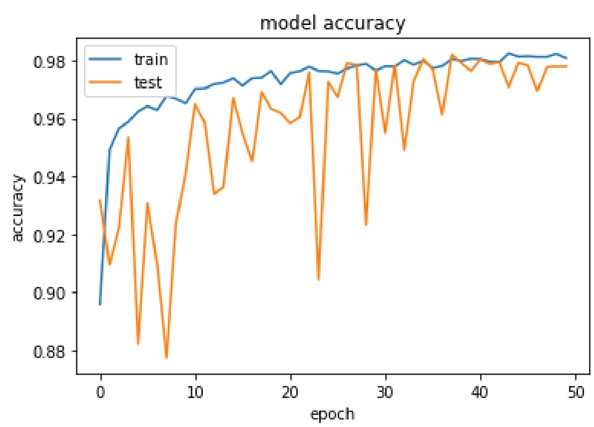


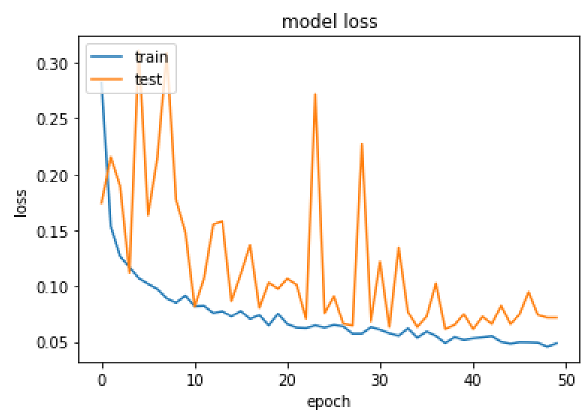
Model 3: This model gave a val_loss of 0.0357 and a validation accuracy of 98.86%.





Model 4: This model gave a val_loss of 0.0632 and a validation accuracy of 98.06%





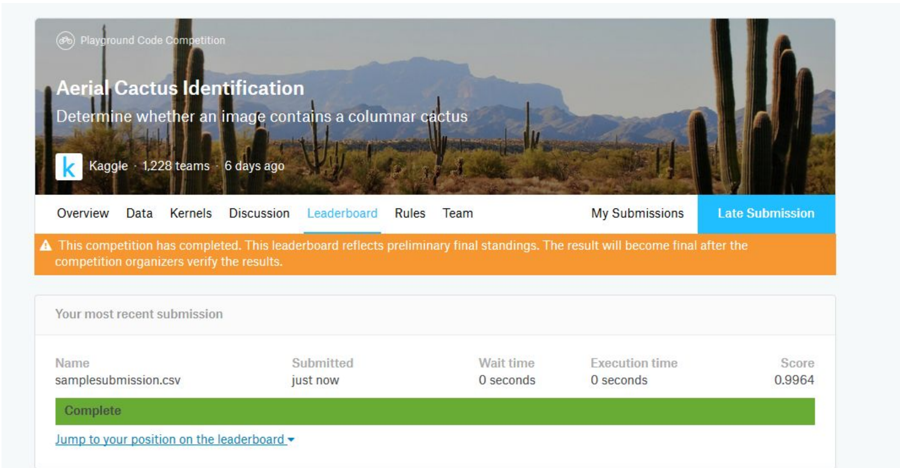
Justification

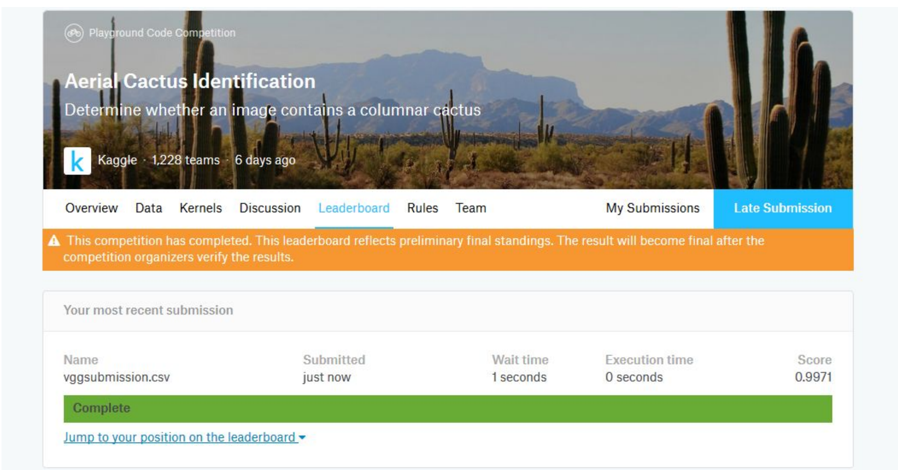
All the models validation accuracy is in the range of 98% which is better than the 95% accuracy obtained in [4], which makes the models good for solving the problem at hand. Model 1 outperforms all of them, yet it is a simple CNN model without Dropout, Image Augmentation. Model 3 was a refinement over Model 2 with that training data being fed were augmented. However, for an unseen dataset, a simple CNN model such as in Model 1 may not be adaptive to new and unseen dataset, so using a pre-trained VGG16 model could help build a generic enough classifier. This was the goal in building Model 4.

CONCLUSION

Free-Form Visualization

The test dataset was predicted using Model 3 and submitted to Kaggle to obtain a score of 0.9964 score for area under ROC curve.





The test dataset was predicted using Model 4 and submitted to Kaggle to obtain a score of 0.9971 score for area under ROC curve. Snapshots from the kaggle submission has been shown here to show that VGG model performed better in the unseen dataset as it has a better area under the ROC curve than Model 3.

Reflection

Reflecting back on the strategy used in this project, key points can be summarized below:

1. Read the train and test data images.
2. Convert JPEG images values to RGB pixel information and to floating tensors to be fed into neural network.
3. Re-scaling is done to all images to a [0,1] interval by dividing by 255.
4. Benchmark model is built to get a simple CNN architecture.
5. Refinement over benchmark model is done by adding Dropout layers and doing image augmentation.

6. To cater for large unseen dataset, a well-established pre-trained model like VGG16 model was used.
7. For each model, their validation losses and validation accuracies were observed.
10. The result were submitted will be in a *.csv* file to Kaggle and of the format as shown below:
    a. **Id -** *name of the image file in the test folder*
    b. **Has_cactus** - *the predicted probability of the image being a cactus*

Improvement

Some improvements for the project could be the following points

1. Using other pre-trained models and see how they perform.
2. Exploring other image augmentation techniques.
3. Exploring other network architecture to connect as lower layers of pre-trained classifiers such as VGG16.
4. Training for more epochs could be done but might overfit so it has been avoided in the project results.

References:

[1] https://jivg.org/research-projects/vigia/
[2] https://www.kaggle.com/c/aerial-cactus-identification/data
[3] https://www.kaggle.com/c/13435/download-all
[4] López-Jiménez, Efren, et al. "Columnar cactus recognition in aerial images using a deep learning approach." *Ecological Informatics* 52 (2019): 131-138.