Capstone Project

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Dog Breed Classifier (CNN)

Overview

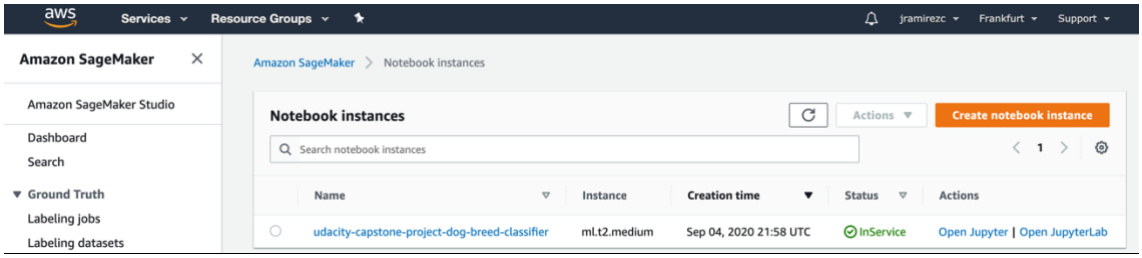
This capstone project has the objective of creating an application able to categorize dogs estimating the closer canine's breed using AWS capabilities. The whole solution will be composed on different components that will be developed in the following steps.

Step 1 Model Selection

The initial section will describe the required steps and the analysis for selecting the best model to perform the classification task.

Step 1.1: Environment Set Up

The initial step is to set up an environment for working. Using Amazon SageMaker Notebook instances we can access to a JupyterLab with preconfigured environments ready with many useful libraries for Machine Learning.



In this case I have selected pytorch_p36 as environment as most of my models will use pytorch library.

Step 1.2: Download and Import Datasets

Once the environment is ready the next step is to download the required datasets into the environment. I have used these code lines to download them.

```
%mkdir ../data
!wget -O ../data/dogImages.zip https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip
!wget -O ../data/lfw.tgz http://vis-www.cs.umass.edu/lfw/lfw.tgz
!tar -zxf ../data/lfw.tgz -C ../data/
!unzip ../data/dogImages.zip -d ../data/
```

The dataset for humans is composed by 13233 total human images and the dog's dataset is composed by 8351 total dog images.

Step 1.3: Detect Humans

In the following step we will create a human detector with the idea of having a function able to detect if there is a human in the image and change the output.
We can use OpenCV's implementation of Haar feature-based cascade classifiers for the human detector. OpenCV provides many pre-trained face detectors, stored as XML files the detector have been downloaded from OpenCV git repository and stored it in the haarcascades directory. The final detector code including a test is shown in the following snippet:

```
def face_detector(img_path):
    img = cv2.imread(img_path)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    faces = face_cascade.detectMultiScale(gray)
    return len(faces) > 0

human_files_short = human_files[:100]
dog_files_short = dog_files[:100]

print("Detecting human faces in human_files_short")
human_results_short = [ face_detector(img_path) for img_path in human_files_short]
print(f" Detected {sum(human_results_short)} human faces")
print("Detecting human faces in dog_files_short")
dog_results_short = [ face_detector(img_path) for img_path in dog_files_short ]
print(f" Detected {sum(dog_results_short)} human faces")

--------------------------------------------------------------------------------
Output:

Detecting human faces in human_files_short
 Detected 99 human faces
Detecting human faces in dog_files_short
 Detected 5 human faces
```

Step 1.4: Detect Dogs

In this step we repeat the operation but creating a detector for dogs. In this case the idea is to use a pretrained version of VGG-16 model. We will apply the weights of a training using ImageNet a very large datasets with 1000 categories selecting just the corresponding for dogs for detecting if there is dog in the image.

For completing the function, we need to apply some transformations to the image like resize for what VGG-16 model is expecting and applying the normalization to the three channels.

```
from PIL import Image, ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True
import torch
import torchvision.models as models
import torchvision.transforms as transforms

VGG16 = models.vgg16(pretrained=True)

def VGG16_predict(img_path):

    transform = transforms.Compose(
    [transforms.Resize(size=(256,256)),transforms.CenterCrop(224),
     transforms.ToTensor(),transforms.Normalize(mean=[0.485, 0.456, 0.406],std=[0.229, 0.224, 0.225])])

    img = Image.open(img_path)
    output = VGG16(transform(img).unsqueeze(0))
    return torch.max(output,1)[1].item()

### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):
    label = VGG16_predict(img_path)
    if label > 150 and label < 269:
        return True
    else:
        return False

human_results_short = [ dog_detector(img_path) for img_path in human_files_short]
dog_results_short = [ dog_detector(img_path) for img_path in dog_files_short]
--------------------------------------------------------------------------------
Output:

Detecting human faces in human_files_short
 Detected 0 dogs
Detecting human faces in dog_files_short
 Detected 99 dogs
```

Step 1.5: Create a CNN to Classify Dog Breeds (from Scratch)

Now that we have functions for detecting humans and dogs in images, we need a way to predict breed from images. In this step, the idea is to build a Convolutional Neural Network that classifies dog breeds from scratch.

First, we need to create different data loaders for the three subsets of the dataset: train, validation and test. For each of the data loaders a different transformer has been applied, there is one common preprocessing for all subsets and some specific steps just for training. In more detail the preprocessing steps are:

1. The image is resized to 224x244 as VGG16 initial layer.
2. In the training transformations a RandomHorizontalFlip, RandomVerticalFlip and RandomRotation are applied to make data augmentation. These steps will add randomness and decrease overfitting while training the model.
3. The image is converted into a tensor
4. The values are normalized following custom datasets pytorch documentation.

```
import os
from torchvision import datasets

data_dir = '/data/dog_images/'
train_dir = os.path.join(data_dir, 'train/')
valid_dir = os.path.join(data_dir, 'valid/')
test_dir = os.path.join(data_dir, 'test/')

transform_train = transforms.Compose(
    [transforms.Resize(size=(224,224)), transforms.RandomHorizontalFlip(),
transforms.RandomVerticalFlip(), transforms.RandomRotation(10),
transforms.ToTensor(),transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])])

transform_valid = transforms.Compose(
    [transforms.Resize(size=(224,224)), transforms.ToTensor(), transforms.Normalize(mean=[0.485, 0.456,
0.406], std=[0.229, 0.224, 0.225])])

transform_test = transforms.Compose(
    [transforms.Resize(size=(224,224)), transforms.ToTensor(), transforms.Normalize(mean=[0.485, 0.456,
0.406], std=[0.229, 0.224, 0.225])])


train_set = datasets.ImageFolder(train_dir, transform=transform_train)
valid_set = datasets.ImageFolder(valid_dir, transform=transform_valid)
test_set = datasets.ImageFolder(test_dir, transform=transform_test)

train_loader = torch.utils.data.DataLoader(train_set, batch_size=batch_size,
                                           shuffle=True, num_workers=num_workers)

valid_loader = torch.utils.data.DataLoader(valid_set, batch_size=batch_size,
                                           shuffle=False, num_workers=num_workers)

test_loader = torch.utils.data.DataLoader(test_set, batch_size=batch_size,
                                          shuffle=False, num_workers=num_workers)
```

Regarding the scratch model, the idea was to replicate VGG-16 architecture in a simplified way removing convolution layers and keeping the 3 layers for the fully connected.

The convolution layers will increment the number of features using a kernel size of 5 and padding 1. After each convolution there is a relu and maxpool layer with a kernel of size 2 and stride 2 reducing to the half.

After the convolution layers there is a flatten layer that creates a vector of size 256 26 26 = 173056 that links with the fully connected of 3 layers reducing the number of features until the final number of classes and applying dropout to reduce overfitting between each of them.

```
import torch.nn.functional as F

class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        num_classes = len(train_set.classes)
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=64, kernel_size=5, padding=1)
        self.conv2 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=5, padding=1)
        self.conv3 = nn.Conv2d(in_channels=128, out_channels=256, kernel_size=5, padding=1)
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)
        #[batch = batch_size, channel=256, height=26, width=26]
        self.fc1 = nn.Linear(in_features=256 * 26 * 26, out_features=512)
        self.fc2 = nn.Linear(in_features=512, out_features=256)
        self.fc3 = nn.Linear(in_features=256, out_features=num_classes)
        self.dropout = nn.Dropout(0.5)

    def forward(self, x):
        ## Define forward behavior
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))
        x = x.view(-1, 256 * 26 * 26)
        x = F.relu(self.fc1(x))
        x = self.dropout(x)
        x = F.relu(self.fc2(x))
        x = self.dropout(x)
        x = self.fc3(x)
        return x

# instantiate the CNN
model_scratch = Net()
```

Once that the data loaders and the model architecture are defined, we have to implement the training and testing methods.

```
def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):

    valid_loss_min = np.Inf

    for epoch in range(1, n_epochs+1):
        train_loss = 0.0
        valid_loss = 0.0
        model.train()
        for batch_idx, (data, target) in enumerate(loaders['train']):
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            optimizer.zero_grad()
            outputs = model(data)
            loss = criterion(outputs, target)
            loss.backward()
            optimizer.step()
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss))

        model.eval()
        for batch_idx, (data, target) in enumerate(loaders['valid']):
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            with torch.no_grad():
                outputs = model(data)
            loss = criterion(outputs, target)
            valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss))

    return model


model_scratch = train(30, loaders_scratch, model_scratch, optimizer_scratch,
                      criterion_scratch, use_cuda, 'model_scratch.pt')
```

In the train method we apply backpropagation on each batch using the optimizer and the criterion specified. In this case I have used CrossEntropy and Stochastic Gradient Descent respectively.

In the test method we change the model to evaluation mode and just calculate the difference with unseen data to compute the final accuracy.

```
def test(loaders, model, criterion, use_cuda):

    test_loss = 0.
    correct = 0.
    total = 0.

    model.eval()
    for batch_idx, (data, target) in enumerate(loaders['test']):
        # move to GPU
        if use_cuda:
            data, target = data.cuda(), target.cuda()
        # forward pass: compute predicted outputs by passing inputs to the model
        output = model(data)
        # calculate the loss
        loss = criterion(output, target)
        # update average test loss
        test_loss = test_loss + ((1 / (batch_idx + 1)) * (loss.data - test_loss))
        # convert output probabilities to predicted class
        pred = output.data.max(1, keepdim=True)[1]
        # compare predictions to true label
        correct += np.sum(np.squeeze(pred.eq(target.data.view_as(pred))).cpu().numpy())
        total += data.size(0)

    print('Test Loss: {:.6f}\n'.format(test_loss))

    print('\nTest Accuracy: %2d%% (%2d/%2d)' % (
        100. * correct / total, correct, total))

# call test function
test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

The obtained values for the scratch models are:

	Test Loss	Test Accuracy
Scratch CNN	3.49	16%

Step 1.6: Create a CNN to Classify Dog Breeds (using Transfer Learning)

In the following section we will create another CNN but, in this case, using Transfer Learning. The idea is to download a pretrained model, freeze the parameters already trained and add some layers at the end to match with our purpose and just retrain those layers.

I have chosen the model resnet50 for the transfer learning and I have added 3 linear layers to solve the dog's breed. I have reused the train and test method and I have used the same optimizer and criterion from Step 1.5.

```
import torchvision.models as models
import torch.nn as nn

## TODO: Specify model architecture
model_transfer = models.resnet50(pretrained=True)

# Freeze parameters of the model to avoid back propagation
for param in model_transfer.parameters():
    param.requires_grad = False

num_classes = len(train_set.classes)

model_transfer.fc = nn.Sequential(nn.Linear(in_features=2048, out_features=512),
                                  nn.Linear(in_features=512, out_features=256),
                                  nn.Linear(in_features=256, out_features=num_classes))

if use_cuda:
    model_transfer = model_transfer.cuda()
```

The performance for this model has improved a lot the previous values for accuracy and loss in the test set.

	Test Loss	Test Accuracy
Transfer Learning CNN	0.68	78%

Step 1.7: Compare with Classical Machine Learning Classification Algorithms: SVM and Logistic Regression

In this section the plan is to try as well with classical machine learning classification algoriths like Support Vector Machines and Logistic Regression. First, we need to transform the images into a dataset that the model can work with.

I have transformed the dataset into a pandas dataframe with the pixel information in the image on each column.

```
from sklearn import datasets, svm, metrics
import pandas as pd


def create_df_from_dir(ds_dir):
    images = []
    data = []
    transform = transforms.Compose(
    [transforms.Resize(size=(64, 64)),
     transforms.Grayscale(num_output_channels = 1),
     transforms.ToTensor(),
     transforms.Normalize(mean=[0.5],
                                std=[0.5])])
    for path, subdirs, files in os.walk(ds_dir):
        files = [path+"/"+file for file in files]
        images += files
    for img in images:
        img = Image.open(img)
        data.append(transform(img).data.numpy()[0,:,:].flatten() )
    labels = [int(path.split("/")[-2].split(".")[0]) for path in images]
    df_dict = {'data':data, 'target':labels}
    return pd.DataFrame(df_dict)

train_df = create_df_from_dir(train_dir)
val_df = create_df_from_dir(valid_dir)
test_df = create_df_from_dir(test_dir)

X_train = train_df.data.apply(pd.Series)
y_train = train_df['target']
X_test = test_df.data.apply(pd.Series)
y_test = test_df['target']
```

Once that we have obtained a X_train, y_train and X_test and y_test we can use the sklearn models for SVM and logistic regression.

```
from sklearn import svm, metrics
# Create a classifier: a support vector machine classifier
classifier = svm.SVC(gamma=0.001)
classifier.fit(X_train,y_train)
y_pred = classifier.predict(X_test)

from sklearn.linear_model import LogisticRegression
# Create a classifier: a support vector machine classifier
classifier = LogisticRegression()
classifier.fit(X_train,y_train)
y_pred = classifier.predict(X_test)
```

The performance using the test set is very far from the previous step with the CNN using transfer learning.

	Test Loss	Test Accuracy
SVM		6.10%
Logistic Regression		2.87%

Step 1.8: Model Benchmark

In this section, we will compare the different performance to select the best model.

	Test Loss	Test Accuracy
Scratch CNN	3.49	16%
Transfer Learning CNN	0.68	78%
SVM		6.10%
Logistic Regression		2.87%

We can conclude that the model with best performance is the CNN using Transfer Learning and it is the selected model for next steps.

Step 2 Model Deployment & Testing

In this section, we will train the selected model from the benchmark using AWS SageMaker training capabilities and deploy it to include this model in a complete application.

Step 2.1: SageMaker Model Training & Deployment

The first step to work with the model in AWS is to upload the data to Amazon S3 so it is easy to read from SageMaker training capabilities.

```
import pandas as pd
import boto3
import sagemaker

# session and role
sagemaker_session = sagemaker.Session()
role = sagemaker.get_execution_role()

# create an S3 bucket
bucket = sagemaker_session.default_bucket()

# should be the name of directory you created to save your features data
data_dir ='/home/ec2-user/SageMaker/data/dogImages'

# set prefix, a descriptive name for a directory
prefix = 'capstone-project-dog-breed-classifier'

# upload all data to S3
sagemaker_session.upload_data(data_dir, key_prefix=prefix)
```

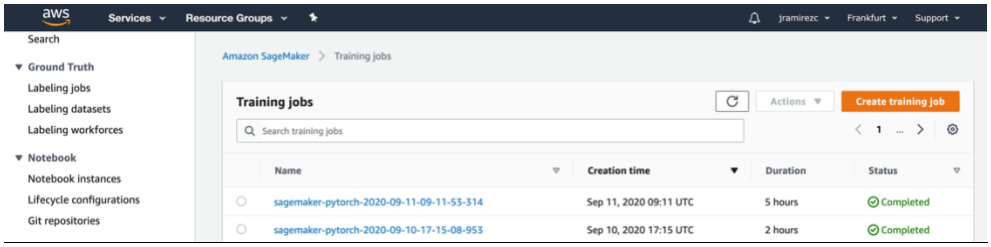
Using a SageMaker session we can upload the data and write down the bucket for future usage.

Then, we just have to set up our model code in a directory including a requirements.txt with the libraries and organizing the code to have a main method that trains the model and a model_fn() method that will load the model.

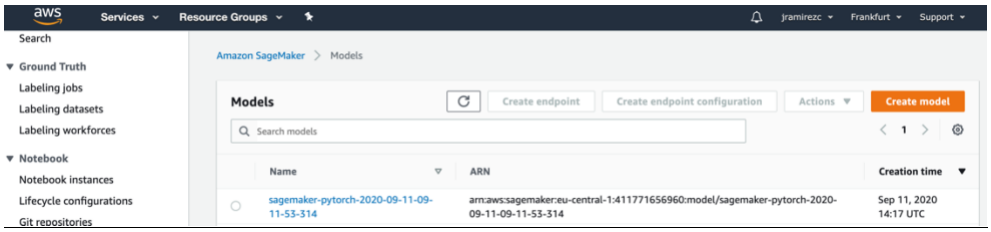
Once that the PyTorch estimator is set up we can call the fit method adding the S3 bucket with the dataset and SageMaker will create a training job.

```
from sagemaker.pytorch import PyTorch

estimator = PyTorch(entry_point="train.py",
                    source_dir="models/cnn_pytorch",
                    role=role,
                    framework_version='0.4.0',
                    train_instance_count=1,
                    train_instance_type='ml.c4.4xlarge',
                    hyperparameters={
                        'epochs': 15
                    })


# Train your estimator on S3 training data
estimator.fit({'train': 's3://sagemaker-eu-central-1-411771656960/capstone-project-dog-breed-
classifier'})
```

We can follow the training process checking the logs of the training job.



Once that the model has been trained, we can see it in the SageMaker web portal.



In this case, in order to see our model performance, we need to recreate the test method to use the model endpoint instead of a local trained model.

```
def test_sagemaker_endpoint(loader, criterion, use_cuda):

    # monitor test loss and accuracy
    test_loss = 0.
    correct = 0.
    total = 0.

    for batch_idx, (data, target) in enumerate(loader):
        # move to GPU
        if use_cuda:
            data, target = data.cuda(), target.cuda()
        # forward pass: compute predicted outputs by passing inputs to the model
        output = torch.from_numpy(predictor.predict(data))
        # calculate the loss
        loss = criterion(output, target)
        # update average test loss
        test_loss = test_loss + ((1 / (batch_idx + 1)) * (loss.data - test_loss))
        # convert output probabilities to predicted class
        pred = output.data.max(1, keepdim=True)[1]
        # compare predictions to true label
        correct += np.sum(np.squeeze(pred.eq(target.data.view_as(pred))).cpu().numpy())
        total += data.size(0)

    print('Test Loss: {:.6f}\n'.format(test_loss))

    print('\nTest Accuracy: %2d%% (%2d/%2d)' % (
        100. * correct / total, correct, total))

# call test function
test_sagemaker_endpoint(test_loader, nn.CrossEntropyLoss(), False)
```

As we have trained the model with more epochs in this case the performance has improved a bit.

	Test Loss	Test Accuracy
Transfer Learning CNN	0.65	81%

I have created as well a method that use the endpoint just adding as input an image as we will need something similar for the final application.

```
# list of class names by index, i.e. a name can be accessed like class_names[0]
class_names = [item[4:].replace("_", " ") for item in test_loader.dataset.classes]

def predict_breed_sagemaker_transfer(img_path):
    # load the image and return the predicted breed
    transform = transforms.Compose(
    [transforms.Resize(size=(224,224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                std=[0.229, 0.224, 0.225])])

    img = Image.open(img_path)
    output = torch.from_numpy(predictor.predict(transform(img).unsqueeze(0)))
    # position 0 return value, position 1 return indices
    output_index = torch.max(output,1)[1].item()
    return class_names[output_index]

predict_breed_sagemaker_transfer('images/Labrador_retriever_06457.jpg')
```

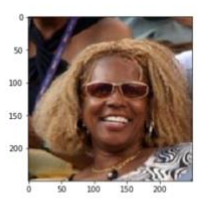
Step 2.2: Write your Algorithm

With the previous method that we have created using the SageMaker endpoint with the deployed model we are ready to create a method that simulates the application workflow.

```
def run_app(img_path):
    ## handle cases for a human face, dog, and neither
    img = Image.open(img_path)
    plt.imshow(img)
    plt.show()
    if dog_detector(img_path) is True:
        prediction = predict_breed_sagemaker_transfer(img_path)
        print("Dogs Detected!\nIt looks like a {0}".format(prediction))
    elif face_detector(img_path) > 0:
        prediction = predict_breed_sagemaker_transfer(img_path)
        print("Hello, human!\nIf you were a dog..You may look like a {0}".format(prediction))
    else:
        print("Error! Can't detect anything..")
```

Step 2.3: Test Your Algorithm

In the following images we can see a test of the outputs that the run_app method returns to several images:



Hello, human!
If you were a dog..You may look like a Pharaoh hound

Dogs Detected!
It looks like a Brittany

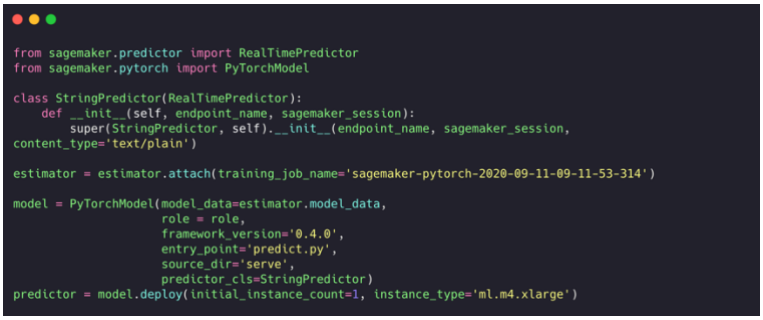
Step 3 Inference Deployment

In this section we will use the training model but in a slightly different way. The standard procedure to use the model is using the model_fn() method that we defined while training but this usually requires to have a similar input as the model while training.

In order to deploy our application we want to use the model but adding some additional code that preprocess our input before using the model in the same endpoint action, we can perform this using a SageMaker predictor.

We need to specify the estimator that we have trained and a directory with a python code containing a predict_fn() method that we will execute when calling the endpoint and two additional methods: input_fn() to preprocess the input and output_fn() to preprocess the output.

With the previous method that we have created I have completed the code in the predict file and I have created the inference endpoint.



```
from sagemaker.predictor import RealTimePredictor
from sagemaker.pytorch import PyTorchModel

class StringPredictor(RealTimePredictor):
    def __init__(self, endpoint_name, sagemaker_session):
        super(StringPredictor, self).__init__(endpoint_name, sagemaker_session,
content_type='text/plain')

estimator = estimator.attach(training_job_name='sagemaker-pytorch-2020-09-11-09-11-53-314')

model = PyTorchModel(model_data=estimator.model_data,
                     role = role,
                     framework_version='0.4.0',
                     entry_point='predict.py',
                     source_dir='serve',
                     predictor_cls=StringPredictor)
predictor = model.deploy(initial_instance_count=1, instance_type='ml.m4.xlarge')
```

Once that the endpoint is deployed we can test it using the runtime.invoke_endpoint function specifying the endpoint namem the content type and the body of the POST request having a json with the image in base64 format. We will take this snippet code as the template for our lambda function.

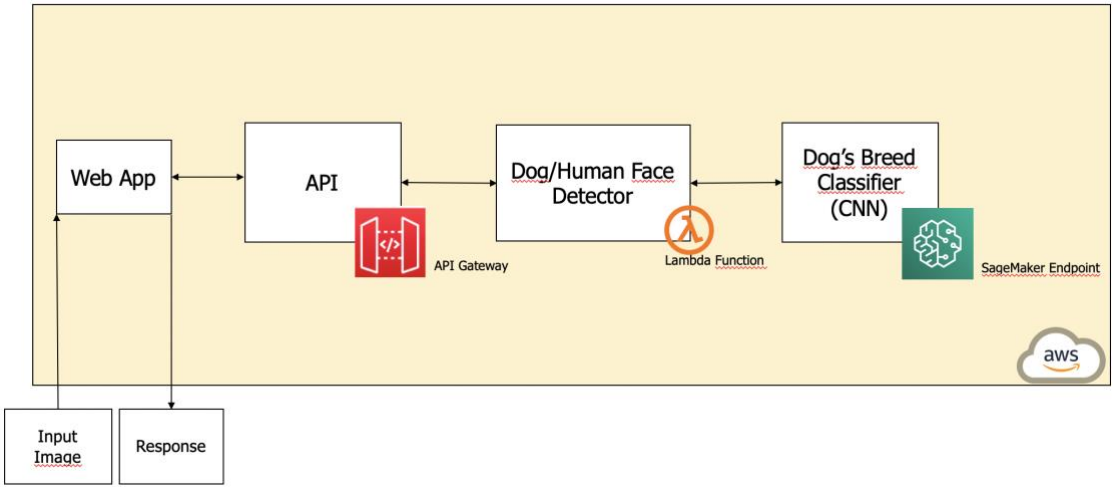
```
import boto3

runtime = boto3.Session().client('sagemaker-runtime')

print("Sending to endpoint")
# Now we use the SageMaker runtime to invoke our endpoint, sending the review we were given
response = runtime.invoke_endpoint(EndpointName = 'sagemaker-pytorch-2020-09-12-20-32-23-128',    # The
name of the endpoint we created
                                   ContentType = 'application/json',                # The data format
that is expected
                                   Body =
'{"file":"
BJSkcgSlBFRyB2NjIpLCBxdWF...k="}')
print("Endpoint request done")
print(response['Body'].read().decode('utf-8'))
```

The code response for that test is:

{"result": "Dogs Detected!\nIt looks like a Labrador retriever"}

Step 4 App Deployment

In this final step we will create the final application with the idea of replicate this architecture:



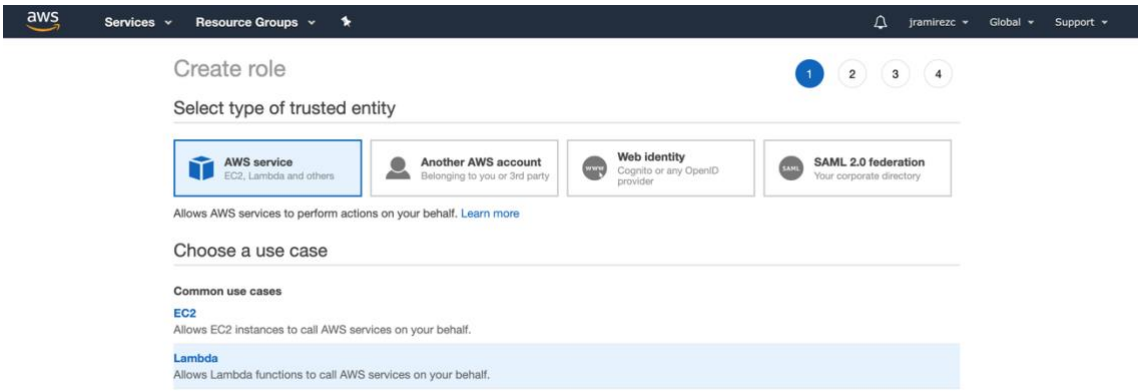
In previous steps we have already deployed the SageMaker Endpoint with the best model and it is ready to receive POST requests with an image inside a json using base64 format.

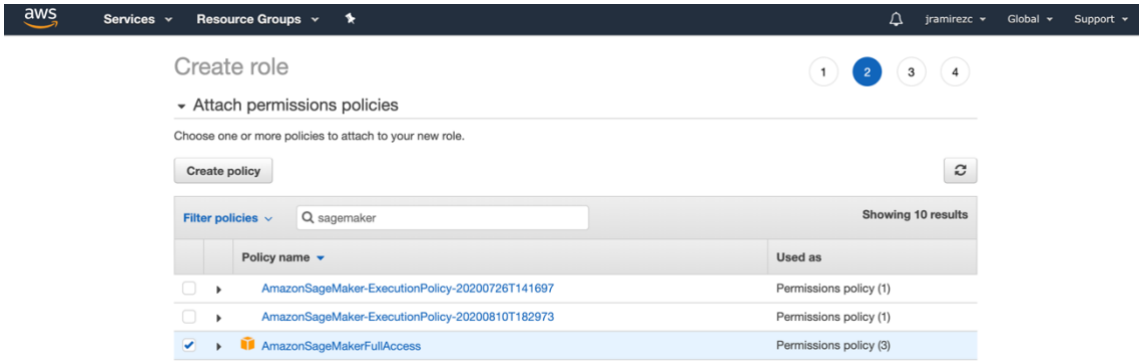
On the opposite side the web app will be a local html file with a form ready to send the request with the image and wait a response from the API.

We just need to set up the two intermediate steps. First, let's create the lambda function with the code to call the endpoint.

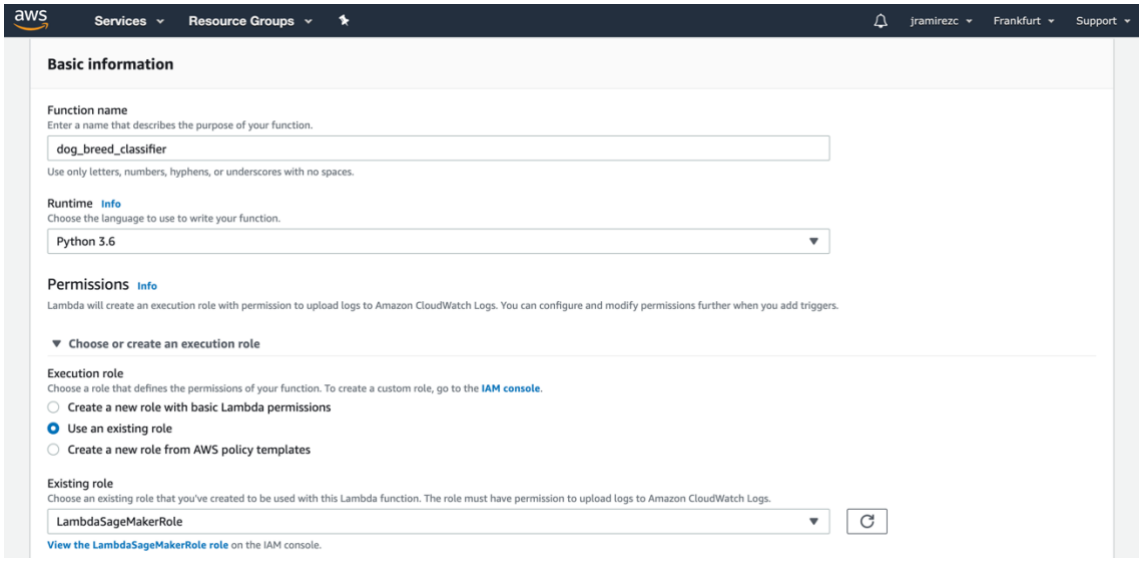
At this point I have changed a bit the workflow from the capstone proposal as it has been easier to process the detector also in the endpoint instead of dealing with requirements and external data in the lambda function where I will just call the endpoint sending the same received image.

First step is to create a role to perform SageMaker invokations from the lambda function.



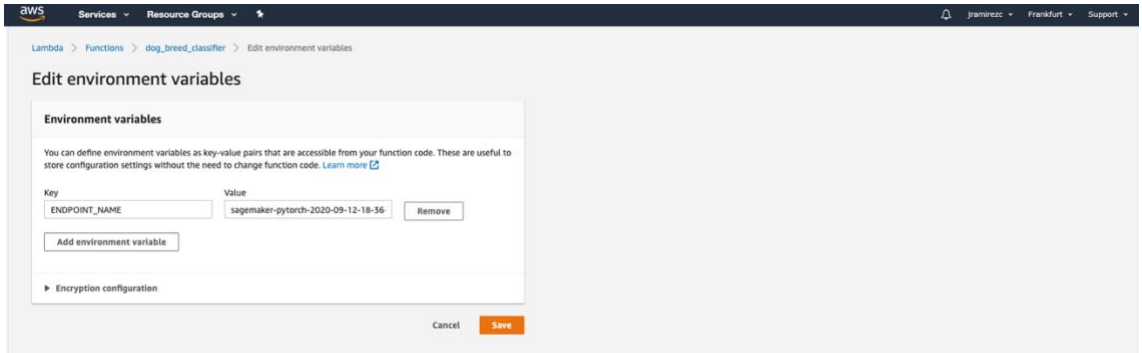


Then, we can create the lambda function attaching the created role and including the desired Runtime, in this case Python 3.6

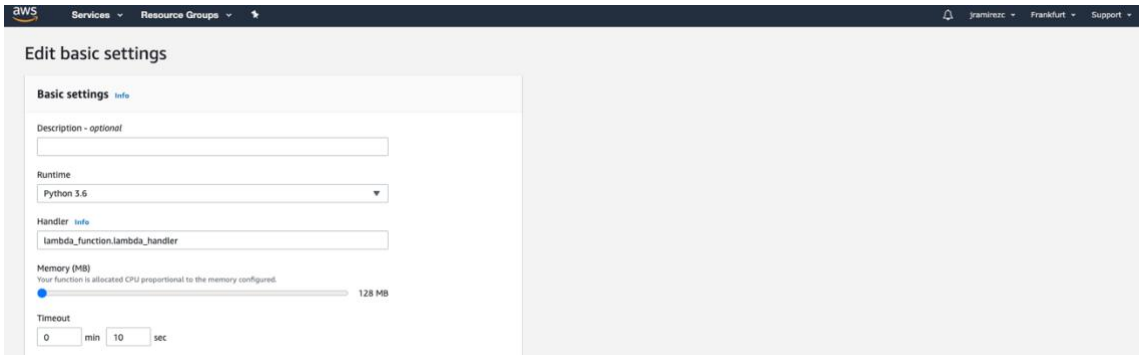


As mentioned initially I tried to add a lot of code inside the lambda function like installing the VGG16 model and other functions but I found a lot of problems and I decided to move that logic inside the inference endpoint and keep as simple as possible the lambda function.

I have copied a similar code to the one used for the endpoint testing and I have included in the lambda function an environment variable with the endpoint name.

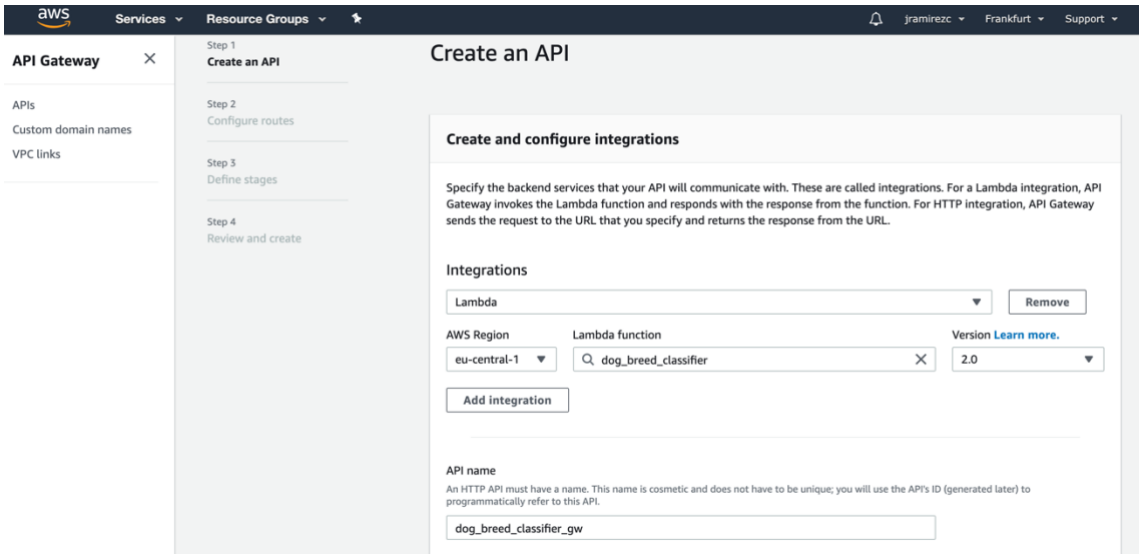


A very important step in my case was to change the timeout to a value bigger that 5-6 seconds. The default values is 3 seconds and my endpoint takes like 5 seconds to make the response. I have spent more time that expected dealing with this issue because I thought the problem was in the endpoint and it is a slow process to debug while waiting to redeploy.

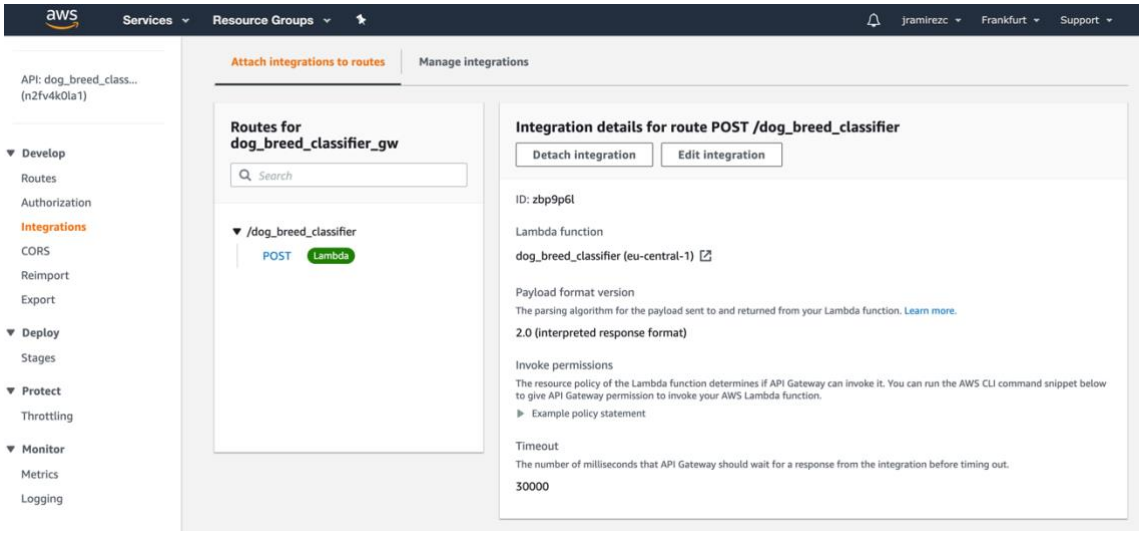


With these steps our lambda function is ready and we are just missing the API gateway.

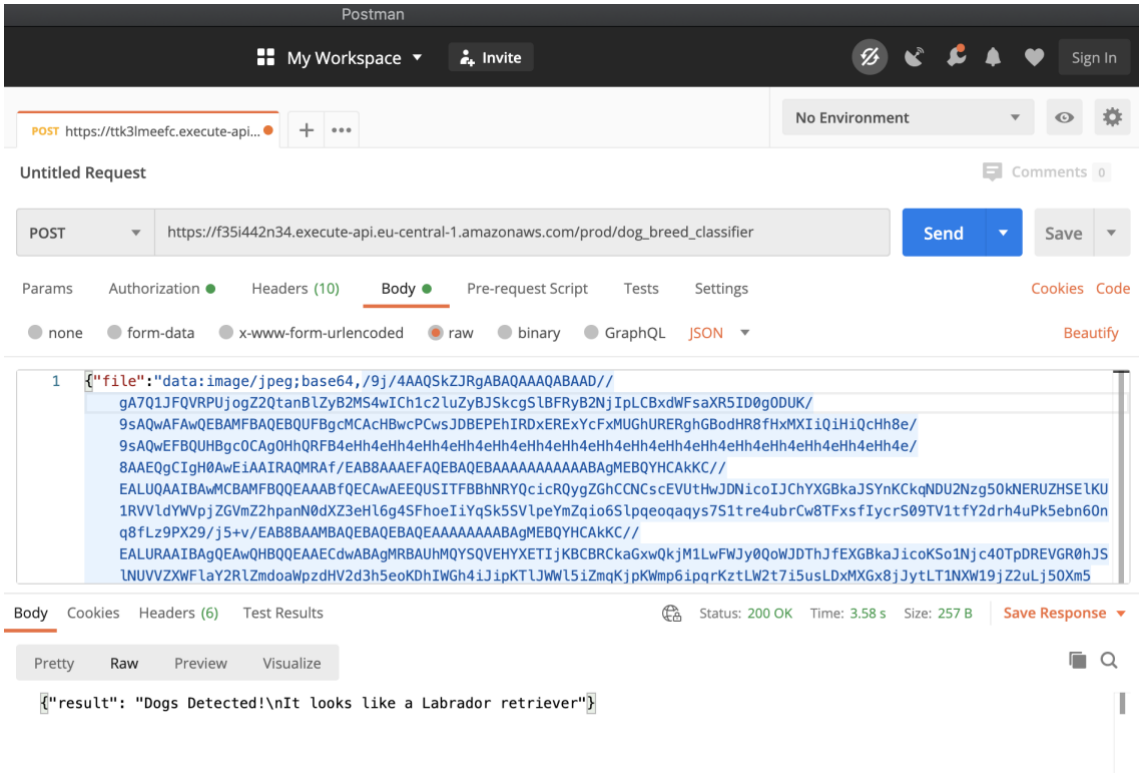
Moving to AWS API Gateway section we can create one api and configure the integration with our lambda function.



Then it is required to create a route, in this case I defined it as "/dog_breed_classifier" and using POST method.



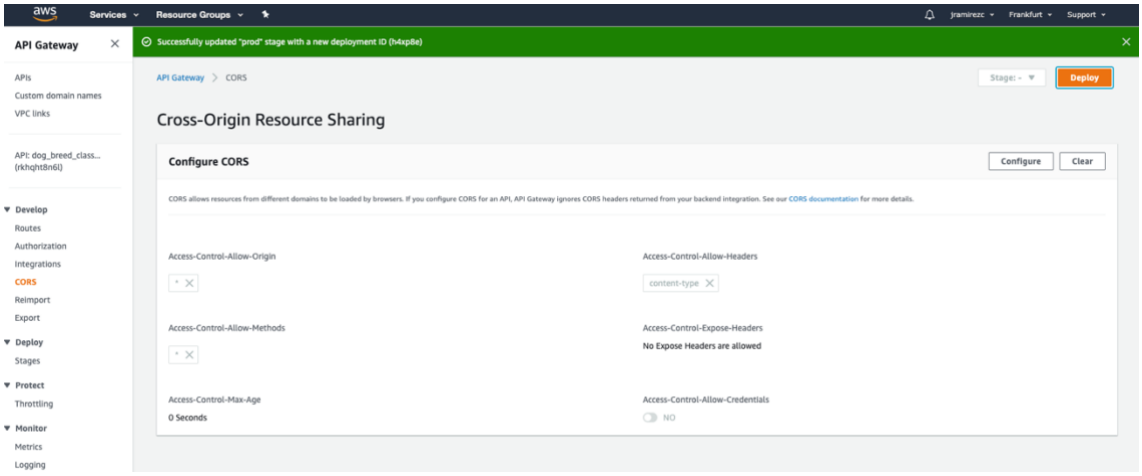
Clicking on deploy we have the API gateway ready and it will work with Postman sending the expected input. In this case I have added the content-type as application/json and in the body a json with an image encoded in base64 format.



As we can see the response took more that 3 seconds and it contains the answer from the system with the dog's breed.

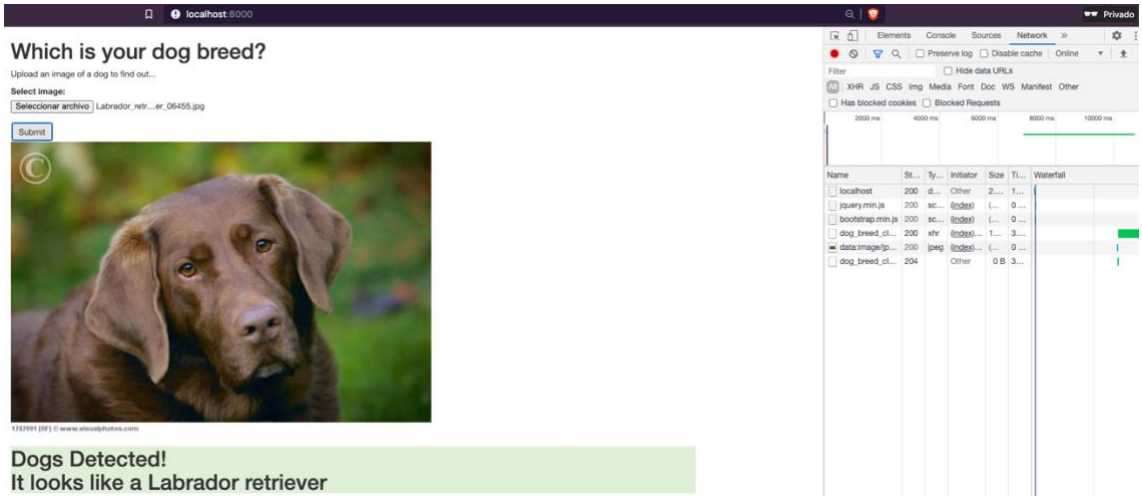
As we want to make it interactive using a web app we need to configure as well from API gateway Cross-Origin Resource Sharing section some values. In this case, it is required to assign Access-Control-Allow-Origin and Access-Control-Allow-Methods so our API will reply the front with that information and we will avoid Cross-Origin errors.

I have used "*" values as I was using just in my local the html but it is a better practice specify the front-end address in the origin.



With those changes we are ready to open our local index.html file that points to our API gateway.

The JavaScript code in the local web app is able to open a file explorer so the user can select an image, the image will be read and converted to base64 format and a json file will be included with the base64 image in the body of a POST request to the gateway.



Once the gateway calls the lambda, and the lambda function calls the endpoint we will receive from the API gateway another json file with the result and our web app will show us the message with the dog's breed that the model has predicted closing our application workflow.

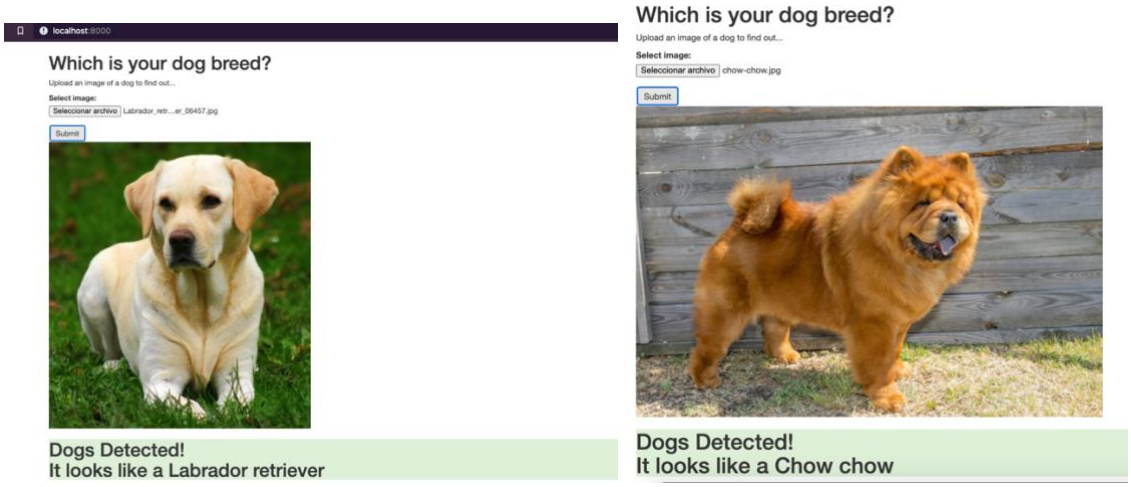
Conclusions

With these 4 steps description I conclude this capstone project report. After the training with AWS the accuracy has improved until 81% for the testing dataset showing a good evolution from my initial approaches.

I have identified some possible improvements for future work like:

- Train the model using more breeds to cover more cases.
- Test with different model configurations like alternatives pretrained models and different configurations for the fully connected or the optimizers.
- Apply different data preprocessing and data augmentation to the images.

In my opinion, testing manually the results are good enough to set up a web app providing a positive user experience.



From the personal point of view it has been a very challenging and enriching experience to work in a whole process and create a complete application that uses a CNN developed with PyTorch and trained with AWS Sagemaker.