UDACITY MACHINE LEARNING NANO DEGREE

CAPSTONE PROJECT

CLASSIFICATION OF DOG BREED USING CONVOLUTION NEURAL NETWORKS

Overview

This project is part of Udacity Machine Learning Nanodegree. Objective of the project is to build a deep learning model using convolution neural networks to classify the given image to one of the dog breeds.
The code will first detect if the input image is a dog image or human image, if the input image is of dog the algorithm will detect the breed. If the input image is human image, the algorithm will detect the reselembing dog breed. If the input device is neither dog of human image the algorithm will print a friendly message.

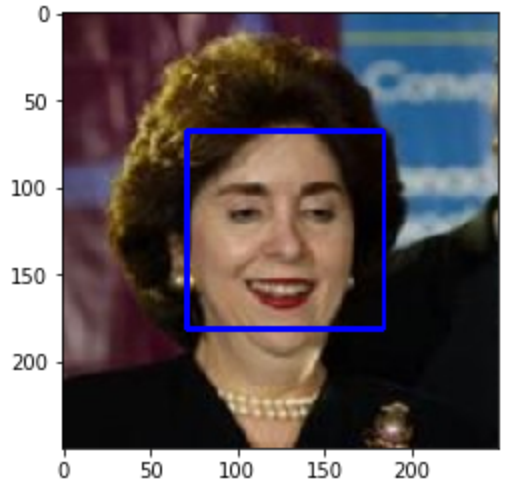
Import datasets

Datasets are provided by Udacity. Downloaded from the below locations.
`dogimages_url = "https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip"`
`humanimages_url = "https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/lfw.zip"`

Both datasets are downloaded and unzipped to project folder.
Human images consists of the 13233 number of images to train human detector.
Dog images are placed in 3 folders train, test and val.
Each of the folders further have 133 sub folders for each of the dog breeds.
Each of the 133 folders in turn have several dog images for training and testing.
Storing the data in this folder format enable the pytorch/keras to read the data with folder name and classification labels

Detect Humans

we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.
We use the pre trained face detector. The algorithm will detect the fact of a human in the given image.



The pre trained algorithm will detect the number of faces in the given images. If the number of faces greater than 0 we classify the image as a human image.

Next step we will test the function to detect the human face. By passing sample of human images and sample of dog images. Algorithm gives fairly good performance of about 98% of accuracy.

Detect Dogs

Next step of the project is to detect if the input image is an image of a dog.
We use Vgg15 pre trained classifier trained on imagenet dataset.

Download the pre trained model weights using pytorch

```
import torch
import torchvision.models as models
# define VGG16 model
VGG16 = models.vgg16(pretrained=True)
```

Vgg16 will classify the image into one of the 1000 categories on which it is trained on. Categories of dogs appear in the index between 151-268 (inclusive). We can use this information to classify if the input image is dog or not. If the model predicts any index number between this range the input image is dog otherwise not.

Dog detection can be done using this simple function.

```
def dog_detector(img_path):
# in VGG16 index 151 to 268 are dog classifications
    return VGG16_predict(img_path)>= 151 and VGG16_predict(img_path)<=268
```

Since Vgg16 is trained on a large number of images it is fairly accurate for this purpose without further training.

Create a CNN to Classify Dog Breeds (from Scratch)

In this step we will implement a deep learning classifier from scratch using pytorch convolution neural networks. Convolution neural networks does great job working with image dataset since each of the convolution layers tries to learn different features of the image like lines, edges and so on.

This involves several steps.

Preproces and specify data loaders.

We apply several transformation function to datasets as follows.

```
transforms.Resize(256),
transforms.CenterCrop(224),
transforms.RandomHorizontalFlip(),
transforms.ToTensor(),
transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
```

Random Horizontal flip is applied only to train dataset to make the model more generalized. Model should be able to predict the dog image even if the image is flipped on horizontal axis.

Image is converted to torch tensor to perform computation on the cuda gpu.

Image data is normalized to avoid any bias due to different scale/magnitude of the numbers.

Build network architecture

We use simple 3 convolution layers with 64 nodes, kernel size of 3 and 2d max pooling between each layer.
One fully connected node with 256 nodes.
A final fully connected layer with 133 nodes for each of the classification categories.

Specify Loss Function and Optimizer

We use categorical cross entropy loss function for multiple class classification.
SGD optimizer with learning reat or 0.001

Train and test the model

We train the model with pytorch library. Training the model for 8 epochs will get us a fair starting performance of 10% accuracy on the validation data. We will further improve the performance of the prediction using transfer learning.

Use a CNN to Classify Dog Breeds (using Transfer Learning)

Building image classification model from scratch requires lot of training images and the great amount computation power/time. After each training fine tuning the model by testing different hyper parameters will take a great amount of time.

We can use the pre trained network weights and tune the model for our custom images will get us great performance advantage. Pretrained network weights will have layers that can detect the basic shapes and image elements like lines, edges and so on.

Transfer learning involve the similar steps as our previous model implementation from scratch.

Preproces and specify data loaders.

We are going to use the same data loading /image processing techniques as our previous implementation.

Build network architecture

Instead of building model architecture from scratch. Let's use resnet18 pretrained network. Freeze the pre trained network weights to avoid training all the initial image features. Add a final fully connected layer with output nodes for each of the classification classes.

In this case we are not using any softmax function in the output layer because we are interested in the prediction of the image into one of the classes and not interested in prediction probabilities.

```
model_ft = models.resnet18(pretrained=True)
num_ftrs = model_ft.fc.in_features
model_ft.fc = nn.Linear(num_ftrs, 133)
model_ft =model_ft.to(device)
```

We need to transfer both the dataset and the model to cuda device to train on available gpu.

Specify Loss Function and Optimizer

We use categorical cross entropy loss function for multiple class classification.
SGD optimizer with learning reat or 0.001

Train and test the model

Using transfer learning gives us the prediction accuracy of 84% with just 8 epochs. That's a great improvement from the model built from scratch.

Write your Algorithm

As a final step to achieve our project goal. We will build a simple function that will take an input image and perform these tasks.
Predict if the image is dog or human or neither of these.
Predict the dog classification and provide the respective output.

```
def run_app(img_path):
    ## handle cases for a human face, dog, and neither
    if haar_face_detector(img_path):
        print('hello human')
        prediction = predict_breed_transfer(img_path)
        print(prediction)
    elif dog_detector(img_path):
        print('hello dog')
        prediction = predict_breed_transfer(img_path)
        print(prediction)
    else:
        print("couldn't detect dog or human image")
```

Test Your Algorithm

We can test the entire implementation using passing some sample images.
We have to normalize the image and convert to torch tensor before passing to the model for prediction.

Further improvements

1. Try different data augmentation methods to make model more robust.
2. Try other optimizers like RMSProp with different learning rate and momentum
3. Try implementing more complex network architecture with,
    a. More nodes in each layer
    b. More CNN layers
    c. More linear layers in the end
    d. Batch normalization
    e. Different kernel size for convolution layers
4. Try other pre trained networks
5. Train the model for more epochs to get better performance. Pay attention to overfitting
6. Use different batch size

Reference

1. https://towardsdatascience.com/transfer-learning-with-convolutional-neural-networks-in-pytorch-dd09190245ce
2. https://pytorch.org/docs/stable/nn.html