

dog_breed_classification

April 25, 2023

1 Project Notebook: Dog Breed Classification using Stanford Dog Breed Dataset

1.1 Introduction:

In this project, we will explore the exciting world of dog breed classification using the Stanford Dogs dataset. With 20,000 images of 120 different dog breeds, we will use the power of convolutional neural networks and transfer learning to build a model that can accurately classify each image.

By leveraging a *pre-trained model*, we can take advantage of low-level features already learned by the model and apply it to our dataset without the need for training from scratch. *This approach saves time and computational resources*, making it accessible to those with limited resources. We will explore *data preprocessing, model building, and hyperparameter tuning to achieve the best possible results*. So let's dive in and start building our dog breed classifier!

1.2 Project Goals:

- Explore the Stanford Dog Breed dataset and visualize the images.
- Create a train-test split and preprocess the data
- Use transfer learning to train a pre-trained ResNet/VGG16/InceptionV3 model on the dataset
- Evaluate the model on the test set and visualize the results

1.3 Tools and Techniques:

- Python
- PyTorch
- Deep Learning
- Transfer Learning
- Inception V3 & VGG 16
- Train-Test Split
- Data Preprocessing

1.4 Dataset:

- The Stanford Dog Breed dataset contains images of 120 different dog breeds.
- The dataset has been built using images and annotations from ImageNet for the task of fine-grained image categorization.
- Number of categories: 120
- Number of images: 20,580
- Annotations: Class labels, Bounding boxes
- URL: <https://www.kaggle.com/datasets/jessicali9530/stanford-dogs-dataset/download?datasetVersionNumber=2>

1.5 Expected Outcome:

- A deep learning model that can classify dog breeds from images with high accuracy.
- A clear understanding of the data preprocessing, transfer learning, and evaluation processes for image classification tasks.

2 Check GPU allocation

```
[1]: !nvidia-smi
```

```
Mon Apr 24 18:36:39 2023
```

```
+-----+
| NVIDIA-SMI 525.85.12      Driver Version: 525.85.12      CUDA Version: 12.0 |
+-----+-----+-----+
| GPU  Name      Persistence-M| Bus-Id      Disp.A | Volatile Uncorr. ECC | |
| Fan  Temp  Perf  Pwr:Usage/Cap|           Memory-Usage | GPU-Util  Compute M. |
|                   |                               |               |          MIG M. |
+=====+=====+=====+=====+=====+=====+=====+=====+
|     0  Tesla T4            Off  | 00000000:00:04.0 Off |                  0 | |
| N/A   49C     P8    10W /  70W |        0MiB / 15360MiB |      0%     Default |
|                   |                               |               |          N/A |
+-----+-----+-----+-----+
+-----+
| Processes:
| GPU  GI  CI      PID  Type  Process name          GPU Memory |
|       ID  ID             |                      | Usage      |
+=====+=====+=====+=====+=====+=====+=====+
| No running processes found
+-----+
```

3 Mount to Google Drive

```
[2]: # Run this cell to mount your Google Drive.  
from google.colab import drive  
drive.mount('/content/drive')
```

Mounted at /content/drive

4 Data Ingestion

Download the data using the following link: <https://drive.google.com/drive/folders/1WtjswTWrJCW04t418gG0t6>

If failed or unable, only then execute this cell.

In either ways you will get the data in required format to execute this notebook.

```
[ ]: # First we need to download the zip file from the URL mentioned above.  
# Next we need to unzip it and copy&paste the "annotation" & "images" folders  
# in a new folder named "stanford_dog_breed_dataset"  
# Also nee to make sure that all the folder names are in lowercase to avoid  
# unforced errors.  
# For now I have done the above steps manually and uploaded the data in my  
# drive.  
# But while building data_ingestion component in our pipeline, we will automate  
# this part.  
# Finally we need to establish the connection between colab and drive to access  
# the data.
```

```
[ ]: #@title dataset Dir preperation  
import os  
import shutil  
import urllib.request  
import zipfile  
  
# URL of the zip file  
url = "https://www.kaggle.com/datasets/jessicali9530/stanford-dogs-dataset/  
download?datasetVersionNumber=2"  
  
# Define the destination directory  
destination_dir = "/content/drive/MyDrive/DL/Assignment2/  
stanford_dog_breed_dataset"  
  
# Create the destination directory if it does not exist  
if not os.path.exists(destination_dir):  
    os.mkdir(destination_dir)  
  
# Download the zip file  
print("Downloading the zip file...")
```

```

urllib.request.urlretrieve(url, "stanford_dog_breed_dataset.zip")

# Extract the zip file
print("Extracting the zip file...")
with zipfile.ZipFile("stanford_dog_breed_dataset.zip", 'r') as zip_ref:
    zip_ref.extractall(destination_dir)

# Rename the folders to lowercase
print("Renaming the folders to lowercase...")
for foldername in os.listdir(os.path.join(destination_dir, "images")):
    os.rename(os.path.join(destination_dir, "images", foldername), os.path.
        join(destination_dir, "images", foldername.lower()))

for foldername in os.listdir(os.path.join(destination_dir, "annotation")):
    os.rename(os.path.join(destination_dir, "annotation", foldername), os.path.
        join(destination_dir, "annotation", foldername.lower()))

# Move the folders to a new folder
print("Moving the folders to a new folder...")
shutil.move(os.path.join(destination_dir, "images"), os.path.
    join(destination_dir, "stanford_dogs_images"))
shutil.move(os.path.join(destination_dir, "annotation"), os.path.
    join(destination_dir, "stanford_dogs_annotation"))

# Delete the zip file
os.remove("stanford_dog_breed_dataset.zip")

print("Task completed successfully!")

```

5 Data Exploration

5.1 Paths to required dirs

```
[3]: import os
from pathlib import Path

root_dir_path = "/content/drive/MyDrive/DL/Assignment2/
    ↪stanford_dog_breed_dataset"
annotation_dir_path = os.path.join(root_dir_path, "annotation")
images_dir_path = os.path.join(root_dir_path, "images")
```

5.2 Create a list of 120 dog classes

```
[4]: dog_classes = os.listdir(images_dir_path)
breeds = []

breeds = [dog_class.split('-', 1)[1] for dog_class in dog_classes]
```

```
[5]: breeds[:10]
```

```
[5]: ['Maltese_dog',
      'Blenheim_spaniel',
      'Pekinese',
      'toy_terrier',
      'papillon',
      'Japanese_spaniel',
      'Afghan_hound',
      'Rhodesian_ridgeback',
      'Shih-Tzu',
      'Chihuahua']
```

```
[6]: print(f"Total number of breeds found = {len(breeds)}")
```

Total number of breeds found = 120

5.3 Save breed_names in json file

```
[29]: import json

# Save the breed names to a file
with open('breed_names.json', 'w') as f:
    json.dump(breeds, f)
```

5.4 Is the Dataset Balanced?

```
[ ]: # We need to check the number of images available for each dog Breed.

def files_count(dir_path):
    num_files = len(os.listdir(dir_path))
    return num_files

image_count = []
for breed_dir in dog_classes: # iterate through each breed folder name
    breed_dir_path = os.path.join(images_dir_path, breed_dir) # path of each ↵breed folder
    image_count.append(files_count(breed_dir_path)) # list down the image count ↵for each breed
```

```
[ ]: import pandas as pd

image_count_df = pd.DataFrame({"DogBreed":breeds, "No_of_Images":image_count})

image_count_df.head()
```

```
[ ]:          DogBreed  No_of_Images
0      Maltese_dog        252
1  Blenheim_spaniel       188
2      Pekinese            149
3    toy_terrier           172
4      papillon            196
```

```
[ ]: import matplotlib.pyplot as plt
%matplotlib inline

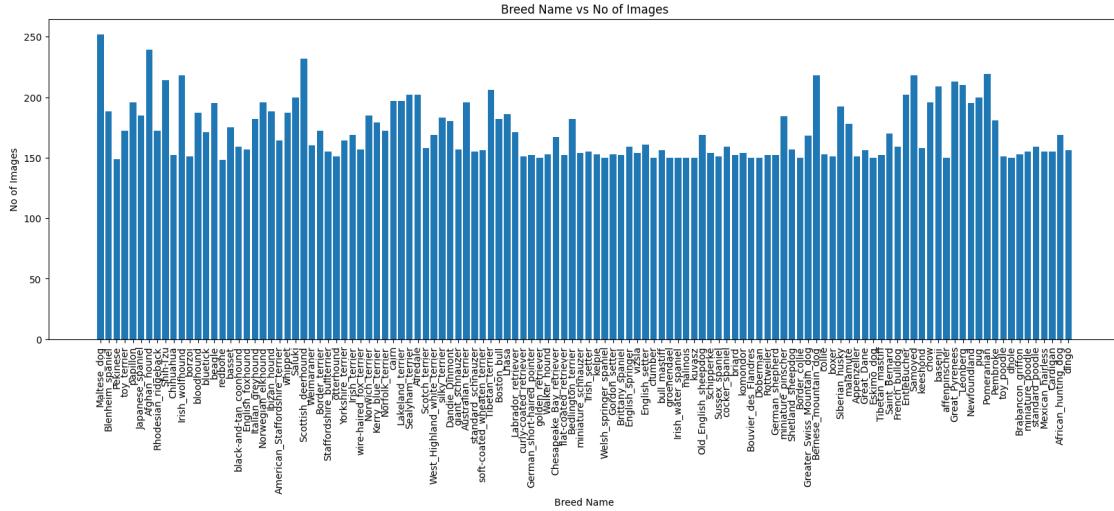
# Create a figure and axis
fig, ax = plt.subplots(figsize=(20,6))

# Plot the bar graph
ax.bar(breeds, image_count)

# Set the x-tick labels
ax.set_xticks(breeds)
ax.set_xticklabels([str(i) for i in breeds], rotation=90)

# Add labels and title
ax.set_xlabel('Breed Name')
ax.set_ylabel('No of Images')
ax.set_title('Breed Name vs No of Images')

# Show the plot
plt.show()
```



The Data set is mostly Balanced. On an average each breed has 150+ images.

[]:

[]:

5.5 Prepearing X and y

- X -> Contains full path of all images
- y -> labels of corresponding images

```
[7]: from itertools import chain

X = []
y = []

fullpaths = [os.path.join(images_dir_path, dog_class) for dog_class in dog_classes]

for counter, fullpath in enumerate(fullpaths):
    for imgname in os.listdir(fullpath):
        X.append([fullpath + '/' + imgname])
        y.append(breeds[counter])

X = list(chain.from_iterable(X)) # unnest the lists and join together into one list
print(f"Total number of pictures -> {len(X)} \n No of breeds -> {len(set(y))}")
```

Total number of pictures -> 20580

No of breeds -> 120

5.6 Shuffle and Plot Images

For observation, we are going to ungroup the images by the breeds and plot them.

```
[ ]: import random
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib.image import imread

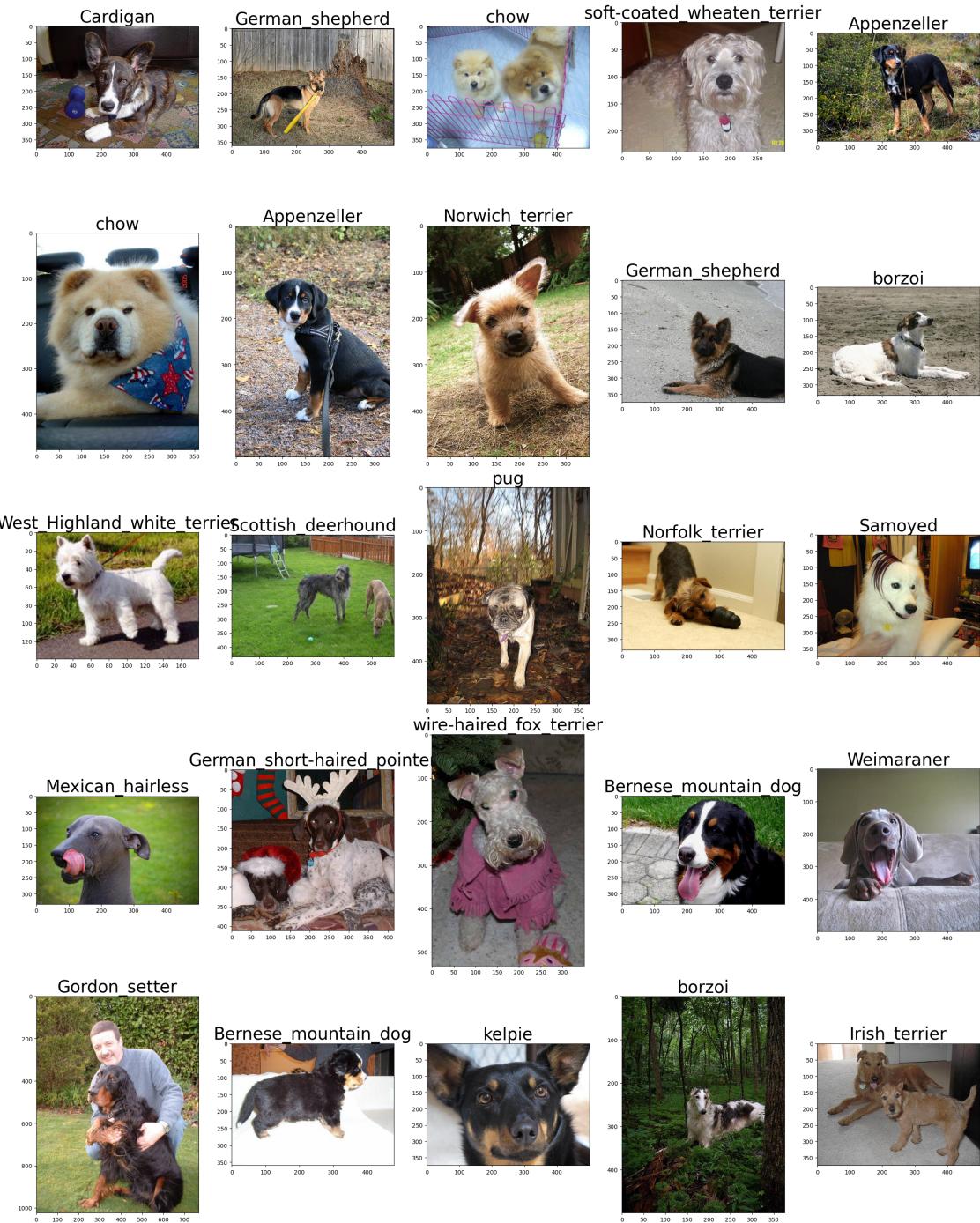
# shuffle X and y
combined = list(zip(X, y))
random.shuffle(combined)

X[:, :], y[:] = zip(*combined)

# Display random dogs pictures
plt.figure(figsize=(30,40))
plt.suptitle("Sample batch of random 25 Dog images", fontsize=50)
for counter, i in enumerate(random.sample(range(0, len(X)), 25)): # random 25
    images
    plt.subplot(5, 5, counter+1)
    plt.subplots_adjust(hspace=0.1)
    filename = X[i]
    image = imread(filename)
    plt.imshow(image)
    plt.title(y[i], fontsize=30)

plt.show()
```

Sample batch of random 25 Dog images



Observations:

- the images have different dimensions, so we will have to resize them later before putting them into the model.
- Few images are not cropped properly and contain goof amount of noise which can effect the accuracy of our model. We can use the bounding box coordinates from annotation to crop all the images properly.

5.7 Crop the images using Bounding Box

Execute these cells if ‘cropped_images’ folder not available.

```
[ ]: import os
import xml.etree.ElementTree as ET
from PIL import Image

[ ]: # path to annotation file of any random image
breed_folder_path = os.path.join(annotation_dir_path, dog_classes[0])
os.path.join(breed_folder_path, os.listdir(breed_folder_path)[0])

[ ]: '/content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/annotation/n02085936-Maltese_dog/n02085936_3947'
```

```
[ ]: # this is how we can get the bbox coordinates from image annotation file
tree = ET.parse(os.path.join(breed_folder_path, os.
    ↪listdir(breed_folder_path)[0]))
root = tree.getroot()
bbox = root.find('object').find('bndbox')
xmin = int(bbox.find('xmin').text)
ymin = int(bbox.find('ymin').text)
xmax = int(bbox.find('xmax').text)
ymax = int(bbox.find('ymax').text)

print(xmin, ymin, xmax, ymax)
```

0 26 332 340

```
[ ]: # path to the image correspomding to above annotation
os.path.join(images_dir_path, dog_classes[0], os.listdir(breed_folder_path)[0]) ↪
    + '.jpg'

[ ]: '/content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/images/n02085936-Maltese_dog/n02085936_3947.jpg'

[ ]: # open the corresponding image file
img_file = os.path.join(images_dir_path, dog_classes[0], os.
    ↪listdir(breed_folder_path)[0]) + '.jpg'
img = Image.open(img_file)
```

```
[ ]: img.show()
```



```
[ ]: # crop the image using the bounding box coordinates  
cropped_img = img.crop((xmin, ymin, xmax, ymax))  
cropped_img.show()
```



Now we are going to perform the same steps for all the images and get perfectly cropped images.

```
[ ]: import os
import xml.etree.ElementTree as ET
from PIL import Image

# path to output directory for cropped images
out_dir = os.path.join(root_dir_path, 'cropped_images')

# loop over each breed folder in the annotation directory
for breed_folder in os.listdir(annotation_dir_path):
    breed_folder_path = os.path.join(annotation_dir_path, breed_folder)
    if not os.path.isdir(breed_folder_path):
        continue

    # create folder for each breed to save the cropped images
    out_class_dir_path = os.path.join(out_dir, breed_folder)
    os.makedirs(out_class_dir_path, exist_ok = True)
    print(f"Created folder named {breed_folder} \n Path : {out_class_dir_path}")
```

```

# loop over each annotation file in the breed folder
for anno_file in os.listdir(breed_folder_path):
    image_name = anno_file+'.jpg'
    if image_name not in os.listdir(out_class_dir_path):
        try:
            # parse the XML file to get the bounding box coordinates
            tree = ET.parse(os.path.join(breed_folder_path, anno_file))
            root = tree.getroot()
            bbox = root.find('object').find('bndbox')
            xmin = int(bbox.find('xmin').text)
            ymin = int(bbox.find('ymin').text)
            xmax = int(bbox.find('xmax').text)
            ymax = int(bbox.find('ymax').text)

            # open the corresponding image file
            img_file = os.path.join(images_dir_path, breed_folder, anno_file + '.jpg')
            img = Image.open(img_file)

            # crop the image using the bounding box coordinates
            cropped_img = img.crop((xmin, ymin, xmax, ymax))

            # save the cropped image to the output directory
            out_file = os.path.join(out_dir, breed_folder, anno_file + '.jpg')
            cropped_img.save(out_file)

        except Exception as e:
            print(f"Failed to crop image {out_file}", '\n', "because", e)

```

```

Created folder named n02085936-Maltese_dog
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped_images/n02085936-Maltese_dog
Created folder named n02085620-Chihuahua
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped_images/n02085620-Chihuahua
Created folder named n02088094-Afghan_hound
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped_images/n02088094-Afghan_hound
Created folder named n02085782-Japanese_spaniel
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped_images/n02085782-Japanese_spaniel
Created folder named n02087046-toy_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped_images/n02087046-toy_terrier
Created folder named n02086910-papillon
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped

```

```
_images/n02086910-papillon
Created folder named n02087394-Rhodesian_ridgeback
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02087394-Rhodesian_ridgeback
Created folder named n02086646-Blenheim_spaniel
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02086646-Blenheim_spaniel
Created folder named n02086240-Shih-Tzu
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02086240-Shih-Tzu
Created folder named n02086079-Pekinese
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02086079-Pekinese
Created folder named n02091032-Italian_greyhound
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02091032-Italian_greyhound
Created folder named n02088364-beagle
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02088364-beagle
Created folder named n02088632-bluetick
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02088632-bluetick
Created folder named n02089973-English_foxhound
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02089973-English_foxhound
Created folder named n02088238-basset
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02088238-basset
Created folder named n02089078-black-and-tan_coonhound
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02089078-black-and-tan_coonhound
Created folder named n02090721-Irish_wolfhound
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02090721-Irish_wolfhound
Created folder named n02090379-redbone
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02090379-redbone
Created folder named n02088466-bloodhound
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02088466-bloodhound
Created folder named n02090622-borzoi
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02090622-borzoi
Created folder named n02093256-Staffordshire_bullterrier
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02093256-Staffordshire_bullterrier
Created folder named n02093754-Border_terrier
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
```

```
_images/n02093754-Border_terrier
Created folder named n02091467-Norwegian_elkhound
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02091467-Norwegian_elkhound
Created folder named n02091134-whippet
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02091134-whippet
Created folder named n02091831-Saluki
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02091831-Saluki
Created folder named n02091635-otterhound
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02091635-otterhound
Created folder named n02091244-Ibizan_hound
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02091244-Ibizan_hound
Created folder named n02092339-Weimaraner
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02092339-Weimaraner
Created folder named n02093428-American_Staffordshire_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02093428-American_Staffordshire_terrier
Created folder named n02092002-Scottish_deerhound
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02092002-Scottish_deerhound
Created folder named n02093859-Kerry_blue_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02093859-Kerry_blue_terrier
Created folder named n02096051-Airedale
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02096051-Airedale
Created folder named n02093991-Irish_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02093991-Irish_terrier
Created folder named n02096177-cairn
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02096177-cairn
Created folder named n02094258-Norwich_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02094258-Norwich_terrier
Created folder named n02094114-Norfolk_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02094114-Norfolk_terrier
Created folder named n02095314-wire-haired_fox_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02095314-wire-haired_fox_terrier
Created folder named n02095889-Sealyham_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
```

```
_images/n02095889-Sealyham_terrier
Created folder named n02095570-Lakeland_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02095570-Lakeland_terrier
Created folder named n02094433-Yorkshire_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02094433-Yorkshire_terrier
Created folder named n02098286-West_HIGHLAND_WHITE_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02098286-West_HIGHLAND_WHITE_terrier
Created folder named n02096437-Dandie_Dinmont
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02096437-Dandie_Dinmont
Created folder named n02097209-standard_schnauzer
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02097209-standard_schnauzer
Created folder named n02097474-Tibetan_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02097474-Tibetan_terrier
Created folder named n02096294-Australian_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02096294-Australian_terrier
Created folder named n02098105-soft-coated_wheaten_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02098105-soft-coated_wheaten_terrier
Created folder named n02097658-silky_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02097658-silky_terrier
Created folder named n02096585-Boston_bull
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02096585-Boston_bull
Created folder named n02097298-Scotch_terrier
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02097298-Scotch_terrier
Created folder named n02097130-giant_schnauzer
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02097130-giant_schnauzer
Created folder named n02100236-German_short-haired_pointer
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02100236-German_short-haired_pointer
Created folder named n02099712-Labrador_retriever
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02099712-Labrador_retriever
Created folder named n02099267-flat-coated_retriever
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02099267-flat-coated_retriever
Created folder named n02099429-curly-coated_retriever
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
```

```
_images/n02099429-curly-coated_retriever
Created folder named n02097047-miniature_schnauzer
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02097047-miniature_schnauzer
Created folder named n02093647-Bedlington_terrier
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02093647-Bedlington_terrier
Created folder named n02099601-golden_retriever
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02099601-golden_retriever
Created folder named n02098413-Lhasa
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02098413-Lhasa
Created folder named n02099849-Chesapeake_Bay_retriever
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02099849-Chesapeake_Bay_retriever
Created folder named n02089867-Walker_hound
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02089867-Walker_hound
Created folder named n02108422-bull_mastiff
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02108422-bull_mastiff
Created folder named n02101388-Brittany_spaniel
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02101388-Brittany_spaniel
Created folder named n02100877-Irish_setter
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02100877-Irish_setter
Created folder named n02100735-English_setter
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02100735-English_setter
Created folder named n02101556-clumber
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02101556-clumber
Created folder named n02101006-Gordon_setter
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02101006-Gordon_setter
Created folder named n02102040-English_springer
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02102040-English_springer
Created folder named n02102177-Welsh_springer_spaniel
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02102177-Welsh_springer_spaniel
Created folder named n02100583-vizsla
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02100583-vizsla
Created folder named n02105412-kelpie
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
```

```
_images/n02105412-kelpie
Created folder named n02105251-briard
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02105251-briard
Created folder named n02102480-Sussex_swan
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02102480-Sussex_swan
Created folder named n02104365-schipperke
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02104365-schipperke
Created folder named n02102318-cocker_swan
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02102318-cocker_swan
Created folder named n02102973-Irish_water_swan
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02102973-Irish_water_swan
Created folder named n02105505-komondor
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02105505-komondor
Created folder named n02105162-malinois
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02105162-malinois
Created folder named n02105641-Old_English_sheepdog
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02105641-Old_English_sheepdog
Created folder named n02105056-groenendael
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02105056-groenendael
Created folder named n02104029-kuvasz
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02104029-kuvasz
Created folder named n02106382-Bouvier_des_Flandres
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02106382-Bouvier_des_Flandres
Created folder named n02107312-miniature_pinscher
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02107312-miniature_pinscher
Created folder named n02106662-German_shepherd
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02106662-German_shepherd
Created folder named n02106166-Border_collie
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02106166-Border_collie
Created folder named n02107683-Bernese_mountain_dog
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02107683-Bernese_mountain_dog
Created folder named n02107142-Doberman
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
```

```
_images/n02107142-Doberman
Created folder named n02106030-collie
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02106030-collie
Created folder named n02105855-Shetland_sheepdog
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02105855-Shetland_sheepdog
Created folder named n02107574-Greater_Swiss_Mountain_dog
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02107574-Greater_Swiss_Mountain_dog
Created folder named n02106550-Rottweiler
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02106550-Rottweiler
Created folder named n02108551-Tibetan_mastiff
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02108551-Tibetan_mastiff
Created folder named n02109961-Eskimo_dog
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02109961-Eskimo_dog
Created folder named n02107908-Appenzeller
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02107908-Appenzeller
Created folder named n02110185-Siberian_husky
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02110185-Siberian_husky
Created folder named n02109525-Saint_Bernard
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02109525-Saint_Bernard
Created folder named n02110063-malamute
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02110063-malamute
Created folder named n02108915-French_bulldog
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02108915-French_bulldog
Created folder named n02108000-EntleBucher
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02108000-EntleBucher
Created folder named n02109047-Great_Dane
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02109047-Great_Dane
Created folder named n02108089-boxer
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02108089-boxer
Created folder named n02111889-Samoyed
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02111889-Samoyed
Created folder named n02111277-Newfoundland
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
```

```
_images/n02111277-Newfoundland
Created folder named n02110806-basenji
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02110806-basenji
Created folder named n02112350-keeshond
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_images/n02112350-keeshond
Created folder named n02110958-pug
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02110958-pug
Created folder named n02111129-Leonberg
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02111129-Leonberg
Created folder named n02110627-affenpinscher
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02110627-affenpinscher
Created folder named n02112137-chow
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02112137-chow
Created folder named n02111500-Great_Pyrenees
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
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Created folder named n02112018-Pomeranian
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
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Created folder named n02113023-Pembroke
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02113023-Pembroke
Created folder named n02112706-Brabancon_griffon
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02112706-Brabancon_griffon
Created folder named n02113624-toy_poodle
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
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Created folder named n02116738-African_hunting_dog
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02116738-African_hunting_dog
Created folder named n02115641-dingo
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02115641-dingo
Created folder named n02115913-dhole
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02115913-dhole
Created folder named n02113712-miniature_poodle
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02113712-miniature_poodle
Created folder named n02113799-standard_poodle
  Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
```

```
_images/n02113799-standard_poodle
Created folder named n02113186-Cardigan
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02113186-Cardigan
Created folder named n02113978-Mexican_hairless
Path : /content/drive/MyDrive/DL/Assignment2/stanford_dog_breed_dataset/cropped
_images/n02113978-Mexican_hairless
```

```
[ ]: # counting total no of cropped images
sum = 0
for dog_class in dog_classes:
    sum += files_count(os.path.join(out_dir, dog_class))

sum
```

```
[ ]: 20580
```

5.8 Prepearng X_cropped and y_cropped

- X_cropped -> Contains full path of all images
- y_cropped -> labels of corresponding images

```
[8]: from itertools import chain

X_cropped = []
y_cropped = []

# path to output directory for cropped images
out_dir = os.path.join(root_dir_path, 'cropped_images')

fullpaths = [os.path.join(out_dir, dog_class) for dog_class in dog_classes]

for counter, fullpath in enumerate(fullpaths):
    for imgname in os.listdir(fullpath):
        X_cropped.append([fullpath + '/' + imgname])
        y_cropped.append(breeds[counter])

X_cropped = list(chain.from_iterable(X_cropped)) # unnest the lists and join
                                                # together into one list
print(f"Total number of pictures -> {len(X_cropped)} \n No of breeds -> "
      f"{len(set(y_cropped))}")
```

Total number of pictures -> 20580
No of breeds -> 120

Comment

Since total no of images is same as before, we can confirm that we have cropped and saved all the images in cropped_images folder.

5.9 Shuffle and Plot Cropped Images

Let us check that we are able to crop all the images properly

We will again plot a batch of 25 random images from cropped_images folder

```
[ ]: import random
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib.image import imread

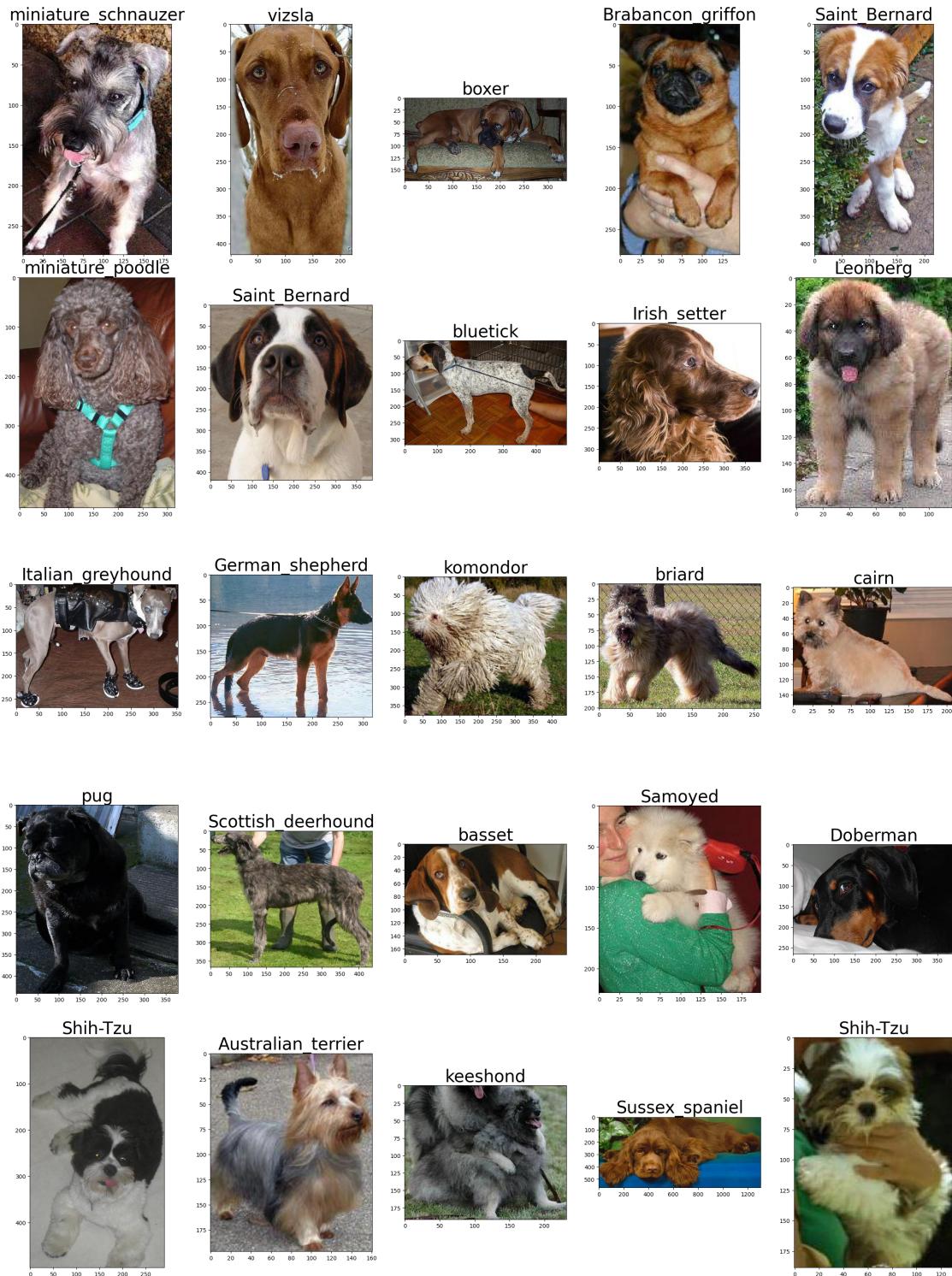
# shuffle X_cropped and y_cropped
combined = list(zip(X_cropped, y_cropped))
random.shuffle(combined)

X_cropped[:, :], y_cropped[:] = zip(*combined)

# Display random dogs pictures
plt.figure(figsize=(30,40))
plt.suptitle("Sample batch of random 25 Dog images", fontsize=50)
for counter, i in enumerate(random.sample(range(0, len(X_cropped)), 25)): #_
    ↪random 25 images
    plt.subplot(5, 5, counter+1)
    plt.subplots_adjust(hspace=0.1)
    filename = X_cropped[i]
    image = imread(filename)
    plt.imshow(image)
    plt.title(y_cropped[i], fontsize=30)

plt.show()
```

Sample batch of random 25 Dog images



Comment

All the random images are perfectly cropped.

6 Lavel Encoding

In deep learning image classification tasks, encoding the classes/breeds is a crucial step. One-hot encoding is commonly used for multi-class classification problems like the Stanford Dog Breed dataset, where each image is associated with one breed out of 120 possible breeds. With one-hot encoding, we create a **binary vector for each image**, with a length of 120 (the number of classes). **Each vector has only one non-zero value, which indicates the class/breed/label associated with that particular image**. This encoding scheme allows the model to learn to distinguish between the different breeds and make accurate predictions.

```
[27]: # Convert labels to one-hot encoded labels
import numpy as np
from sklearn.preprocessing import LabelEncoder
from keras.utils import to_categorical

# Label and one-hot encoding y labels
# Here we can use y or y_cropped as both contain the same data
le = LabelEncoder()
le.fit(y_cropped)
y_ohe = to_categorical(le.transform(y_cropped), len(breeds))
y_ohe = np.array(y_ohe)
```

6.1 Save le.classes_ as json file

```
[28]: import json

# assume that you have a LabelEncoder object named "le"
class_names = list(le.classes_)

# save the list as a JSON file
with open('class_names.json', 'w') as f:
    json.dump(class_names, f)
```

7 Prepearng a subset of Dataset

- Anyone with good computational power can avoid this step.
- With the free version of colab, it will take long to prepear train, test and validation data and also for Model training. So we need to reduce our data or number of images.

```
[11]: X_cropped = X_cropped[:3600]
y_cropped = y_cropped[:3600]
```

```
y_ohe = y_ohe[:3600]
```

8 Preparing Train, Validation & Test Data

- To prepare our dataset, we resize and preprocess the images to match the pre-trained model's dimensions.
- We load the images and convert them to a standard size and format using image processing libraries like **keras preprocessing or OpenCV or Pillow**.
- We then split our dataset into training, validation, and testing sets using the **train_test_split** function from the **sklearn** module.

8.1 For Inception Model

```
[ ]: import numpy as np
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.image import load_img
from tensorflow.keras.utils import img_to_array

img_data = np.array([img_to_array(load_img(img, target_size = (299,299)))
                     for img in X_cropped]) # load, resize images, and store as array

x_train, x_test, y_train, y_test = train_test_split(img_data, y_ohe,
                                                    test_size = 0.2,
                                                    stratify=np.array(y_cropped), # stratify makes sure that proportion of each class in the output is same as the input
                                                    random_state = 2)

x_train, x_val, y_train, y_val = train_test_split(x_train, y_train,
                                                    test_size = 0.2,
                                                    stratify=np.array(y_train),
                                                    random_state = 2)

print('Training Dataset Size: ', x_train.shape)
print('Validation Dataset Size: ', x_val.shape)
print('Testing Dataset Size: ', x_test.shape)
print('Training Label Size: ', y_train.shape)
print('Validation Label Size: ', y_val.shape)
print('Testing Label Size: ', y_test.shape)
```

```
Training Dataset Size: (2304, 299, 299, 3)
Validation Dataset Size: (576, 299, 299, 3)
Testing Dataset Size: (720, 299, 299, 3)
Training Label Size: (2304, 120)
Validation Label Size: (576, 120)
Testing Label Size: (720, 120)
```

Comment

We can see that we have - 2304 training, - 576 validation, and - 720 testing images.

Each image has a 299x299 dimension, with 3 channels, representing the RGB channels.

```
[ ]: # clear unnecessary memory occupied by the code
      import gc

      #delete the variable img_data from the program's memory,
      #effectively freeing up the memory that was being used by this variable.
      del img_data

      #free up any other memory
      #that may have been allocated by the program but is no longer being used.
      gc.collect()
```

```
[ ]: 41
```

8.2 For VGG16 Model

```
[12]: import numpy as np
       from sklearn.model_selection import train_test_split
       from tensorflow.keras.preprocessing.image import load_img
       from tensorflow.keras.utils import img_to_array

       img_data = np.array([img_to_array(load_img(img, target_size = (224,224)))
                           for img in X_cropped]) # load, resize images, and store as
                           ↪array

       x_train, x_test, y_train, y_test = train_test_split(img_data, y_ohe,
                                                          test_size = 0.2,
                                                          stratify=np.
                                                          ↪array(y_cropped), # stratify makes sure that proportion of each class in the
                                                          ↪output is same as the input
                                                          random_state = 2)

       x_train, x_val, y_train, y_val = train_test_split(x_train, y_train,
                                                          test_size = 0.2,
                                                          stratify=np.array(y_train),
                                                          random_state = 2)

       print('Training Dataset Size: ', x_train.shape)
       print('Validation Dataset Size: ', x_val.shape)
       print('Testing Dataset Size: ', x_test.shape)
       print('Training Label Size: ', y_train.shape)
       print('Validation Label Size: ', y_val.shape)
       print('Testing Label Size: ', y_test.shape)
```

```
Training Dataset Size: (2304, 224, 224, 3)
Validation Dataset Size: (576, 224, 224, 3)
Testing Dataset Size: (720, 224, 224, 3)
Training Label Size: (2304, 120)
Validation Label Size: (576, 120)
Testing Label Size: (720, 120)
```

```
[13]: # clear unnecessary memory occupied by the code
import gc

#delete the variable img_data from the program's memory,
#effectively freeing up the memory that was being used by this variable.
del img_data

#free up any other memory
#that may have been allocated by the program but is no longer being used.
gc.collect()
```

```
[13]: 556
```

9 Data Augmentation

Our dataset already has a sufficient number of images, with 150+ images for each of the 120 classes. Data augmentation may not be necessary at this point. However, if our model is overfitting on the training data or has difficulty generalizing on the validation or test set, applying data augmentation techniques can help create additional image variations and potentially improve performance.

** But due to low computational power I was able to take only 3600 images from the dataset. So I am going to perform Data Augmentation before training the model.

```
[14]: # Required libraries for Data Augmentation
from keras.applications.inception_v3 import preprocess_input
from keras.preprocessing.image import ImageDataGenerator
```

```
[15]: batch_size = 32

# Create train generator
train_datagen = ImageDataGenerator(preprocessing_function=preprocess_input, #_
    ↪only use rescale=1./255 if training from scratch
        rotation_range = 30,
        width_shift_range = 0.2,
        height_shift_range = 0.2,
        horizontal_flip = True) # CHECK

train_generator = train_datagen.flow(x_train, y_train,
                                    shuffle = False, batch_size = batch_size, ↪
    ↪seed = 1)
```

```
# Create validation generator
val_datagen = ImageDataGenerator(preprocessing_function=preprocess_input) # donot
    ↳not augment validation data

val_generator = val_datagen.flow(x_val, y_val,
                                 shuffle = False, batch_size = batch_size, seed=u
    ↳= 1)
```

```
[16]: import matplotlib.pyplot as plt
%matplotlib inline
# Here is an example of Augmentation to transform any image into new images
img_id = 16

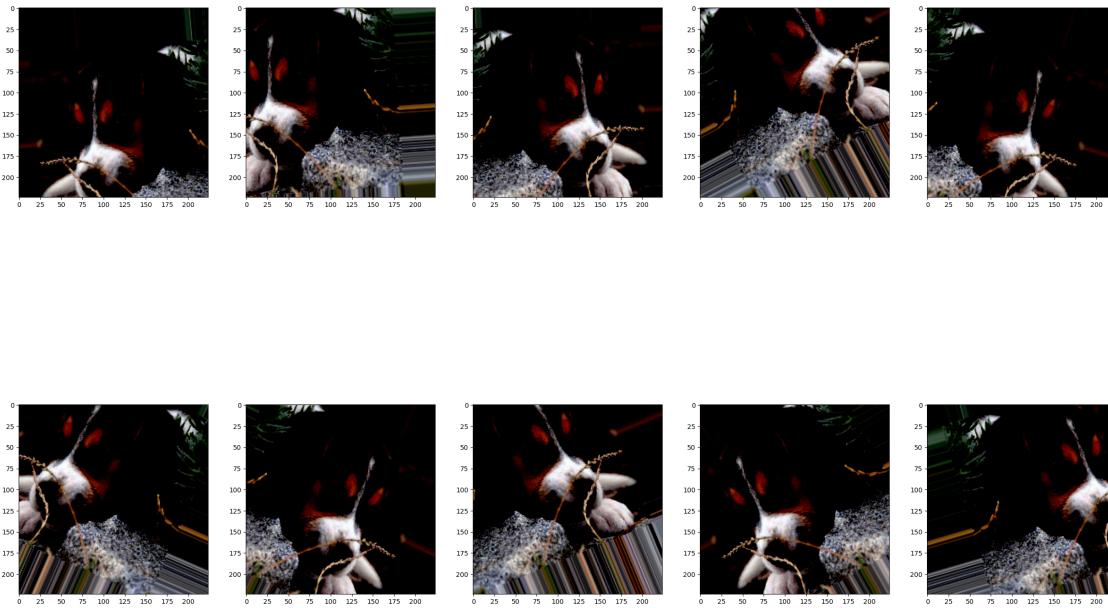
dog_generator = train_datagen.flow(x_train[img_id:img_id+1], y_train[img_id:
    ↳img_id+1],
                                    shuffle = False, batch_size = batch_size,u
    ↳seed = 1)

plt.figure(figsize=(30,20))
dogs = [next(dog_generator) for i in range(0,10)]
for counter, dog in enumerate(dogs):
    plt.subplot(2, 5, counter+1)
    plt.imshow(dog[0][0])
    #plt.axis('off')

plt.show()
```

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

RGB data ([0..1] for floats or [0..255] for integers).



10 Model Building

10.1 Experiment 1 : Google's Inception V3

Inception v3 is a pre-trained convolutional neural network architecture developed by Google. It is designed for image classification tasks and has shown impressive performance on various image datasets. The model consists of 48 layers and has approximately 23 million trainable parameters.

To use Inception v3, you can first load the pre-trained model using a deep learning framework like TensorFlow or Keras. Then, you can pass your own dataset of images through the model to make predictions on the class labels of the images.

By leveraging the low-level features learned by the pre-trained model, we can reduce the training time and improve the accuracy of the model.

```
[ ]: from keras import models
from keras import layers
from keras.optimizers import Adam
from keras.layers import GlobalAveragePooling2D, Dense, Flatten, Dropout
from keras.applications.inception_v3 import InceptionV3
from keras.utils.np_utils import to_categorical
from keras.utils.vis_utils import plot_model

# load InceptionV3 pre-trained model
base_model = InceptionV3(weights = 'imagenet', include_top = False, input_shape=(299,299,3))
```

```

inception_model = models.Sequential()
inception_model.add(base_model) # add pre-trained layers
inception_model.add(GlobalAveragePooling2D())
inception_model.add(Dropout(0.3))
inception_model.add(Dense(512, activation = 'relu'))
inception_model.add(Dense(512, activation = 'relu'))
inception_model.add(Dense(len(breeds), activation = 'softmax'))

# Freeze pre-trained layers
print('Number of trainable weights before freezing the base layer:', len(inception_model.trainable_weights))
inception_model.layers[0].trainable = False
print('Number of trainable weights after freezing the base layer:', len(inception_model.trainable_weights))

# Compile the Model
inception_model.compile(Adam(learning_rate=.0001), loss='categorical_crossentropy', metrics=['accuracy'])
inception_model.summary()

```

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/inception_v3/inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5
87910968/87910968 [=====] - 4s 0us/step
Number of trainable weights before freezing the base layer: 194
Number of trainable weights after freezing the base layer: 6
Model: "sequential"

Layer (type)	Output Shape	Param #
inception_v3 (Functional)	(None, 8, 8, 2048)	21802784
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
dropout (Dropout)	(None, 2048)	0
dense (Dense)	(None, 512)	1049088
dense_1 (Dense)	(None, 512)	262656
dense_2 (Dense)	(None, 120)	61560

Total params: 23,176,088
Trainable params: 1,373,304
Non-trainable params: 21,802,784

10.2 Experiment 2 : VGG16

VGG16 is a popular pre-trained convolutional neural network architecture for image classification tasks. It was developed by the Visual Geometry Group at the University of Oxford and achieved state-of-the-art performance on the ImageNet dataset in 2014. The model has 16 layers and over 138 million trainable parameters.

```
[17]: import numpy as np
from keras.preprocessing.image import ImageDataGenerator
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.applications.vgg16 import VGG16
from keras.utils import to_categorical

# Set the input size of the VGG16 model
img_rows, img_cols = 224, 224

# Load the pre-trained VGG16 model without the top layers
base_model = VGG16(weights='imagenet', include_top=False,
                     input_shape=(img_rows, img_cols, 3))

# Freeze the base_model layers
for layer in base_model.layers:
    layer.trainable = False

# Create a new model on top of the VGG16 base_model
vgg16_model = Sequential()
vgg16_model.add(base_model)
vgg16_model.add(Flatten())
vgg16_model.add(Dense(512, activation='relu'))
vgg16_model.add(Dropout(0.5))
vgg16_model.add(Dense(120, activation='softmax'))

# Compile the model with categorical cross-entropy loss and Adam optimizer
vgg16_model.compile(loss='categorical_crossentropy', optimizer='adam',
                     metrics=['accuracy'])
vgg16_model.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58889256/58889256 [=====] - 3s 0us/step
Model: "sequential"
```

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 7, 7, 512)	14714688

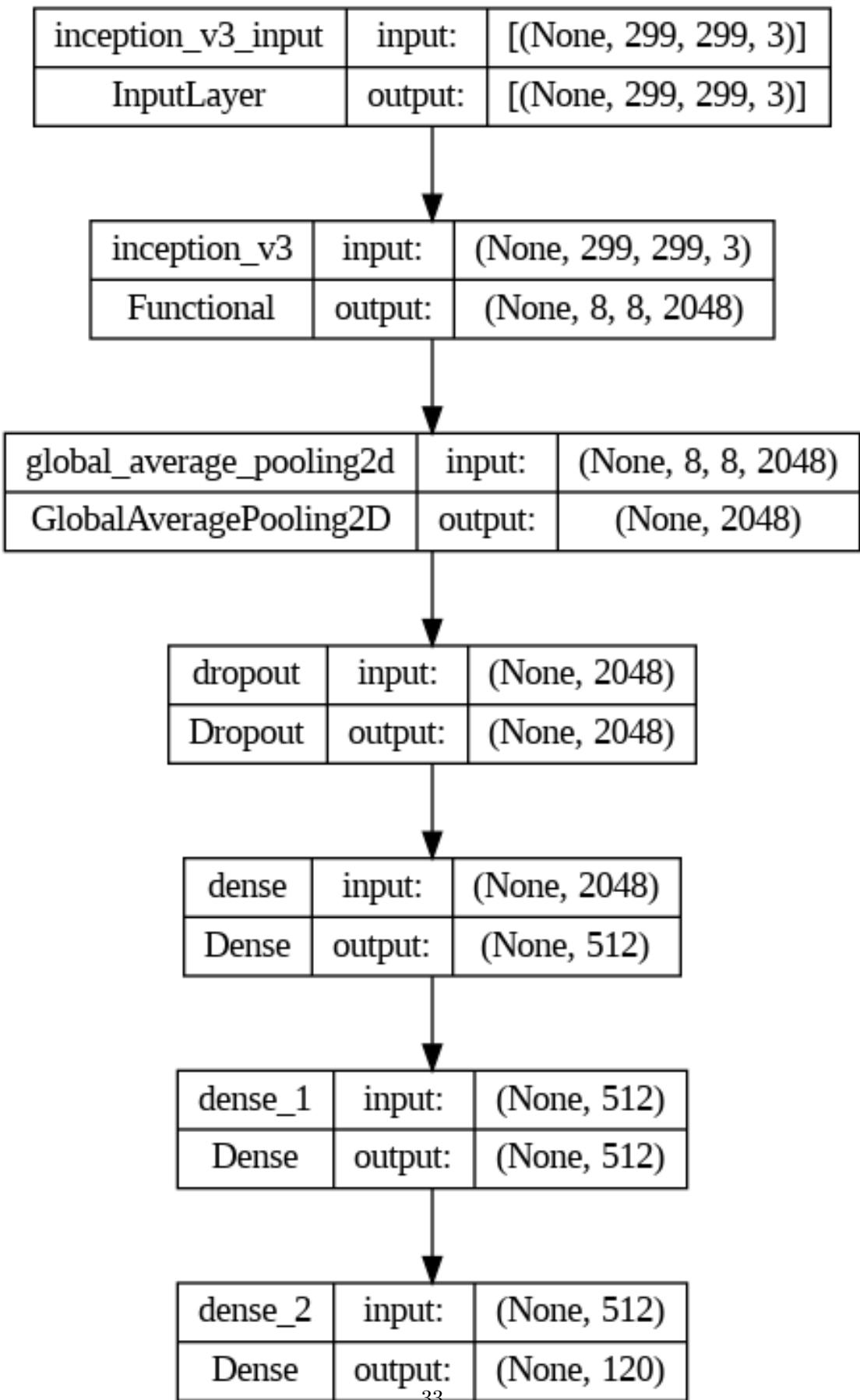
```
flatten (Flatten)           (None, 25088)          0
dense (Dense)               (None, 512)            12845568
dropout (Dropout)           (None, 512)            0
dense_1 (Dense)             (None, 120)            61560
=====
Total params: 27,621,816
Trainable params: 12,907,128
Non-trainable params: 14,714,688
```

11 Model Visualization

11.1 Inception V3 Model

```
[ ]: from keras.utils.vis_utils import plot_model
plot_model(inception_model, to_file='inception_model.png', show_shapes=True,
           show_layer_names=True)
```

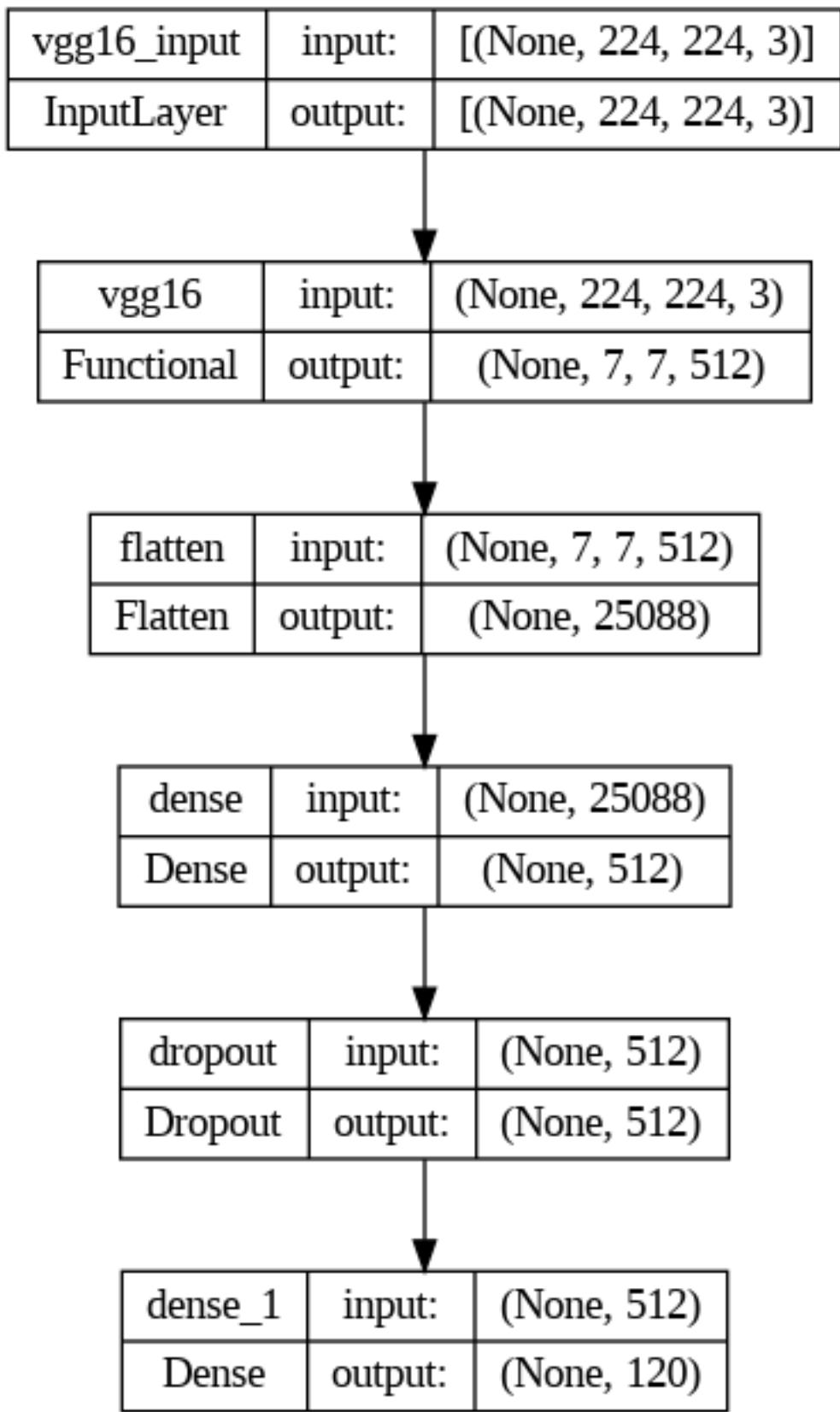
```
[ ]:
```



11.2 VGG16

```
[18]: from keras.utils.vis_utils import plot_model  
  
plot_model(vgg16_model, to_file='vgg16_model.png', show_shapes=True,  
           show_layer_names=True)
```

[18]:



12 Model Training

12.1 Inception V3 Model

```
[ ]: train_steps_per_epoch = x_train.shape[0] // batch_size
val_steps_per_epoch = x_val.shape[0] // batch_size
epochs = 20

history = inception_model.fit_generator(train_generator,
                                         steps_per_epoch = train_steps_per_epoch,
                                         validation_data = val_generator,
                                         validation_steps = val_steps_per_epoch,
                                         epochs = epochs, verbose = 1)

<ipython-input-35-a5a803a83040>:5: UserWarning: `Model.fit_generator` is
deprecated and will be removed in a future version. Please use `Model.fit`,
which supports generators.
    history = inception_model.fit_generator(train_generator,
Epoch 1/20
72/72 [=====] - 68s 731ms/step - loss: 2.5050 -
accuracy: 0.5373 - val_loss: 0.6526 - val_accuracy: 0.9410
Epoch 2/20
72/72 [=====] - 57s 791ms/step - loss: 0.5361 -
accuracy: 0.8863 - val_loss: 0.1973 - val_accuracy: 0.9670
Epoch 3/20
72/72 [=====] - 60s 829ms/step - loss: 0.3556 -
accuracy: 0.8997 - val_loss: 0.2015 - val_accuracy: 0.9444
Epoch 4/20
72/72 [=====] - 52s 726ms/step - loss: 0.2995 -
accuracy: 0.9119 - val_loss: 0.1255 - val_accuracy: 0.9688
Epoch 5/20
72/72 [=====] - 63s 870ms/step - loss: 0.2986 -
accuracy: 0.9084 - val_loss: 0.1127 - val_accuracy: 0.9705
Epoch 6/20
72/72 [=====] - 53s 743ms/step - loss: 0.2760 -
accuracy: 0.9141 - val_loss: 0.1060 - val_accuracy: 0.9670
Epoch 7/20
72/72 [=====] - 53s 727ms/step - loss: 0.2303 -
accuracy: 0.9271 - val_loss: 0.0936 - val_accuracy: 0.9740
Epoch 8/20
72/72 [=====] - 53s 732ms/step - loss: 0.2578 -
accuracy: 0.9184 - val_loss: 0.0957 - val_accuracy: 0.9792
Epoch 9/20
72/72 [=====] - 53s 739ms/step - loss: 0.2372 -
accuracy: 0.9214 - val_loss: 0.0979 - val_accuracy: 0.9670
```

```

Epoch 10/20
72/72 [=====] - 54s 744ms/step - loss: 0.2174 -
accuracy: 0.9310 - val_loss: 0.0952 - val_accuracy: 0.9618
Epoch 11/20
72/72 [=====] - 53s 734ms/step - loss: 0.2246 -
accuracy: 0.9258 - val_loss: 0.0934 - val_accuracy: 0.9688
Epoch 12/20
72/72 [=====] - 52s 727ms/step - loss: 0.2213 -
accuracy: 0.9301 - val_loss: 0.0913 - val_accuracy: 0.9740
Epoch 13/20
72/72 [=====] - 53s 724ms/step - loss: 0.2057 -
accuracy: 0.9353 - val_loss: 0.1127 - val_accuracy: 0.9618
Epoch 14/20
72/72 [=====] - 54s 751ms/step - loss: 0.2049 -
accuracy: 0.9280 - val_loss: 0.0972 - val_accuracy: 0.9688
Epoch 15/20
72/72 [=====] - 54s 754ms/step - loss: 0.1758 -
accuracy: 0.9418 - val_loss: 0.0885 - val_accuracy: 0.9740
Epoch 16/20
72/72 [=====] - 54s 748ms/step - loss: 0.2117 -
accuracy: 0.9262 - val_loss: 0.0892 - val_accuracy: 0.9740
Epoch 17/20
72/72 [=====] - 53s 736ms/step - loss: 0.1801 -
accuracy: 0.9392 - val_loss: 0.0831 - val_accuracy: 0.9826
Epoch 18/20
72/72 [=====] - 53s 733ms/step - loss: 0.1687 -
accuracy: 0.9466 - val_loss: 0.0902 - val_accuracy: 0.9688
Epoch 19/20
72/72 [=====] - 53s 728ms/step - loss: 0.1681 -
accuracy: 0.9405 - val_loss: 0.0874 - val_accuracy: 0.9792
Epoch 20/20
72/72 [=====] - 54s 745ms/step - loss: 0.1725 -
accuracy: 0.9392 - val_loss: 0.0941 - val_accuracy: 0.9705

```

12.2 VGG16

```
[19]: train_steps_per_epoch = x_train.shape[0] // batch_size
val_steps_per_epoch = x_val.shape[0] // batch_size
epochs = 20

history = vgg16_model.fit(train_generator,
                           steps_per_epoch = train_steps_per_epoch,
                           validation_data = val_generator,
                           validation_steps = val_steps_per_epoch,
                           epochs = epochs, verbose = 1)
```

```

Epoch 1/20
72/72 [=====] - 48s 479ms/step - loss: 3.6162 -

```

```
accuracy: 0.1745 - val_loss: 1.9766 - val_accuracy: 0.3785
Epoch 2/20
72/72 [=====] - 31s 426ms/step - loss: 2.3035 -
accuracy: 0.2865 - val_loss: 1.5917 - val_accuracy: 0.4826
Epoch 3/20
72/72 [=====] - 31s 431ms/step - loss: 2.0574 -
accuracy: 0.3294 - val_loss: 1.4562 - val_accuracy: 0.5156
Epoch 4/20
72/72 [=====] - 31s 436ms/step - loss: 1.8341 -
accuracy: 0.3989 - val_loss: 1.2500 - val_accuracy: 0.6128
Epoch 5/20
72/72 [=====] - 32s 439ms/step - loss: 1.8106 -
accuracy: 0.3980 - val_loss: 1.2742 - val_accuracy: 0.5781
Epoch 6/20
72/72 [=====] - 32s 441ms/step - loss: 1.7254 -
accuracy: 0.4175 - val_loss: 1.1885 - val_accuracy: 0.5816
Epoch 7/20
72/72 [=====] - 32s 443ms/step - loss: 1.6056 -
accuracy: 0.4566 - val_loss: 1.0790 - val_accuracy: 0.6476
Epoch 8/20
72/72 [=====] - 33s 458ms/step - loss: 1.5576 -
accuracy: 0.4631 - val_loss: 1.0408 - val_accuracy: 0.6545
Epoch 9/20
72/72 [=====] - 31s 432ms/step - loss: 1.4993 -
accuracy: 0.4800 - val_loss: 1.0059 - val_accuracy: 0.6632
Epoch 10/20
72/72 [=====] - 32s 439ms/step - loss: 1.4889 -
accuracy: 0.4891 - val_loss: 0.9820 - val_accuracy: 0.6840
Epoch 11/20
72/72 [=====] - 47s 654ms/step - loss: 1.4528 -
accuracy: 0.5035 - val_loss: 0.9443 - val_accuracy: 0.6927
Epoch 12/20
72/72 [=====] - 32s 438ms/step - loss: 1.4465 -
accuracy: 0.4996 - val_loss: 1.0012 - val_accuracy: 0.6806
Epoch 13/20
72/72 [=====] - 33s 454ms/step - loss: 1.4822 -
accuracy: 0.4974 - val_loss: 0.9186 - val_accuracy: 0.6736
Epoch 14/20
72/72 [=====] - 36s 497ms/step - loss: 1.4216 -
accuracy: 0.5213 - val_loss: 0.9303 - val_accuracy: 0.6944
Epoch 15/20
72/72 [=====] - 39s 538ms/step - loss: 1.3491 -
accuracy: 0.5386 - val_loss: 0.8869 - val_accuracy: 0.6858
Epoch 16/20
72/72 [=====] - 32s 440ms/step - loss: 1.3808 -
accuracy: 0.5299 - val_loss: 0.9126 - val_accuracy: 0.6823
Epoch 17/20
72/72 [=====] - 31s 435ms/step - loss: 1.3351 -
```

```

accuracy: 0.5421 - val_loss: 0.9183 - val_accuracy: 0.6875
Epoch 18/20
72/72 [=====] - 32s 442ms/step - loss: 1.3715 -
accuracy: 0.5217 - val_loss: 0.9624 - val_accuracy: 0.6545
Epoch 19/20
72/72 [=====] - 33s 460ms/step - loss: 1.3556 -
accuracy: 0.5291 - val_loss: 0.8388 - val_accuracy: 0.7153
Epoch 20/20
72/72 [=====] - 32s 444ms/step - loss: 1.3005 -
accuracy: 0.5395 - val_loss: 0.8763 - val_accuracy: 0.6944

```

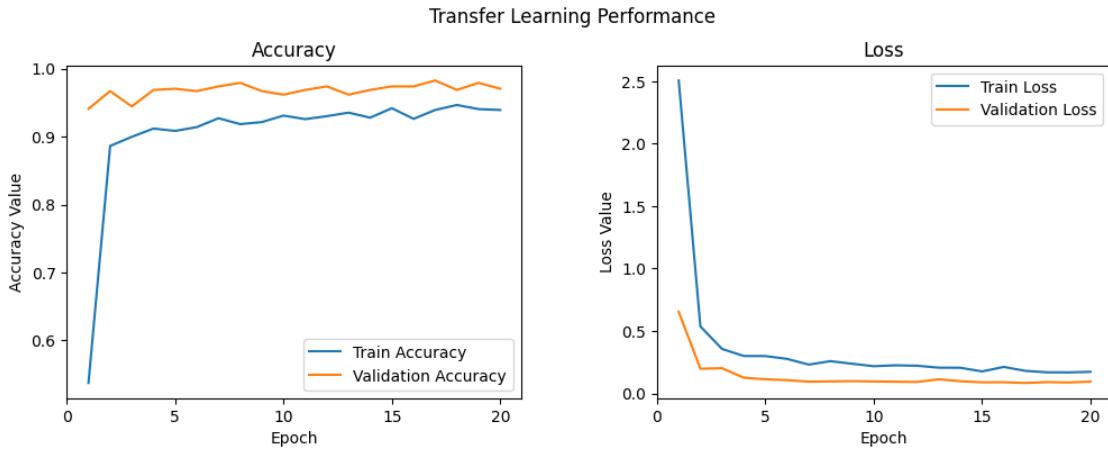
13 Accuracy and Loss Plots

13.1 Inception V3 Model

```
[ ]: f, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
t = f.suptitle('Transfer Learning Performance', fontsize=12)
f.subplots_adjust(top=0.85, wspace=0.3)

epoch_list = list(range(1,epochs+1))
ax1.plot(epoch_list, history.history['accuracy'], label='Train Accuracy')
ax1.plot(epoch_list, history.history['val_accuracy'], label='Validation Accuracy')
ax1.set_xticks(np.arange(0, epochs+1, 5))
ax1.set_ylabel('Accuracy Value')
ax1.set_xlabel('Epoch')
ax1.set_title('Accuracy')
l1 = ax1.legend(loc="best")

ax2.plot(epoch_list, history.history['loss'], label='Train Loss')
ax2.plot(epoch_list, history.history['val_loss'], label='Validation Loss')
ax2.set_xticks(np.arange(0, epochs+1, 5))
ax2.set_ylabel('Loss Value')
ax2.set_xlabel('Epoch')
ax2.set_title('Loss')
l2 = ax2.legend(loc="best")
```

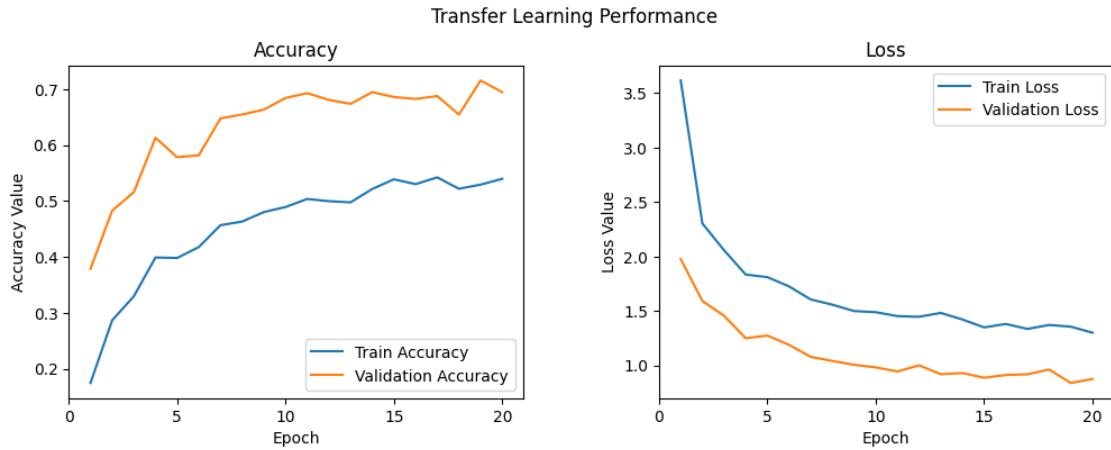


13.2 VGG16

```
[20]: f, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
t = f.suptitle('Transfer Learning Performance', fontsize=12)
f.subplots_adjust(top=0.85, wspace=0.3)

epoch_list = list(range(1,epochs+1))
ax1.plot(epoch_list, history.history['accuracy'], label='Train Accuracy')
ax1.plot(epoch_list, history.history['val_accuracy'], label='Validation Accuracy')
ax1.set_xticks(np.arange(0, epochs+1, 5))
ax1.set_ylabel('Accuracy Value')
ax1.set_xlabel('Epoch')
ax1.set_title('Accuracy')
l1 = ax1.legend(loc="best")

ax2.plot(epoch_list, history.history['loss'], label='Train Loss')
ax2.plot(epoch_list, history.history['val_loss'], label='Validation Loss')
ax2.set_xticks(np.arange(0, epochs+1, 5))
ax2.set_ylabel('Loss Value')
ax2.set_xlabel('Epoch')
ax2.set_title('Loss')
l2 = ax2.legend(loc="best")
```



14 Save & Load Model

14.1 Inception V3

```
[ ]: inception_model.save('/content/drive/MyDrive/DL/Assignment2/models/
↪inception_model.h5')

[ ]: from tensorflow.keras.models import load_model

# Load the saved model
inception_model = load_model('/content/drive/MyDrive/DL/Assignment2/models/
↪inception_model.h5')
```

14.2 VGG16

```
[21]: # Save model
vgg16_model.save('/content/drive/MyDrive/DL/Assignment2/models/vgg16_model.h5')

[22]: from tensorflow.keras.models import load_model

# Load saved model
vgg16_model = load_model('/content/drive/MyDrive/DL/Assignment2/models/
↪vgg16_model.h5')
```

15 Predicting on Test Set

15.1 Inception V3 Model

```
[ ]: import pandas as pd

x_test1 = x_test / 255. # rescale to 0-1. Divide by 255 as its the max RGB value
test_predictions = inception_model.predict(x_test1)

# get model predictions
predictions = le.classes_[np.argmax(test_predictions, axis=1)] # get labels and ↴
    ↴reverse back to get the text labels
# get target labels
target_labels = le.classes_[np.argmax(y_test, axis=1)]

# Store in dataframe
predict_df = pd.DataFrame({'Target_Labels': target_labels, 'Predictions': ↴
    ↴predictions})
predict_df.head(20)
```

23/23 [=====] - 8s 190ms/step

```
[ ]:          Target_Labels          Predictions
0      Irish_wolfhound      Irish_wolfhound
1      Afghan_hound      Afghan_hound
2      bloodhound      bloodhound
3      Blenheim_spaniel      Blenheim_spaniel
4      Chihuahua      toy_terrier
5      borzoi      borzoi
6      Blenheim_spaniel      Blenheim_spaniel
7      Italian_greyhound      Italian_greyhound
8      Pekinese      Pekinese
9  black-and-tan_coonhound  black-and-tan_coonhound
10     Italian_greyhound      Italian_greyhound
11      bloodhound      bloodhound
12      borzoi      borzoi
13      Pekinese      Pekinese
14  black-and-tan_coonhound  black-and-tan_coonhound
15      Rhodesian_ridgeback      Rhodesian_ridgeback
16      papillon      papillon
17      Afghan_hound      Afghan_hound
18      redbone      redbone
19      Japanese_spaniel      Japanese_spaniel
```

```
[ ]: correct_predictions = (predict_df['Target_Labels'] == ↴
    ↴predict_df['Predictions']).sum()
total_predictions = len(predict_df)
test_accuracy = (correct_predictions / total_predictions) * 100
```

```
print('Test Accuracy: {:.2f}%'.format(test_accuracy))
```

Test Accuracy: 94.58%

15.2 VGG16

```
[23]: import pandas as pd

x_test1 = x_test / 255. # rescale to 0-1. Divide by 255 as its the max RGB value
test_predictions = vgg16_model.predict(x_test1)

# get model predictions
predictions = le.classes_[np.argmax(test_predictions, axis=1)] # get labels and
    ↪reverse back to get the text labels
# get target labels
target_labels = le.classes_[np.argmax(y_test, axis=1)]

# Store in dataframe
predict_df = pd.DataFrame({'Target_Labels': target_labels, 'Predictions':predictions})
predict_df.head(20)
```

23/23 [=====] - 6s 242ms/step

```
[23]:      Target_Labels          Predictions
 0        Irish_wolfhound    Irish_wolfhound
 1        Afghan_hound       Afghan_hound
 2           bloodhound      bloodhound
 3     Blenheim_spaniel     Chihuahua
 4           Chihuahua       toy_terrier
 5           borzoi          Maltese_dog
 6     Blenheim_spaniel     Blenheim_spaniel
 7   Italian_greyhound     Italian_greyhound
 8           Pekinese         Pekinese
 9 black-and-tan_coonhound      bloodhound
10   Italian_greyhound     Italian_greyhound
11           bloodhound      bloodhound
12           borzoi          borzoi
13           Pekinese         bloodhound
14 black-and-tan_coonhound black-and-tan_coonhound
15   Rhodesian_ridgeback      bloodhound
16           papillon        papillon
17        Afghan_hound       Afghan_hound
18           redbone          bloodhound
19   Japanese_spaniel        borzoi
```

```
[24]: correct_predictions = (predict_df['Target_Labels'] == predict_df['Predictions']).sum()
total_predictions = len(predict_df)
test_accuracy = (correct_predictions / total_predictions) * 100
print('Test Accuracy: {:.2f}%'.format(test_accuracy))
```

Test Accuracy: 50.42%

16 Model Evaluation Metrics

16.1 Inception V3 Model

```
[ ]: # Get accuracy of measure

correct = (target_labels == predictions)
accuracy = correct.sum() / correct.size
print(accuracy)
```

0.9458333333333333

```
[ ]: # Evaluate Model Performance
from sklearn.metrics import classification_report

# get model predictions
predictions = le.classes_[np.argmax(test_predictions, axis=1)] # get labels and
    ↪reverse back to get the text labels
# get target labels
target_labels = le.classes_[np.argmax(y_test, axis=1)]

# print classification report
print(classification_report(target_labels, predictions, labels=le.classes_))
```

	precision	recall	f1-score	support
Afghan_hound	1.00	0.98	0.99	48
African_hunting_dog	0.00	0.00	0.00	0
Airedale	0.00	0.00	0.00	0
American_Staffordshire_terrier	0.00	0.00	0.00	0
Appenzeller	0.00	0.00	0.00	0
Australian_terrier	0.00	0.00	0.00	0
Bedlington_terrier	0.00	0.00	0.00	0
Bernese_mountain_dog	0.00	0.00	0.00	0
Blenheim_spaniel	1.00	0.95	0.97	38
Border_collie	0.00	0.00	0.00	0
Border_terrier	0.00	0.00	0.00	0
Boston_bull	0.00	0.00	0.00	0
Bouvier_des_Flandres	0.00	0.00	0.00	0

Brabancon_griffon	0.00	0.00	0.00	0
Brittany_spaniel	0.00	0.00	0.00	0
Cardigan	0.00	0.00	0.00	0
Chesapeake_Bay_retriever	0.00	0.00	0.00	0
Chihuahua	1.00	0.80	0.89	30
Dandie_Dinmont	0.00	0.00	0.00	0
Doberman	0.00	0.00	0.00	0
English_foxhound	0.78	0.94	0.85	31
English_setter	0.00	0.00	0.00	0
English_springer	0.00	0.00	0.00	0
EntleBucher	0.00	0.00	0.00	0
Eskimo_dog	0.00	0.00	0.00	0
French_bulldog	0.00	0.00	0.00	0
German_shepherd	0.00	0.00	0.00	0
German_short-haired_pointer	0.00	0.00	0.00	0
Gordon_setter	0.00	0.00	0.00	0
Great_Dane	0.00	0.00	0.00	0
Great_Pyrenees	0.00	0.00	0.00	0
Greater_Swiss_Mountain_dog	0.00	0.00	0.00	0
Ibizan_hound	0.00	0.00	0.00	0
Irish_setter	0.00	0.00	0.00	0
Irish_terrier	0.00	0.00	0.00	0
Irish_water_spaniel	0.00	0.00	0.00	0
Irish_wolfhound	0.98	1.00	0.99	44
Italian_greyhound	0.92	1.00	0.96	24
Japanese_spaniel	0.90	0.95	0.92	37
Kerry_blue_terrier	0.00	0.00	0.00	0
Labrador_retriever	0.00	0.00	0.00	0
Lakeland_terrier	0.00	0.00	0.00	0
Leonberg	0.00	0.00	0.00	0
Lhasa	0.00	0.00	0.00	0
Maltese_dog	0.98	0.98	0.98	50
Mexican_hairless	0.00	0.00	0.00	0
Newfoundland	0.00	0.00	0.00	0
Norfolk_terrier	0.00	0.00	0.00	0
Norwegian_elkhound	0.00	0.00	0.00	0
Norwich_terrier	0.00	0.00	0.00	0
Old_English_sheepdog	0.00	0.00	0.00	0
Pekinese	0.90	0.93	0.92	30
Pembroke	0.00	0.00	0.00	0
Pomeranian	0.00	0.00	0.00	0
Rhodesian_ridgeback	1.00	0.85	0.92	34
Rottweiler	0.00	0.00	0.00	0
Saint_Bernard	0.00	0.00	0.00	0
Saluki	0.00	0.00	0.00	0
Samoyed	0.00	0.00	0.00	0
Scotch_terrier	0.00	0.00	0.00	0
Scottish_deerhound	0.00	0.00	0.00	0

Sealyham_terrier	0.00	0.00	0.00	0
Shetland_sheepdog	0.00	0.00	0.00	0
Shih-Tzu	0.98	0.93	0.95	43
Siberian_husky	0.00	0.00	0.00	0
Staffordshire_bullterrier	0.00	0.00	0.00	0
Sussex_spaniel	0.00	0.00	0.00	0
Tibetan_mastiff	0.00	0.00	0.00	0
Tibetan_terrier	0.00	0.00	0.00	0
Walker_hound	0.00	0.00	0.00	0
Weimaraner	0.00	0.00	0.00	0
Welsh_springer_spaniel	0.00	0.00	0.00	0
West_Highland_white_terrier	0.00	0.00	0.00	0
Yorkshire_terrier	0.00	0.00	0.00	0
affenpinscher	0.00	0.00	0.00	0
basenji	0.00	0.00	0.00	0
basset	0.95	1.00	0.97	35
beagle	0.97	0.74	0.84	39
black-and-tan_coonhound	0.97	1.00	0.98	32
bloodhound	0.95	0.95	0.95	38
bluetick	0.97	1.00	0.99	34
borzoi	0.97	0.97	0.97	30
boxer	0.00	0.00	0.00	0
briard	0.00	0.00	0.00	0
bull_mastiff	0.00	0.00	0.00	0
cairn	0.00	0.00	0.00	0
chow	0.00	0.00	0.00	0
clumber	0.00	0.00	0.00	0
cocker_spaniel	0.00	0.00	0.00	0
collie	0.00	0.00	0.00	0
curly-coated_retriever	0.00	0.00	0.00	0
dhole	0.00	0.00	0.00	0
dingo	0.00	0.00	0.00	0
flat-coated_retriever	0.00	0.00	0.00	0
giant_schnauzer	0.00	0.00	0.00	0
golden_retriever	0.00	0.00	0.00	0
groenendael	0.00	0.00	0.00	0
keeshond	0.00	0.00	0.00	0
kelpie	0.00	0.00	0.00	0
komondor	0.00	0.00	0.00	0
kuvasz	0.00	0.00	0.00	0
malamute	0.00	0.00	0.00	0
malinois	0.00	0.00	0.00	0
miniature_pinscher	0.00	0.00	0.00	0
miniature_poodle	0.00	0.00	0.00	0
miniature_schnauzer	0.00	0.00	0.00	0
otterhound	0.00	0.00	0.00	0
papillon	0.95	0.97	0.96	39
pug	0.00	0.00	0.00	0

	redbone	0.85	0.97	0.91	30
	schipperke	0.00	0.00	0.00	0
	silky_terrier	0.00	0.00	0.00	0
soft-coated_wheaten_terrier		0.00	0.00	0.00	0
	standard_poodle	0.00	0.00	0.00	0
	standard_schnauzer	0.00	0.00	0.00	0
	toy_poodle	0.00	0.00	0.00	0
	toy_terrier	0.89	1.00	0.94	34
	vizsla	0.00	0.00	0.00	0
	whippet	0.00	0.00	0.00	0
wire-haired_fox_terrier		0.00	0.00	0.00	0
	micro avg	0.95	0.95	0.95	720
	macro avg	0.16	0.16	0.16	720
	weighted avg	0.95	0.95	0.95	720

```
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.

    _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0
in labels with no true samples. Use `zero_division` parameter to control this
behavior.

    _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
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in labels with no true samples. Use `zero_division` parameter to control this
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0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.

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/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0
in labels with no true samples. Use `zero_division` parameter to control this
behavior.

    _warn_prf(average, modifier, msg_start, len(result))
```

16.2 VGG16

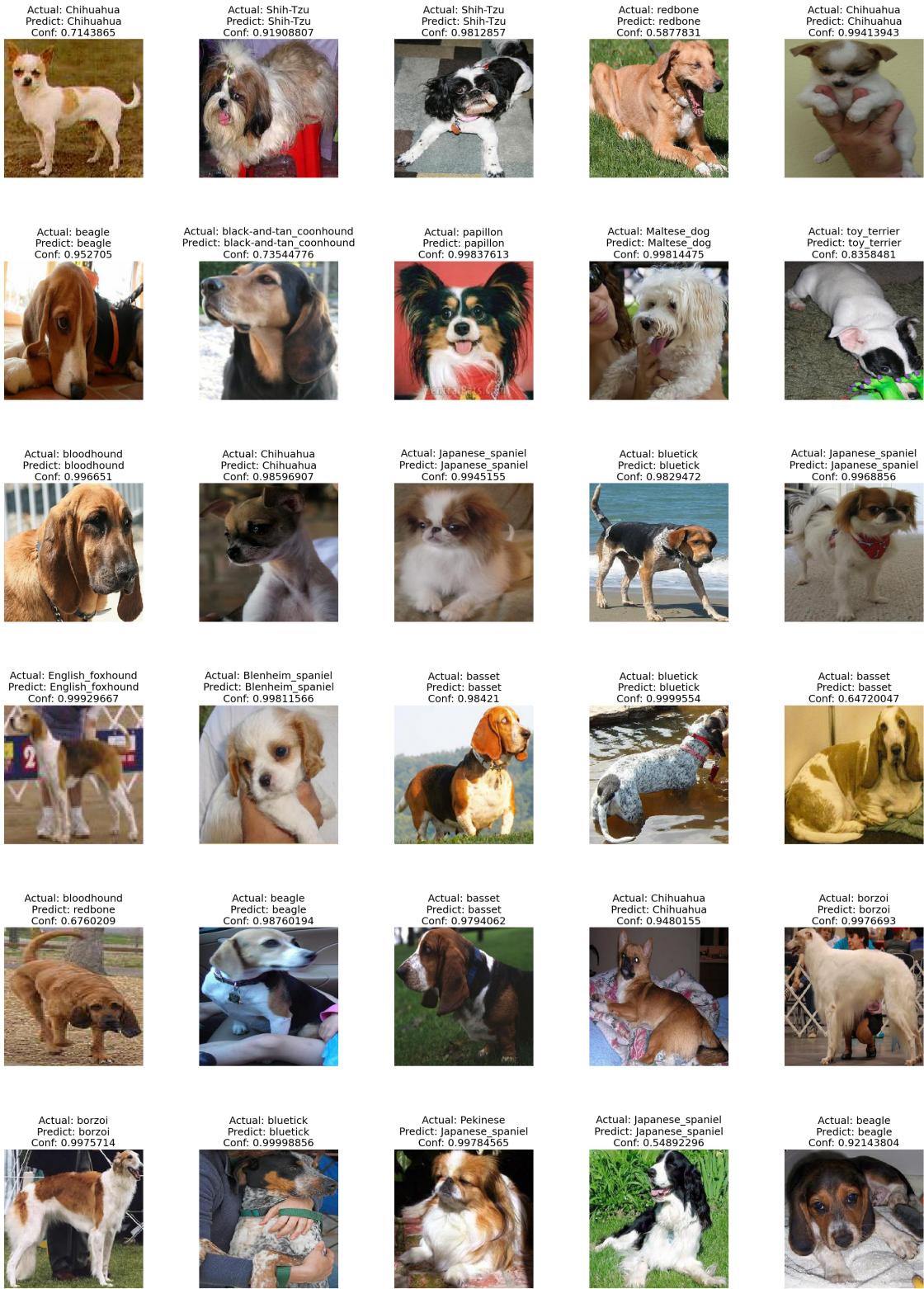
```
[25]: # Get accuracy of measure  
  
correct = (target_labels == predictions)  
accuracy = correct.sum() / correct.size  
print(accuracy)
```

0.5041666666666667

17 Plot Predictions against Actual Labels

Along with confidence score

```
[ ]: import random  
  
plt.figure(figsize=(30,40))  
for counter, i in enumerate(random.sample(range(0, len(y_test)), 30)): # random  
    ↪30 images  
    plt.subplot(6, 5, counter+1)  
    plt.subplots_adjust(hspace=0.6)  
    actual = str(target_labels[i])  
    predicted = str(predictions[i])  
    conf = str(max(test_predictions[i]))  
    plt.imshow(x_test[i]/255.0)  
    plt.axis('off')  
    plt.title('Actual: ' + actual + '\nPredict: ' + predicted + '\nConf: ' +  
    ↪conf, fontsize=18)  
  
plt.show()
```



18 Testing Model Performance with Random Google Images

18.1 Inception V3

```
[ ]: import os
import numpy as np
from tensorflow.keras.preprocessing.image import load_img
from tensorflow.keras.utils import img_to_array
from keras.models import load_model

test_dir = "/content/drive/MyDrive/DL/Assignment2/model_testing"

# set image size
img_width, img_height = 299, 299

# create a list of class names
class_names = [file_name.split(".")[0] for file_name in os.listdir(test_dir)]

# load and preprocess test images
test_images = []
for img_file in os.listdir(test_dir):
    img_path = os.path.join(test_dir, img_file)
    img = load_img(img_path, target_size=(img_width, img_height))
    img = img_to_array(img)
    img /= 255.0 # Scale pixel values to between 0 and 1
    img = np.expand_dims(img, axis=0)
    test_images.append(img)

# convert test images to a numpy array
test_images = np.vstack(test_images)

# make predictions on the test images
test_predictions = inception_model.predict(test_images)
predictions = le.classes_[np.argmax(test_predictions, axis=1)]
```

```
# print predicted class for each image
for i in range(5):
    print(f'{class_names[i]} --> {predictions[i]}')
```

```
1/1 [=====] - 2s 2s/step
pekinese --> Pekinese
papillon --> papillon
Afghan_hound --> Afghan_hound
Rhodesian_ridgeback --> Rhodesian_ridgeback
toy_terrier --> toy_terrier
```

Comment

Our model has predicted Breed name of all the 5 test images correctly with 100% accuracy.

18.2 VGG16

```
[26]: import os
import numpy as np
from tensorflow.keras.preprocessing.image import load_img
from tensorflow.keras.utils import img_to_array
from keras.models import load_model

test_dir = "/content/drive/MyDrive/DL/Assignment2/model_testing"

# set image size
img_width, img_height = 224, 224

# create a list of class names
class_names = [file_name.split(".")[0] for file_name in os.listdir(test_dir)]

# load and preprocess test images
test_images = []
for img_file in os.listdir(test_dir):
    img_path = os.path.join(test_dir, img_file)
    img = load_img(img_path, target_size=(img_width, img_height))
    img = img_to_array(img)
    img /= 255.0 # Scale pixel values to between 0 and 1
    img = np.expand_dims(img, axis=0)
    test_images.append(img)

# convert test images to a numpy array
test_images = np.vstack(test_images)

# make predictions on the test images
test_predictions = vgg16_model.predict(test_images)
predictions = le.classes_[np.argmax(test_predictions, axis=1)]

# print predicted class for each image
for i in range(5):
    print(f'{class_names[i]} --> {predictions[i]}')
```

```
1/1 [=====] - 1s 1s/step
pekinese --> Afghan_hound
papillon --> papillon
Afghan_hound --> Afghan_hound
Rhodesian_ridgeback --> Rhodesian_ridgeback
```

```
toy_terrier --> English_foxhound
```

19 *Inception V3 has out performed VGG16 model.*

20 Conclusions

Based on the results obtained in this notebook, we can conclude that using a pre-trained deep learning model such as Inception V3 or VGG16 can be an effective approach for dog breed classification.

The InceptionV3 model achieved high accuracy on the test set (~ **94.58%**), indicating their ability to generalize to new data. Fine-tuning the pre-trained models on the dog breed dataset improved the performance of the models even further.

Additionally, data augmentation techniques such as rotation, zooming, and horizontal flipping helped to increase the size of the training set and improve the model's ability to recognize different variations of dog breeds.

Overall, this notebook provides a good starting point for anyone interested in working with image classification problems using pre-trained deep learning models. There is still room for improvement in terms of fine-tuning the models, optimizing hyperparameters, and exploring different architectures.

Reference : <https://www.kaggle.com/code/teyang/dog-breeds-classification-using-transfer-learning/notebook>