FIRST\_NAME = "Mel"

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Final Class Project - ITCS 5154

Dog Breed Classifier - Student Mel Gerst

Duplicating project originally by TechVidvan

Resources X

You are not subscribed. Learn more

Available: 50.66 compute units

Usage rate: approximately 10.59 per hour

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Upgrade to Colab Pro

Python 3 Google Compute Engine backend (GPU)

Showing resources from 4:40 PM to 6:15 PM

System RAM 17.6 / 83.5 GB

**GPU RAM** 19.7 / 40.0 GB



Disk

35.5 / 112.6 GB

```
# Dog Breed Classifier
# ITCS 5154 - Student Mel Gerst
# Duplicating project by TechVidvan
# Import necessary packages for dog breed
import cv2
import numpy as np
import pandas as pd
import tensorflow
import pathlib
import os
from tensorflow.keras.preprocessing.image
from sklearn.model_selection import train_
from sklearn.preprocessing import LabelEnc
from tensorflow.keras.models import load_n
from tensorflow.keras.optimizers import RN
from tensorflow.keras.layers import Dense,
from tensorflow.keras.applications.resnet_
print("Imports Complete")
print(pathlib.Path().resolve())
from google.colab import drive
# drive. mount('/content/drive')
drive.mount('/content/drive/')
# My files are mounted in Google drive for
# file_path = '/content/drive/My Drive/dat
```

```
# Initialize Variables
encoder = LabelEncoder()
image_size = 224
breed_count = 60
batch_size = 64

# Grab input files and data
df_labels = pd_read_csv("/content/drive/My
#store training and testing images folder
training_data = '/content/drive/My Drive/(
testing_data = '/content/drive/My Drive/(
# Check and print the total number of unic
print("Total number of unique Dog Breeds i
print(os.listdir(testing_data))
```

Total number of unique Dog Breeds in d ['06b727fc8e24e46fd7ea78b08091cab5.jpg

# Drop breeds considered to 60 breeds to 9 breed\_dict = list(df\_labels['breed'].valuenew\_list = sorted(breed\_dict,reverse=True)
# Limit dataset to have only those 60 unicdf\_labels = df\_labels.query('breed in @nev# Add new column which will contain imagedf\_labels['img\_file'] = df\_labels['id'].apprint("Total number of unique Dog Breeds uprint("The breeds used for training and teff the contain image for the shape (number for model)

Total number of unique Dog Breeds used The breeds used for training and testi <ipython-input-3-e80864a923a5>:7: Sett A value is trying to be set on a copy Try using loc[row\_indexer,col\_indexer]

See the caveats in the documentation: df\_labels['img\_file'] = df\_labels['i

```
# #iterate over img_file column of our dat
# for i, img_id in enumerate(df_labels['in
# Read the image file and convert into
# Resize all images to one dimension i
# We will get array with the shape of
# (224,224,3) where 3 is the RGB chand
img = cv2.resize(cv2.imread(training_out
# Scale array into the range of -1 to
# Preprocess the array and expand its
# img_array = preprocess_input(np.expanout
# Update the train_x variable with nev
# train_x[i] = img_array
```

```
# print(train_x.shape)
# np.save('/content/drive/My Drive/ColabNo
```

train\_x = np.load('/content/drive/My Drive
print(train\_x.shape)

```
→ (5175, 224, 224, 3)
```

```
# This will be target for model.
# Convert breed names into numerical forma
train_y = encoder.fit_transform(df_labels|

# Split the dataset in the ratio of 80:20.
#80% for training and 20% for testing purp
x_train, x_test, y_train, y_test = train_t
```

```
#Image augmentation using ImageDataGenerat
train_datagen = ImageDataGenerator(rotation)
                                     width s
                                     height_
                                      shear_r
                                      zoom_ra
                                     horizor
                                     fill_mc
# Generate images for training sets
train_generator = train_datagen.flow(x_train_generator)
                                        y_tra
                                        batch
# Same process for Testing sets also by de
test_datagen = ImageDataGenerator()
test_generator = test_datagen.flow(x_test,
                                        batch
```

```
# Model #1 - Build the model using ResNet!
# Weights for our network will be from of
# We will not include the first Dense lave
resnet = ResNet50V2(input_shape = [image_s
# Freeze all trainable layers and train or
for layer in resnet.layers:
    laver.trainable = False
# Add global average pooling layer and Bat
x = resnet_output
x = BatchNormalization()(x)
x = GlobalAveragePooling2D()(x)
x = Dropout(0.5)(x)
# Add fully connected layer
x = Dense(1024, activation='relu')(x)
x = Dropout(0.5)(x)
# Add output layer having the shape equal
predictions = Dense(breed_count, activation)
# Create model class with inputs and outpu
model = Model(inputs=resnet.input, outputs
# model.summary()
# Set the num_epochs for model training ar
num epochs = 20
learning rate = 1e-3
# Using RMSprop optimizer compile or build
optimizer = RMSprop(learning rate=learning)
model.compile(optimizer=optimizer,
              loss='sparse_categorical_crc
              metrics=["accuracy"])
# Fit the training generator data and trai
model.fit(train_generator,
                 steps_per_epoch= x_train.
                 epochs= num epochs,
                 validation data= test ger
                 validation_steps= x_test.
test_loss, test_accuracy = model.evaluate(
```

print(f'Resnet Test accuracy: {test\_accura
# Save the model for prediction
model.save("model.keras")



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64/64		0s :	397us/st
33/33			15ms/ste
Resnet	t Test accuracy: 0.78		

```
# Load the model
model = load_model("model.keras")
```

```
# Get the image of the dog #1 for predicti
pred img path = '/content/drive/My Drive/(
# Read the image file and convert into num
# Resize all images to one dimension i.e.
pred_img_array = cv2.resize(cv2.imread(predimed))
# Scale array into the range of -1 to 1.
# Expand the dimesion on the axis 0 and no
pred_img_array = preprocess_input(np.expar
# Feed the model with the image array for
pred_val = model.predict(np.array(pred_imc
# Display the image of dog
from google.colab.patches import cv2_imshc
cv2 imshow(cv2.resize(cv2.imread(pred img
# Display the predicted breed of dog
predicted_breed = sorted(new_list)[np.argn
print("Predicted Breed for this Dog is :",
# Get the image of the dog #2 for predicti
pred_img_path2 = '/content/drive/My Drive/
# Read the image file and convert into num
# Resize all images to one dimension i.e.
pred_img_array2 = cv2.resize(cv2.imread(pr
# Scale array into the range of -1 to 1.
# Expand the dimesion on the axis 0 and no
pred_img_array2 = preprocess_input(np.expa
# Feed the model with the image array for
pred val2 = model.predict(np.array(pred in
# Display the image of dog
from google.colab.patches import cv2_imshc
cv2 imshow(cv2.resize(cv2.imread(pred img
# Display the predicted breed of dog
predicted_breed2 = sorted(new_list)[np.arc
print("Predicted Breed for this Dog is :",
# Get the image of the dog #3 for predicti
pred_img_path3 = '/content/drive/My Drive/
# Read the image file and convert into num
# Resize all images to one dimension i.e.
```

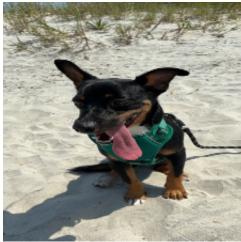
```
pred img array3 = cv2.resize(cv2.imread(pr
# Scale array into the range of -1 to 1.
# Expand the dimesion on the axis 0 and no
pred_img_array3 = preprocess_input(np.expa
# Feed the model with the image array for
pred_val3 = model.predict(np.array(pred_in
# Display the image of dog
from google.colab.patches import cv2_imshc
cv2_imshow(cv2.resize(cv2.imread(pred_img_
# Display the predicted breed of dog
predicted breed3 = sorted(new list)[np.arc
print("Predicted Breed for this Dog is :",
# Get the image of the dog #4 for predicti
pred_img_path4 = '/content/drive/My Drive/
# Read the image file and convert into num
# Resize all images to one dimension i.e.
pred_img_array4 = cv2.resize(cv2.imread(pr
# Scale array into the range of -1 to 1.
# Expand the dimesion on the axis 0 and no
pred_img_array4 = preprocess_input(np.expa
# Feed the model with the image array for
pred_val4 = model.predict(np.array(pred_in
# Display the image of dog
from google.colab.patches import cv2_imshc
cv2_imshow(cv2.resize(cv2.imread(pred_img_
# Display the predicted breed of dog
predicted breed4 = sorted(new list)[np.arc
print("Predicted Breed for this Dog is :",
# Get the image of the dog #5 for predicti
pred_img_path5 = '/content/drive/My Drive/
# Read the image file and convert into num
# Resize all images to one dimension i.e.
pred_img_array5 = cv2.resize(cv2.imread(pr
# Scale array into the range of -1 to 1.
# Expand the dimesion on the axis 0 and no
pred_img_array5 = preprocess_input(np.expa
# Feed the model with the image array for
pred val5 = model.predict(np.array(pred_in
# Display the image of dog
from google.colab.patches import cv2_imshc
```

cv2\_imshow(cv2.resize(cv2.imread(pred\_img\_
#Display the predicted breed of dog
predicted\_breed5 = sorted(new\_list)[np.arc
print("Predicted Breed for this Dog is :",
print("Check image size: ", image\_size)

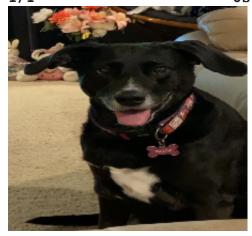


Predicted Breed for this Dog is : rott

1/1 \_\_\_\_\_\_ 0s 24ms/step



Predicted Breed for this Dog is : mini
1/1 \_\_\_\_\_\_ 0s 25ms/step



Predicted Breed for this Dog is : labr
1/1 \_\_\_\_\_\_ 0s 24ms/step



Predicted Breed for this Dog is: scot

1/1 \_\_\_\_\_\_ 0s 24ms/step



Predicted Breed for this Dog is : whip Check image size: 224

#VGG model
import tensorflow as tf
from tensorflow.keras import layers, model
from sklearn.model\_selection import train\_
# This will be target for model.

# Convert breed names into numerical forma
train\_y = encoder.fit\_transform(df\_labels|

# Assuming train\_y is one-hot encoded, if
train\_y = tf.keras.utils.to\_categorical(tr

# Split the data

```
x_train, x_test, y_train, y_test = train_t
def create_vgg_model(input_shape, num_clas
    base_model = tf.keras.applications.VG(
    # Freeze the base model
    base model.trainable = False
    model = models.Sequential([
        base model,
        layers.Flatten(),
        layers.Dense(512, activation='relu
        layers.Dropout(0.5),
        layers.Dense(num_classes, activati
    ])
    return model, base_model # Return both
input\_shape = (224, 224, 3)
num classes = 60
model, base_model = create_vgg_model(input
model.compile(optimizer='adam',
              loss='categorical_crossentro
              metrics=['accuracy'])
history = model.fit(x_train, y_train,
                    epochs=50,
                    batch size=32,
                    validation_data=(x_tes
test_loss, test_accuracy = model.evaluate(
print(f'Test accuracy: {test_accuracy:.2f}
base_model.trainable = True # Now base_mc
for layer in base_model.layers[:-4]: # Ur
    layer.trainable = False
model.compile(optimizer=tf.keras.optimizer
              loss='categorical_crossentro
              metrics=['accuracy'])
history_finetune = model.fit(x_train, y_tr
                              epochs=10,
```

batch\_size=3
validation\_c

test\_loss, test\_accuracy = model.evaluate(
print(f'VGG Test accuracy: {test\_accuracy:

Epoch 33/50  130/130  Epoch 34/50  130/130  Sepoch 35/50  130/130  Sepoch 36/50  130/130  Sepoch 36/50  130/130  Sepoch 37/50  130/130  Sepoch 38/50  130/130  Sepoch 38/50  130/130  Sepoch 38/50  130/130  Sepoch 40/50  130/130  Sepoch 41/50  130/130  Sepoch 42/50  130/130  Sepoch 43/50  130/130  Sepoch 43/50  130/130  Sepoch 44/50  130/130  Sepoch 44/50  130/130  Sepoch 44/50  130/130  Sepoch 45/50  130/130  Sepoch 45/50  130/130  Sepoch 47/50  130/130  Sepoch 47/50  130/130  Sepoch 48/50  130/130  Sepoch 49/50  130/130  Sepoch 49/50  130/130  Sepoch 49/50  130/130  Sepoch 50/50  Sepoch 50/50				
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                            - 3s 25ms/s
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130/130 -
                            - 3s 26ms/s
Epoch 8/10
130/130 -
                         --- 3s 26ms/s
Epoch 9/10
130/130 -
                           -- 3s 26ms/s
Epoch 10/10
130/130 -
                            - 3s 26ms/s
                       1s 18ms/ste
33/33 -
```

```
# Second round of predictions with VGG mod
print("Check image size: ", image_size)
# Get the image of the dog #1 for predicti
pred_img_path = '/content/drive/My Drive/(
# Read the image file and convert into num
# Resize all images to one dimension i.e.
pred_img_array = cv2.resize(cv2.imread(pred_img_array))
# Scale array into the range of -1 to 1.
# Expand the dimesion on the axis 0 and no
pred_img_array = preprocess_input(np.expar
# Feed the model with the image array for
pred_val = model.predict(np.array(pred_img
# Display the image of dog
from google.colab.patches import cv2_imshc
cv2_imshow(cv2.resize(cv2.imread(pred_img_
# Display the predicted breed of dog
predicted_breed = sorted(new_list)[np.argn
print("Predicted Breed for this Dog is :",
# Get the image of the dog #2 for predicti
pred_img_path2 = '/content/drive/My Drive/
# Read the image file and convert into num
# Resize all images to one dimension i.e.
pred_img_array2 = cv2.resize(cv2.imread(pr
# Scale array into the range of -1 to 1.
# Expand the dimesion on the axis 0 and no
```

```
pred_img_array2 = preprocess_input(np.expa
# Feed the model with the image array for
pred val2 = model.predict(np.array(pred in
# Display the image of dog
from google.colab.patches import cv2_imshc
cv2 imshow(cv2.resize(cv2.imread(pred img
# Display the predicted breed of dog
predicted_breed2 = sorted(new_list)[np.arc
print("Predicted Breed for this Dog is :",
# Get the image of the dog #3 for predicti
pred_img_path3 = '/content/drive/My Drive/
# Read the image file and convert into num
# Resize all images to one dimension i.e.
pred_img_array3 = cv2.resize(cv2.imread(pr
# Scale array into the range of -1 to 1.
# Expand the dimesion on the axis 0 and no
pred_img_array3 = preprocess_input(np.expa
# Feed the model with the image array for
pred val3 = model.predict(np.array(pred in
# Display the image of dog
from google.colab.patches import cv2_imshc
cv2_imshow(cv2.resize(cv2.imread(pred_img_
# Display the predicted breed of dog
predicted_breed3 = sorted(new_list)[np.arg
print("Predicted Breed for this Dog is :",
# Get the image of the dog #4 for predicti
pred_img_path4 = '/content/drive/My Drive/
# Read the image file and convert into num
# Resize all images to one dimension i.e.
pred_img_array4 = cv2.resize(cv2.imread(pr
# Scale array into the range of -1 to 1.
# Expand the dimesion on the axis 0 and no
pred_img_array4 = preprocess_input(np.expa
# Feed the model with the image array for
pred_val4 = model.predict(np.array(pred_in
# Display the image of dog
from google.colab.patches import cv2_imshc
cv2 imshow(cv2.resize(cv2.imread(pred img
# Display the predicted breed of dog
predicted_breed4 = sorted(new_list)[np.arg
```

print("Predicted Breed for this Dog is :",

# Get the image of the dog #5 for predicti
pred\_img\_path5 = '/content/drive/My Drive/
# Read the image file and convert into nun
# Resize all images to one dimension i.e.
pred\_img\_array5 = cv2.resize(cv2.imread(pr
# Scale array into the range of -1 to 1.
# Expand the dimesion on the axis 0 and nc
pred\_img\_array5 = preprocess\_input(np.expa

# Feed the model with the image array for
pred\_val5 = model.predict(np.array(pred\_in
# Display the image of dog
from google.colab.patches import cv2\_imsho
cv2\_imshow(cv2.resize(cv2.imread(pred\_img\_
#Display the predicted breed of dog
predicted\_breed5 = sorted(new\_list)[np.arc
print("Predicted Breed for this Dog is :",

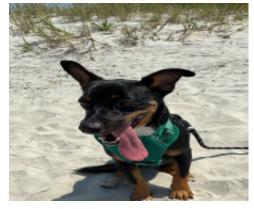


1/1 \_\_\_\_\_\_ 1s 1s/step



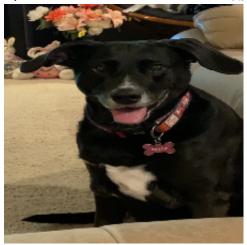
Predicted Breed for this Dog is: rott

1/1 \_\_\_\_\_\_ 0s 20ms/step





Predicted Breed for this Dog is : mini
1/1 \_\_\_\_\_\_ 0s 21ms/step



Predicted Breed for this Dog is: boxe
1/1 \_\_\_\_\_\_ 0s 20ms/step



Predicted Breed for this Dog is: iris
1/1 \_\_\_\_\_\_ 0s 21ms/step



Predicted Breed for this Dog is : grea

```
print(len(np.unique(y_train)))
```

## **→** 2

```
# new SimpleCNN model
import torch
import torch.nn as nn
import torchvision.transforms as transforms
from torch.utils.data import DataLoader, Da
from sklearn.model_selection import train_t
import numpy as np
# Assume train x and train y are defined
# train_x: numpy array of shape (5175, 224,
# train_y: numpy array of shape (5175,)
# Split the dataset
# x_train, x_test, y_train, y_test = train_
# Set batch size
# batch size = 64
# Define data augmentation and normalizatio
train_transforms = transforms.Compose([
    transforms.ToPILImage(), # Convert num
    transforms.RandomRotation(45),
    transforms.RandomAffine(degrees=0, tran
    transforms.RandomResizedCrop(size=(224,
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
])
test_transforms = transforms.Compose([
    transforms.ToPILImage(),
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
1)
# Custom Dataset Class
class CustomDataset(Dataset):
    def __init__(self, images, labels, tran
        self.images = images
        self.labels = labels
        self.transform = transform
```

```
def __len__(self):
        return len(self.images)
   def __getitem__(self, idx):
        image = self.images[idx]
        label = self.labels[idx]
        if self.transform:
            image = self.transform(image)
        return image, label
# Create datasets
y_train_indices = np.argmax(y_train, axis=1
y_test_indices = np.argmax(y_test, axis=1)
train_dataset = CustomDataset(x_train, y_tr
test_dataset = CustomDataset(x_test, y_test
# Create DataLoaders
train_loader = DataLoader(train_dataset, ba
test loader = DataLoader(test dataset, batc
# Define the SimpleCNN model
class SimpleCNN(nn.Module):
    def init (self):
        super(SimpleCNN, self).__init__()
        self.conv1 = nn.Conv2d(3, 32, kerne
        self.pool = nn.MaxPool2d(kernel_siz
        self.conv2 = nn.Conv2d(32, 64, kern
        self.conv3 = nn.Conv2d(64, 128, ker
        # Calculate the input size for the
        self.fc1 input size = 128 * (224 //
        self.fc1 = nn.Linear(self.fc1_input
        self.fc2 = nn.Linear(256, 60) # Ou
   def forward(self, x):
        x = self.conv1(x)
        x = nn.ReLU()(x)
        x = self.pool(x)
        x = self.conv2(x)
        x = nn.ReLU()(x)
        x = self.pool(x)
```

```
x = self.conv3(x)
        x = nn.ReLU()(x)
        x = self.pool(x)
        x = torch.flatten(x, 1) # Flatten
        x = self.fc1(x)
        x = nn.ReLU()(x)
        x = self_fc2(x)
        return nn.LogSoftmax(dim=1)(x)
# Initialize model, loss function, and opti
device = torch.device("cuda" if torch.cuda.
model = SimpleCNN().to(device)
criterion = nn.NLLLoss()
optimizer = torch.optim.Adam(model.paramete
# Training Loop
num epochs = 200
for epoch in range(num epochs):
    model.train() # Set model to training
    for images, labels in train_loader:
        images, labels = images.to(device),
        optimizer.zero_grad() # Clear grad
        outputs = model(images) # Forward
        loss = criterion(outputs, labels)
        loss.backward() # Backward pass
        optimizer.step() # Update weights
    print(f'Epoch [{epoch + 1}/{num_epochs}
# Evaluation on the test set
model.eval() # Set model to evaluation mod
test loss = 0
correct = 0
with torch.no_grad():
    for images, labels in test_loader:
        images, labels = images.to(device),
        outputs = model(images)
        test_loss += criterion(outputs, lab
        pred = outputs.argmax(dim=1) # Get
        correct += (pred == labels).sum().i
```

test\_accuracy = correct / len(test\_dataset)
print(f'Test Loss: {test\_loss/len(test\_load

Epoch [142/200], Loss: 2.4036 Epoch [143/200], Loss: 2.2013 Epoch [144/200], Loss: 2.0762 Epoch [145/200], Loss: 2.0533 Epoch [146/200], Loss: 1.9337 Epoch [147/200], Loss: 2.3631 Epoch [148/200], Loss: 2.1085 Epoch [149/200], Loss: 1.9786 Epoch [150/200], Loss: 2.1217 Epoch [151/200], Loss: 2.1622 Epoch [152/200], Loss: 2.2347 Epoch [153/200], Loss: 2.1163 Epoch [154/200], Loss: 2.4530 Epoch [155/200], Loss: 2.5614 Epoch [156/200], Loss: 2.2602 Epoch [157/200], Loss: 1.7063 Epoch [158/200], Loss: 1.9796 Epoch [159/200], Loss: 1.9819 Epoch [160/200], Loss: 2.4385 Epoch [161/200], Loss: 1.5695 Epoch [162/200], Loss: 1.6115 Epoch [163/200], Loss: 1.6151 Epoch [164/200], Loss: 2.1459 Epoch [165/200], Loss: 2.3970 Epoch [166/200], Loss: 2.2453 Epoch [167/200], Loss: 1.8896 Epoch [168/200], Loss: 1.8341 Epoch [169/200], Loss: 2.0265 Epoch [170/200], Loss: 2.2931 Epoch [171/200], Loss: 1.7738 Epoch [172/200], Loss: 1.8996 Epoch [173/200], Loss: 2.0559 Epoch [174/200], Loss: 2.3785 Epoch [175/200], Loss: 1.7810 Epoch [176/200], Loss: 1.9395 Epoch [177/200], Loss: 2.1476 Epoch [178/200], Loss: 1.5677 Epoch [179/200], Loss: 1.9600 Epoch [180/200], Loss: 1.8884 Epoch [181/200], Loss: 2.0575 Epoch [182/200], Loss: 1.3027 Epoch [183/200], Loss: 2.1412 Epoch [184/200], Loss: 1.7419 Epoch [185/200], Loss: 1.8414 Epoch [186/200], Loss: 2.4970 Epoch [187/200], Loss: 1.4430

```
Epoch [188/200], Loss: 1.9959
    Epoch [189/200], Loss: 1.5419
    Epoch [190/200], Loss: 2.1794
    Epoch [191/200], Loss: 1.6998
    Epoch [192/200], Loss: 1.3166
    Epoch [193/200], Loss: 1.8938
    Epoch [194/200], Loss: 1.6965
    Epoch [195/200], Loss: 2.0326
    Epoch [196/200], Loss: 1.8422
    Epoch [197/200], Loss: 1.9226
    Epoch [198/200], Loss: 1.7423
    Epoch [199/200], Loss: 1.8963
    Epoch [200/200], Loss: 1.5288
# Prediction 1
pred_img_path = '/content/drive/My Drive/Co
# image size = 224 # Resize to this if nec
# Read and preprocess the image
pred_img_array = cv2.imread(pred_img_path)
pred_img_array = cv2.resize(pred_img_array,
pred img tensor = transforms.ToTensor()(pre
# Feed the model for prediction
with torch.no_grad():
    pred val = model(pred img tensor)
    predicted_breed = sorted(new_list)[torc
from google.colab.patches import cv2_imshow
cv2_imshow(cv2.resize(cv2.imread(pred_img_p
# Display the predicted breed
print("Predicted Breed for this Dog is:", p
# Prediction 2
pred img path = '/content/drive/My Drive/Co
# image_size = 224 # Resize to this if nec
# Read and preprocess the image
pred img array = cv2.imread(pred img path)
pred_img_array = cv2.resize(pred_img_array,
pred_img_tensor = transforms.ToTensor()(pre
# Feed the model for prediction
with torch.no_grad():
    pred_val = model(pred_img_tensor)
    predicted_breed = sorted(new_list)[torc
```

```
from google.colab.patches import cv2_imshow
cv2_imshow(cv2.resize(cv2.imread(pred_img_p
# Display the predicted breed
print("Predicted Breed for this Dog is:", p
# Prediction 3
pred_img_path = '/content/drive/My Drive/Co
# image_size = 224 # Resize to this if nec
# Read and preprocess the image
pred_img_array = cv2.imread(pred_img_path)
pred_img_array = cv2.resize(pred_img_array,
pred_img_tensor = transforms.ToTensor()(pre
# Feed the model for prediction
with torch.no_grad():
    pred_val = model(pred_img_tensor)
    predicted breed = sorted(new list)[torc
from google.colab.patches import cv2_imshow
cv2_imshow(cv2.resize(cv2.imread(pred_img_p
# Display the predicted breed
print("Predicted Breed for this Dog is:", p
# Prediction 4
pred_img_path = '/content/drive/My Drive/Co
# image size = 224 # Resize to this if nec
# Read and preprocess the image
pred img array = cv2.imread(pred img path)
pred_img_array = cv2.resize(pred_img_array,
pred_img_tensor = transforms.ToTensor()(pre
# Feed the model for prediction
with torch.no_grad():
    pred_val = model(pred_img_tensor)
    predicted_breed = sorted(new_list)[torc
from google.colab.patches import cv2_imshow
cv2_imshow(cv2.resize(cv2.imread(pred_img_p
# Display the predicted breed
print("Predicted Breed for this Dog is:", p
# Prediction 5
```

```
pred_img_path = '/content/drive/My Drive/Co
# image_size = 224  # Resize to this if nec

# Read and preprocess the image
pred_img_array = cv2.imread(pred_img_path)
pred_img_array = cv2.resize(pred_img_array,
pred_img_tensor = transforms.ToTensor()(pre

# Feed the model for prediction
with torch.no_grad():
    pred_val = model(pred_img_tensor)
    predicted_breed = sorted(new_list)[torc

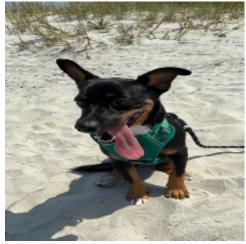
from google.colab.patches import cv2_imshow
```

from google.colab.patches import cv2\_imshow
cv2\_imshow(cv2.resize(cv2.imread(pred\_img\_p
# Display the predicted breed
print("Predicted Breed for this Dog is:", p





Predicted Breed for this Dog is: whipp



Predicted Breed for this Dog is: whipp



Predicted Breed for this Dog is: whipp



Predicted Breed for this Dog is: dingo



Predicted Breed for this Dog is: ibiza

**Change runtime type**