```
from google.colab import drive
drive.mount('/content/gdrive', force_remount=True)
```

```
     Mounted at /content/gdrive
```

```
import cv2
import numpy as np
import pandas as pd
from tensorflow.keras.applications.resnet_v2 import ResNet50V2,preprocess_input
import matplotlib.pyplot as plt

from sklearn.metrics import classification_report
from tqdm import tqdm
```

```
im_size = 224
train_x = []
train_y= []
val_x = []
val_y= []
dict_label={}
import os
trainfolder_list = os.listdir("/content/gdrive/MyDrive/FindCareer/FellowshipAI/imagewoof-320/train")
valfolder_list = os.listdir("/content/gdrive/MyDrive/FindCareer/FellowshipAI/imagewoof-320/val")
i=0
for folder in trainfolder_list:
  dict_label[folder] = i
  i+=1
```

```
for folder in tqdm(trainfolder_list):
  for filename in os.listdir('/content/gdrive/MyDrive/FindCareer/FellowshipAI/imagewoof-320/train/'+folder):
    img = cv2.resize(cv2.imread('/content/gdrive/MyDrive/FindCareer/FellowshipAI/imagewoof-320/train/'+folder+'/'+filename,cv2.IMREAD_
    img_array = preprocess_input(np.expand_dims(np.array(img[...,::-1].astype(np.float32)).copy(), axis=0))
    train_x.append(img_array.reshape(3,im_size,im_size))
    train_y.append(dict_label[folder])
```

```
     100%|██████████| 10/10 [01:48<00:00, 10.88s/it]
```

```
for folder in tqdm(valfolder_list):
  for filename in os.listdir('/content/gdrive/MyDrive/FindCareer/FellowshipAI/imagewoof-320/val/'+folder):
    img = cv2.resize(cv2.imread('/content/gdrive/MyDrive/FindCareer/FellowshipAI/imagewoof-320/val/'+folder+'/'+filename,cv2.IMREAD_CO
    img_array = preprocess_input(np.expand_dims(np.array(img[...,::-1].astype(np.float32)).copy(), axis=0))
    val_x.append(img_array.reshape(3,im_size,im_size))
    val_y.append(dict_label[folder])
```

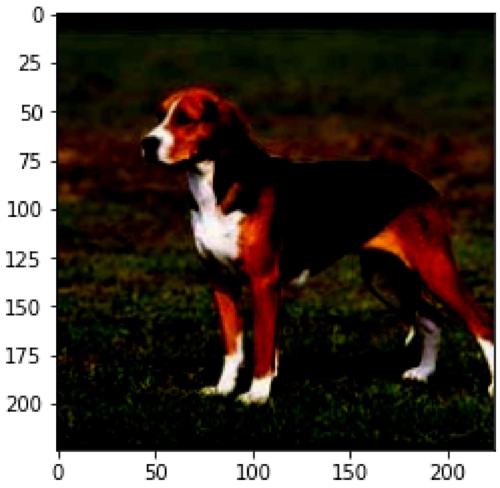
```
100%|██████████| 10/10 [00:03<00:00,  2.86it/s]
```

```
plt.imshow(train_x[150].reshape(224,224,3))
plt.show()
print(train_y[150])
print(dict_label)

print("images-size:", train_x[0].shape)
print(len(train_y))

print(val_y)
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [
```



```
0
{'n02089973': 0, 'n02115641': 1, 'n02111889': 2, 'n02093754': 3, 'n02099601': 4, 'n0210
images-size: (3, 224, 224)
12464
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
import torch
import torchvision.models as models
model = models.resnet18(pretrained = True)
model

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

```
# Freeze the parameters
for param in model.parameters():
    param.requires_grad = False
```

```
#Classifier architecture to put on top of resnet18
from torch import nn
from collections import OrderedDict
fc = nn.Sequential(OrderedDict([
    ('fc1', nn.Linear(512,100)),
    ('relu', nn.ReLU()),
    ('fc2', nn.Linear(100,10)),
    ('output', nn.LogSoftmax(dim=1))
]))

model.fc = fc
```

```
#shifting model to gpu
model.to(device)
model
```

```
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Sequential(
    (fc1): Linear(in_features=512, out_features=100, bias=True)
    (relu): ReLU()
    (fc2): Linear(in_features=100, out_features=10, bias=True)
    (output): LogSoftmax(dim=1)
  )
)
```

```
from torch.utils.data import Dataset, DataLoader, ConcatDataset
dataset=list(zip(train_x, train_y))
```

```
dataloader = DataLoader(dataset, batch_size = 64, shuffle=True)

validataset=list(zip(val_x, val_y))
valiloader = DataLoader(validataset, batch_size = 64, shuffle=False)
```

```


from torch import optim
def train(model, trainloader, criterion, optimizer, epochs = 5):
    train_loss =[]
    validate_loss =[]
    for e in range(epochs):
        running_loss =0
        for images, labels in trainloader:
            inputs, labels = images.to(device), labels.to(device)
            optimizer.zero_grad()
            img = model(inputs)

            loss = criterion(img, labels)
            running_loss+=loss
            loss.backward()
            optimizer.step()
        print("Epoch : {}/{}..".format(e+1,epochs),
         "Training Loss: {:.6f}".format(running_loss/len(train_y)))
        train_loss.append(running_loss)




epochs = 7
model.train()
optimizer = optim.Adam(model.fc.parameters(), lr=0.001)
criterion = nn.NLLLoss()
train(model,dataloader,criterion, optimizer, epochs)
```

```
     Epoch : 1/7.. Training Loss: 0.033367
     Epoch : 2/7.. Training Loss: 0.031000
     Epoch : 3/7.. Training Loss: 0.030367
     Epoch : 4/7.. Training Loss: 0.029788
     Epoch : 5/7.. Training Loss: 0.029524
     Epoch : 6/7.. Training Loss: 0.029287
     Epoch : 7/7.. Training Loss: 0.028981
```

```
model.eval()
fn_list = []
pred_list = []
for x, fn in valiloader:
    with torch.no_grad():
        x = x.to(device)
        output = model(x)
        pred = torch.argmax(output, dim=1)
        pred_list += [p.item() for p in pred]

print(pred_list)
print(val_y)
```

```
[7, 5, 9, 7, 9, 1, 9, 9, 4, 1, 7, 9, 9, 7, 8, 0, 9, 7, 7, 9, 1, 9, 8, 9, 0, 1, 9, 1, 4, 8, 7, 8, 9, 9, 0, 5, 2, 2, 8, 1, 4, 9, 9,
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
```

```
from sklearn.metrics import confusion_matrix, classification_report
array=confusion_matrix(val_y, pred_list)
print(array)
```

```
[[ 5  6  2  0  3  3  1  7  5 18]
 [ 1 19  0  2  6  3  1 11  3  4]
 [ 0  3 25  1  3  5  1  3  6  3]
 [ 0  5  2  7  2  2 11 15  4  2]
 [ 0  6  1  3  8  1  7 15  5  4]
 [ 1  2  4  2  4  9  6  8  7  7]
 [ 0  2  0  2  4  0 22 13  4  3]
 [ 1  8  1  3  2  0  9 22  0  4]
 [ 0  4  3  2  2  2  5  8 16  8]
 [ 2  8  0  0  2  0  7  7  7 17]]
```

```
#Doing dummy classifier
from sklearn.dummy import DummyClassifier
X = val_y
y = val_y
dummy_clf = DummyClassifier(strategy="stratified")  #or most_frequent,stratified
dummy_clf.fit(X, y)
print("dummy classifier result\n")
#print(dummy_clf.score(X, y))
```

```
x_dummy=dummy_clf.predict(X)
print(classification_report(val_y, x_dummy))
```

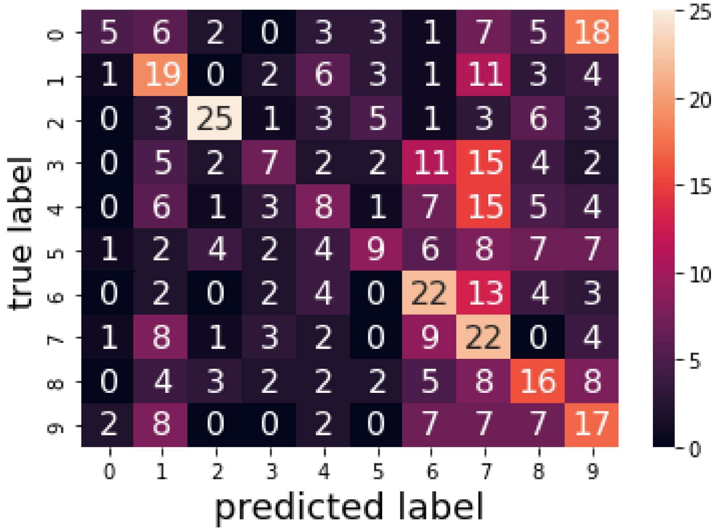
```
dummy classifier result

              precision    recall  f1-score   support

           0       0.07      0.08      0.07        50
           1       0.08      0.10      0.09        50
           2       0.22      0.26      0.24        50
           3       0.10      0.08      0.09        50
           4       0.06      0.04      0.05        50
           5       0.04      0.04      0.04        50
           6       0.09      0.10      0.09        50
           7       0.00      0.00      0.00        50
           8       0.07      0.08      0.07        50
           9       0.10      0.10      0.10        50

    accuracy                           0.09       500
   macro avg       0.08      0.09      0.08       500
weighted avg       0.08      0.09      0.08       500
```

```
#plot the confusion_matrix, and classification_report
import seaborn as sn
df_cm = pd.DataFrame(array, range(10), range(10))
sn.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')
plt.xlabel('predicted label', fontsize=18)
plt.ylabel('true label', fontsize=16)
plt.show()
print("\n\nclassification report:\n\n"+classification_report(val_y, pred_list))
```



true label \ predicted label	0	1	2	3	4	5	6	7	8	9
0	5	6	2	0	3	3	1	7	5	18
1	1	19	0	2	6	3	1	11	3	4
2	0	3	25	1	3	5	1	3	6	3
3	0	5	2	7	2	2	11	15	4	2
4	0	6	1	3	8	1	7	15	5	4
5	1	2	4	2	4	9	6	8	7	7
6	0	2	0	2	4	0	22	13	4	3
7	1	8	1	3	2	0	9	22	0	4
8	0	4	3	2	2	2	5	8	16	8
9	2	8	0	0	2	0	7	7	7	17

```
classification report:

              precision    recall  f1-score   support

           0       0.50      0.10      0.17        50
           1       0.30      0.38      0.34        50
           2       0.66      0.50      0.57        50
           3       0.32      0.14      0.19        50
           4       0.22      0.16      0.19        50
           5       0.36      0.18      0.24        50
           6       0.31      0.44      0.37        50
           7       0.20      0.44      0.28        50
           8       0.28      0.32      0.30        50
           9       0.24      0.34      0.28        50

    accuracy                           0.30       500
   macro avg       0.34      0.30      0.29       500
weighted avg       0.34      0.30      0.29       500
```