Unzip file Caltech101 from the internet

```
!unzip /content/caltech-101.zip
```

```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, models, transforms
from torch.utils.data import DataLoader, random_split
import matplotlib.pyplot as plt
import torchvision
import numpy as np
import random
```

Continue to extract file tar gz

```
Start coding or generate with AI.
```

```
!tar -xvzf /content/caltech-101/101_ObjectCategories.tar.gz
```

Check device which using GPU ('cuda') or CPU

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
device
```

```
device(type='cpu')
```

Using Data Augumentation to setting the transform image and resize image to 128 for practicing. Input the mean and std of nomalize to make standard color values

```
transform_image = transforms.Compose(
    [
        transforms.Resize((128, 128)),
        transforms.RandomHorizontalFlip(),
        transforms.RandomRotation(10),
        transforms.ToTensor(),
        transforms.Normalize(mean = [0.485, 0.456, 0.406], std = [0.229, 0.224, 0.225])
])

dataset = datasets.ImageFolder(root = '/content/101_ObjectCategories', transform = transform_image)
```

Split random data

```
train_dataset, val_dataset = random_split(dataset, [int(0.8 * len(dataset)), len(dataset) - int(0.8 * len(dataset))])
```

```
len(train_dataset), len(val_dataset)
```

```
(7315, 1829)
```

Create train and test loader for training

```
train_loader = DataLoader(train_dataset, batch_size = 32, shuffle = True)
val_loader = DataLoader(val_dataset, batch_size = 32, shuffle = False)
```

Check images and labels torch size

```
for images, labels in train_loader:
  print(images.shape, labels.shape)
  break
```

```
torch.Size([32, 3, 128, 128]) torch.Size([32])
```

```
random_index = random.randint(0, len(dataset) - 1)
random_index
```

```
8518
```

Double-click (or enter) to edit

```
len(dataset.classes)
```

```
102
```

Create and check classes from *dataset*

```
classes = dataset.classes
classes
```

```
['BACKGROUND_Google',
 'Faces',
 'Faces_easy',
```

```
'Leopards',
'Motorbikes',
'accordion',
'airplanes',
'anchor',
'ant',
'barrel',
'bass',
'beaver',
'binocular',
'bonsai',
'brain',
'brontosaurus',
'buddha',
'butterfly',
'camera',
'cannon',
'car_side',
'ceiling_fan',
'cellphone',
'chair',
'chandelier',
'cougar_body',
'cougar_face',
'crab',
'crayfish',
'crocodile',
'crocodile_head',
'cup',
'dalmatian',
'dollar_bill',
'dolphin',
'dragonfly',
'electric_guitar',
'elephant',
'emu',
'euphonium',
'ewer',
'ferry',
'flamingo',
'flamingo_head',
```

```
    'garfield',
    'gerenuk',
    'gramophone',
    'grand_piano',
    'hawksbill',
    'headphone',
    'hedgehog',
    'helicopter',
    'ibis',
    'inline_skate',
    'joshua_tree',
    'kangaroo',
    'ketch',
```

Print out first single image from dataset

```
single_image = dataset[50][0]
single_image = single_image.permute(1,2,0)
plt.imshow(single_image)
plt.title(dataset.classes[dataset[50][1]])
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]

Print out 32 images randomly

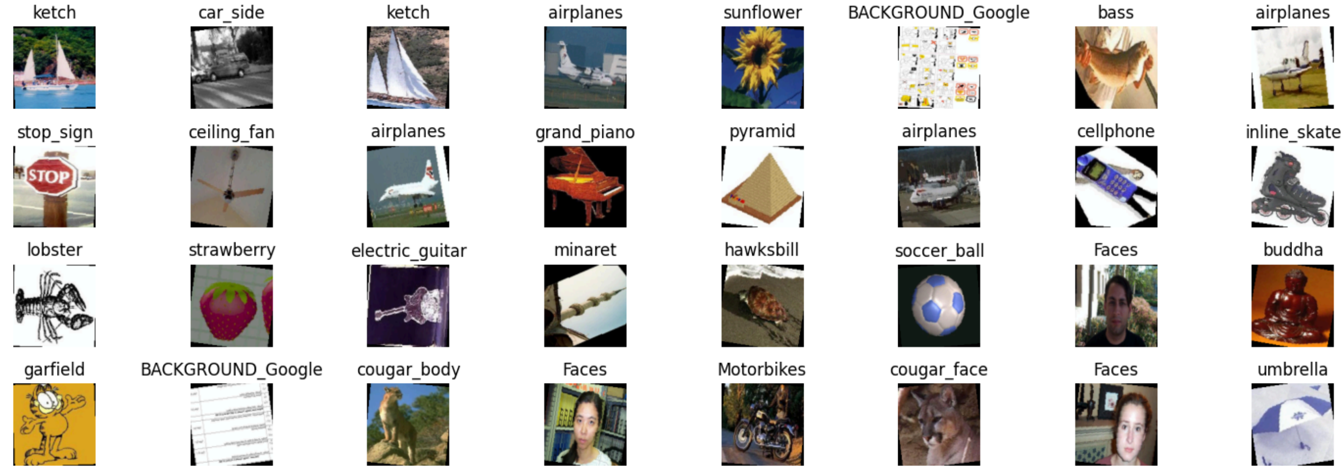
```
fig, axes = plt.subplots(nrows=4, ncols=8, figsize=(15, 5))
axes = axes.flatten()
for i in range(32):
    random_index = random.randint(0, len(dataset) - 1)
    image, label = dataset[random_index]

    # Reverse normalization
    mean = np.array([0.485, 0.456, 0.406])
    std = np.array([0.229, 0.224, 0.225])
```

```
    image = image.permute(1, 2, 0).numpy()  # Convert to NumPy array
    image = std * image + mean  # Reverse normalization
    image = np.clip(image, 0, 1)  # Clip values to [0, 1]


    axes[i].imshow(image)
    axes[i].set_title(dataset.classes[label])
    axes[i].axis('off')

plt.tight_layout()
plt.show()
```



Create 2D Convolution neuron network define which a sequence of layers with 3 chanels (RGB) then return output of the network has been processed by all layers

```
class CNN(nn.Module):
  def __init__(self, number_output):
    super(CNN, self).__init__()
    self.network = nn.Sequential(
        nn.Conv2d(in_channels = 3, out_channels = 32, kernel_size = 3, padding = 'same'), # 32,128,128
        nn.ReLU(),
        nn.MaxPool2d(kernel_size = 2, stride=2),   # 32, 64,64

        nn.Conv2d(in_channels = 32, out_channels = 64, kernel_size = 3, padding = 'same'),  # 32, 64,64
        nn.ReLU(),
        nn.MaxPool2d(kernel_size = 2, stride=2),  # 64, 32,32

        nn.Flatten(),
        nn.Linear(in_features = 64 * 32 * 32, out_features = 256),
        nn.ReLU(),
        nn.Linear(in_features = 256, out_features = 128),
        nn.ReLU(),
        nn.Linear(in_features = 128, out_features = number_output)
    )
  def forward(self, x):
      return self.network(x)
```

Training model with train and test model then get the accuracy from scratch

```
# Training loop
def train_model(model, optimizer, criterion, train_loader,val_loader, num_epochs=5):
    for epoch in range(num_epochs):
```

```
        model.train()
        running_loss = 0.0
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()
        print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {running_loss/len(train_loader):.4f}")


def test_model(model, val_loader):
  with torch.no_grad():
      model.eval()
      total = 0
      correct = 0
      for images, labels in val_loader:
        images, labels = images.to(device), labels.to(device)

        outputs = model(images)
        _, predicted = torch.max(outputs.data, 1)
        correct += (predicted == labels).sum().item()
        total += labels.size(0)
  print(f"accuracy : {100 * correct / total:.4f}")

test_model(model, val_loader)
```

```
accuracy : 45.0519
```

```
num_classes
```

```
102
```

Using 1 function to training and evaluation model

```
# Training loop
def train_model2(model, optimizer, criterion, train_loader,val_loader, num_epochs=1):
    for epoch in range(num_epochs):
        model.train()
        running_loss = 0.0
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()
        print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {running_loss/len(train_loader):.4f}")

    with torch.no_grad():
        model.eval()
        total = 0
        correct = 0
        for images, labels in val_loader:
            images, labels = images.to(device), labels.to(device)

            outputs = model(images)
            _, predicted = torch.max(outputs.data, 1)
            correct += (predicted == labels).sum().item()
            total += labels.size(0)
        print(f"accuracy : {100 * correct / total:.4f}")
```

Try with Pretrained model call Resnet18 to compare the accuracy

```
from torchvision import models

model = models.resnet18(pretrained=True)
model.fc = nn.Linear(model.fc.in_features, num_classes)

model = model.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

train_model2(model, optimizer, criterion, train_loader, val_loader, num_epochs=1)
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is dep
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enu
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /root/.cache/torch/hub/checkpoints/resnet18-
100%|██████████| 44.7M/44.7M [00:00<00:00, 164MB/s]
Epoch [1/1], Loss: 2.0244
accuracy : 63.1493
```

Pretrained with EfficientNet

```
model = models.efficientnet_b0(weights = 'DEFAULT')
model.classifier[-1] = nn.Linear(model.classifier[-1].in_features, num_classes)
model = model.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)
train_model2(model, optimizer, criterion, train_loader, val_loader, num_epochs=1)
```

```
Epoch [1/1], Loss: 1.4579
accuracy : 85.3472
```

We can see, the 2 pretrained model got better accrurancy than nornal training.

Print out 25 images randomly to check the accuracy of the model

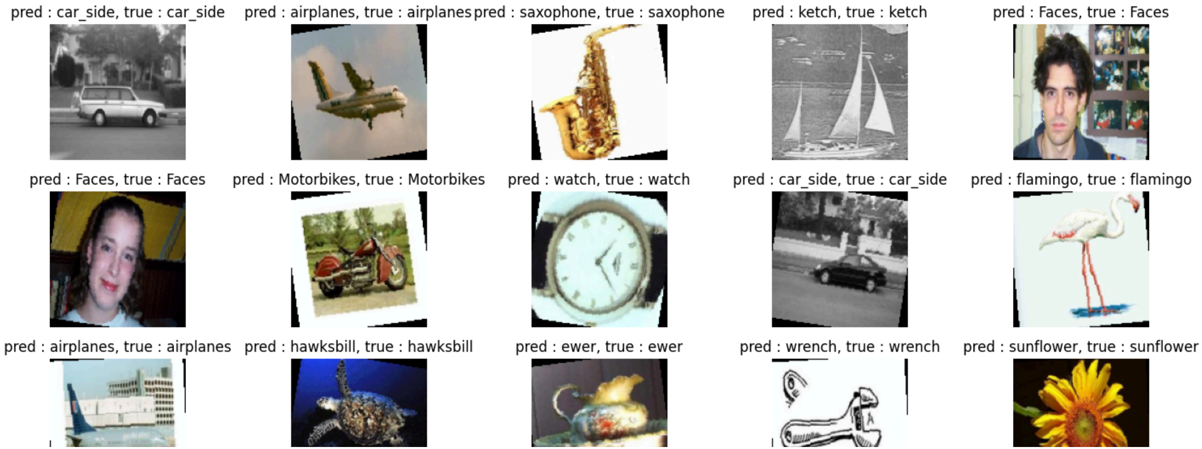
Double-click (or enter) to edit

```
fig, axes = plt.subplots(nrows=5, ncols=5, figsize=(15, 10))
axes = axes.flatten()
for i in range(25):
    random_index = random.randint(0, len(dataset) - 1)  # Get a random image from the dataset
    image, label = dataset[random_index]                # Get the image and its label

    # Make prediction for the image (Move image to device and get prediction)
    image_tensor = image.unsqueeze(0).to(device)       # Add a batch dimension
    with torch.no_grad():
        model.eval()
        output = model(image_tensor)
    _, predicted = torch.max(output.data, 1)
    predicted_class = predicted.item()                  # Get the predicted class as an integer

    # Display the image with predicted and true labels
    image = image.permute(1, 2, 0).cpu().numpy()
    mean = np.array([0.485, 0.456, 0.406])
    std = np.array([0.229, 0.224, 0.225])
    image = std * image + mean
    image = np.clip(image, 0, 1)
    axes[i].imshow(image)
    axes[i].set_title(f"pred : {classes[predicted_class]}, true : {classes[label]}")
    axes[i].axis('off')
```

```
plt.tight_layout()
plt.show()
```


pred : car_side, true : car_side
pred : airplanes, true : airplanes
pred : saxophone, true : saxophone
pred : ketch, true : ketch
pred : Faces, true : Faces
pred : Faces, true : Faces
pred : Motorbikes, true : Motorbikes
pred : watch, true : watch
pred : car_side, true : car_side
pred : flamingo, true : flamingo
pred : airplanes, true : airplanes
pred : hawksbill, true : hawksbill
pred : ewer, true : ewer
pred : wrench, true : wrench
pred : sunflower, true : sunflower