

Deep Learning (CS 470, CS 570)

Module 4, Lecture 3: CNN Implementation

CNN Object Classification

Mount Google drive and import Python packages:

```
[1] from google.colab import drive
    # Mounting my Google drive
    drive.mount('/content/drive')
```

Mounted at /content/drive



```
#Include libraries
import os
import numpy as np
import cv2
from matplotlib import pyplot as plt
from copy import deepcopy
import tensorflow as tf
from tensorflow.keras import datasets, layers, models

#Setting the local folder path
os.getcwd()
os.chdir(r"/content/drive/My Drive/Assignment")
```

CNN Object Classification

Load datasets, normalize data, and display shape of the datasets:

```
[3] (train_images, train_labels), (test_images, test_labels) = datasets.cifar10.load_data()

# Normalize pixel values to be between 0 and 1
train_images, test_images = train_images / 255.0, test_images / 255.0
```

Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>
170500096/170498071 [=====] - 11s 0us/step



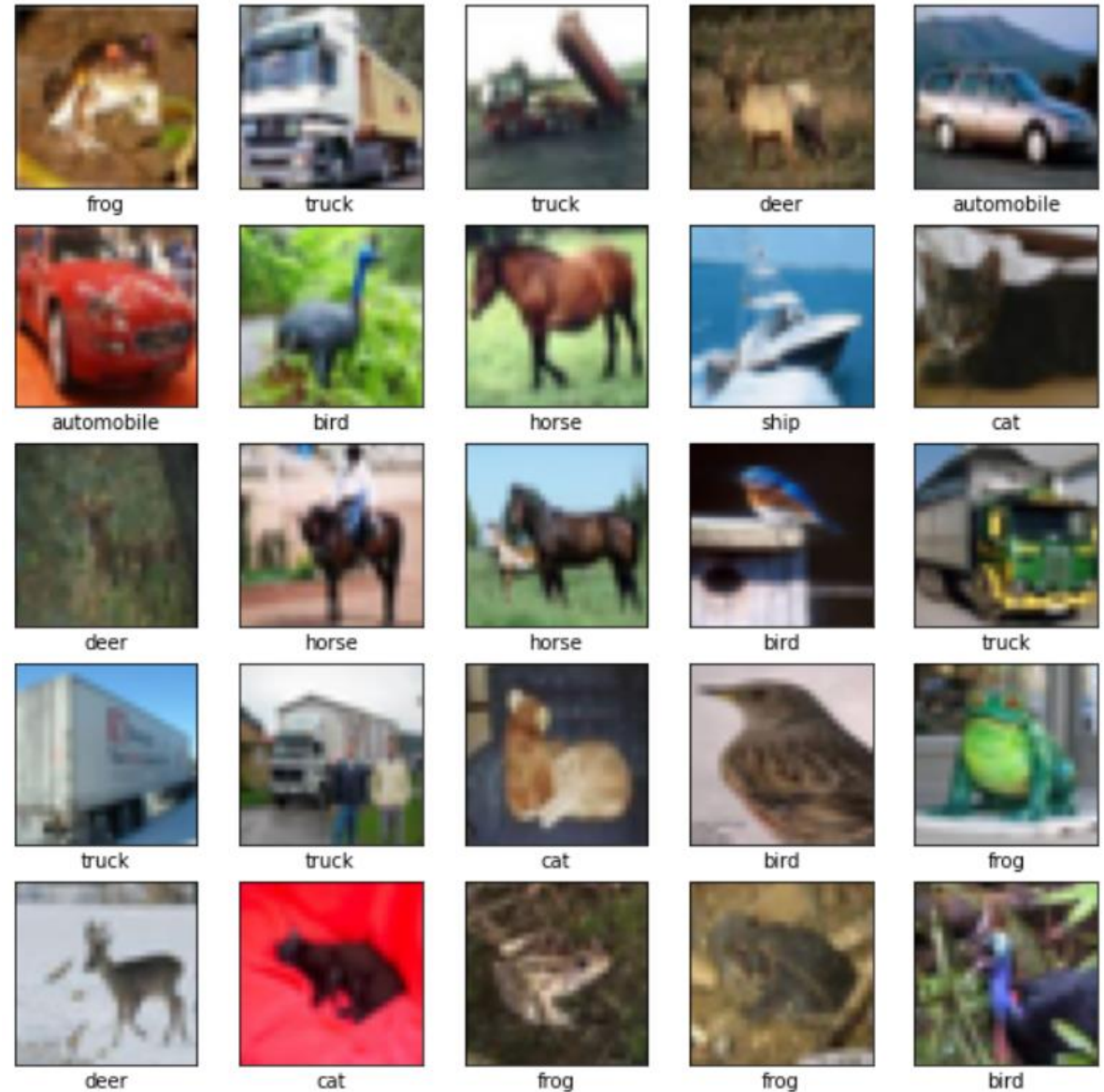
```
print("Shape of the training dataset, number of images and resolution:", train_images.shape)
print("Shape of the training dataset, number of images and resolution:", test_images.shape)
print("All distinct training labels:", np.unique(train_labels))
```

```
Shape of the training dataset, number of images and resolution: (50000, 32, 32, 3)
Shape of the training dataset, number of images and resolution: (10000, 32, 32, 3)
All distinct training labels: [0 1 2 3 4 5 6 7 8 9]
```

CNN Object Classification

Plot sample data:

```
▶ class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',  
                'dog', 'frog', 'horse', 'ship', 'truck']  
  
plt.figure(figsize=(10,10))  
for i in range(25):  
    plt.subplot(5,5,i+1)  
    plt.xticks([])  
    plt.yticks([])  
    plt.grid(False)  
    plt.imshow(train_images[i], cmap=plt.cm.binary)  
    # The CIFAR labels happen to be arrays,  
    # which is why you need the extra index  
    plt.xlabel(class_names[train_labels[i][0]])  
plt.show()
```



CNN Object Classification

Generate CNN architecture:

```
▶ model = models.Sequential()  
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))  
model.add(layers.MaxPooling2D((2, 2)))  
model.add(layers.Conv2D(64, (3, 3), activation='relu'))  
model.add(layers.MaxPooling2D((2, 2)))  
model.add(layers.Conv2D(64, (3, 3), activation='relu'))  
model.add(layers.Flatten())  
model.add(layers.Dense(64, activation='relu'))  
model.add(layers.Dense(10))  
  
model.summary()
```

2D convolution with 3D convolutional filters. Filters' depth is determined based on the depth of input image/feature map.

Reshaping the feature maps for fully connected layer.

CNN Object Classification

Output of model.summary():

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_1 (Conv2D)	(None, 13, 13, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 64)	0
conv2d_2 (Conv2D)	(None, 4, 4, 64)	36928
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 64)	65600
dense_1 (Dense)	(None, 10)	650
=====		
Total params: 122,570		
Trainable params: 122,570		
Non-trainable params: 0		
=====		

CNN Object Classification

Training and validation of CNN model:

```
model.compile(optimizer='adam',  
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),  
              metrics=['accuracy'])
```

```
CNN_trained = model.fit(train_images, train_labels, epochs=10,  
                        validation_data=(test_images, test_labels))
```

```
Epoch 1/10  
1563/1563 [=====] - 66s 42ms/step - loss: 1.4840 - accuracy: 0.4595 - val_loss: 1.3019 - val_accuracy: 0.5403  
Epoch 2/10  
1563/1563 [=====] - 65s 42ms/step - loss: 1.1186 - accuracy: 0.6060 - val_loss: 1.1216 - val_accuracy: 0.6133  
Epoch 3/10  
1563/1563 [=====] - 65s 42ms/step - loss: 0.9642 - accuracy: 0.6605 - val_loss: 0.9913 - val_accuracy: 0.6519  
Epoch 4/10  
1563/1563 [=====] - 65s 42ms/step - loss: 0.8678 - accuracy: 0.6956 - val_loss: 0.8788 - val_accuracy: 0.6968  
Epoch 5/10  
1563/1563 [=====] - 65s 42ms/step - loss: 0.8017 - accuracy: 0.7176 - val_loss: 0.8592 - val_accuracy: 0.7061  
Epoch 6/10  
1563/1563 [=====] - 64s 41ms/step - loss: 0.7474 - accuracy: 0.7369 - val_loss: 0.8448 - val_accuracy: 0.7134  
Epoch 7/10  
1563/1563 [=====] - 65s 41ms/step - loss: 0.7014 - accuracy: 0.7535 - val_loss: 0.8323 - val_accuracy: 0.7149  
Epoch 8/10  
1563/1563 [=====] - 65s 42ms/step - loss: 0.6579 - accuracy: 0.7696 - val_loss: 0.8381 - val_accuracy: 0.7129  
Epoch 9/10  
1563/1563 [=====] - 67s 43ms/step - loss: 0.6203 - accuracy: 0.7813 - val_loss: 0.8887 - val_accuracy: 0.7039  
Epoch 10/10  
1563/1563 [=====] - 66s 43ms/step - loss: 0.5825 - accuracy: 0.7951 - val_loss: 0.8691 - val_accuracy: 0.7172
```