Neural Networks and Deep Learning Assignment-7

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Github Link: https://github.com/pxc99740/neural_networks_assignment_7.git

Video Link: https://drive.google.com/drive/folders/1Benn6rUZWV1rPn-B-MmmKgJhRPR1ygpv

```
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow import keras
from tensorflow import confusionMatrixDisplay
from sklearn.metrics import classification_report, confusion_matrix
import warnings
warnings.filterwarnings("ignore")

(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()

Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==========] - 4s @us/step

classes = ["airplane", "automobile", "bird", "cat", "deer", "dog", "frog", "horse", "ship", "truck"]

y_train = y_train.reshape(-1,)
```

```
# Reshape converting 2D to 1D
y_test = y_test.reshape(-1,)
y_train = y_train.reshape(-1,)

# This code normalazation
x_train = x_train / 255.0
x_test = x_test / 255.0

x_train.shape

(50000, 32, 32, 3)
import tensorflow as tf
```

```
import tensorflow as tf
from tensorflow.keras import layers, models

lenet = models.Sequential([
    layers.Conv2D(6, kernel_size=5, strides=1, activation='relu', input_shape=(32,32,3), padding='same'), #C1
    layers.AveragePooling2D(pool_size=(2, 2)), #S1
    layers.Conv2D(16, kernel_size=5, strides=1, activation='relu', padding='valid'), #C2
    layers.AveragePooling2D(pool_size=(2, 2)), #S2
    layers.Conv2D(120, kernel_size=5, strides=1, activation='relu', padding='valid'), #C3
    layers.Flatten(), #Flatten
    layers.Dense(84, activation='relu'), #F1
    layers.Dense(10, activation='softmax') #Output layer
])
```

lenet.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 6)	456
average_pooling2d (Average Pooling2D)	(None, 16, 16, 6)	0
conv2d_1 (Conv2D)	(None, 12, 12, 16)	2416
average_pooling2d_1 (Avera gePooling2D)	(None, 6, 6, 16)	0
conv2d_2 (Conv2D)	(None, 2, 2, 120)	48120
flatten (Flatten)	(None, 480)	0
dense (Dense)	(None, 84)	40404
dense_1 (Dense)	(None, 10)	850

Total params: 92246 (360.34 KB) Trainable params: 92246 (360.34 KB) Non-trainable params: 0 (0.00 Byte)

lenet.compile(optimizer='adam', loss=keras.losses.sparse_categorical_crossentropy, metrics=['accuracy'])

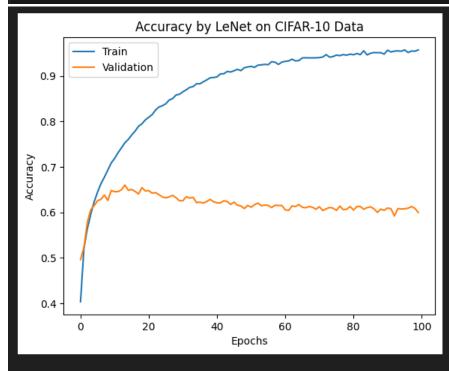
hist = lenet.fit(x_train, y_train, epochs=100, validation_data=(x_test, y_test),verbose=1)

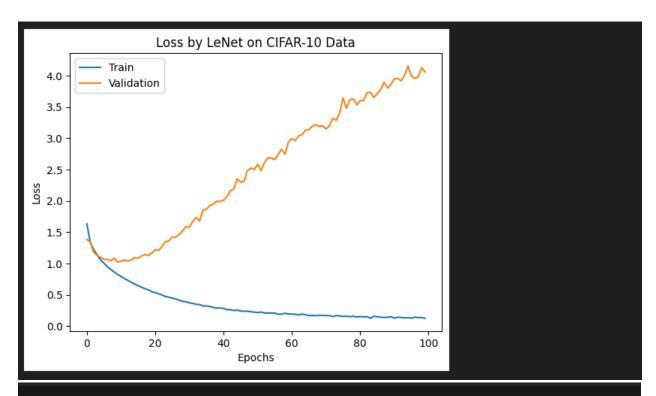
```
Epoch 1/100
1563/1563 [=
                                                  =] - 14s 6ms/step - loss: 1.6344 - accuracy: 0.4072 - val_loss: 1.3989 - val_accuracy: 0.4972
Epoch 2/100
1563/1563 [=
Epoch 3/100
1563/1563 [==
Epoch 4/100
1563/1563 [==
Epoch 5/100
1563/1563 [==
Epoch 6/100
                                                ==] - 8s 5ms/step - loss: 1.0338 - accuracy: 0.6352 - val_loss: 1.1170 - val_accuracy: 0.6106
1563/1563 [==
Epoch 7/100
1563/1563 [==
                                            =====] - 7s 5ms/step - loss: 0.9818 - accuracy: 0.6535 - val_loss: 1.0541 - val_accuracy: 0.6289
                                                ==] - 9s 5ms/step - loss: 0.9301 - accuracy: 0.6720 - val_loss: 1.0452 - val_accuracy: 0.6337
Epoch 8/100
1563/1563 [=
                                                 ==] - 8s 5ms/step - loss: 0.8856 - accuracy: 0.6885 - val_loss: 1.0623 - val_accuracy: 0.6276
Epoch 9/100
1563/1563 [=
Epoch 10/100
1563/1563 [=
                                         ======] - 7s 5ms/step - loss: 0.8141 - accuracy: 0.7122 - val_loss: 1.0748 - val_accuracy: 0.6269
Epoch 11/100
Epoch 12/100
1563/1563 [=
Epoch 13/100
1563/1563 [==:
Epoch 71/100
1563/1563 [==
Epoch 72/100
1101/1563 [==
                                           ======] - 8s 5ms/step - loss: 0.1486 - accuracy: 0.9488 - val_loss: 3.7648 - val_accuracy: 0.6010
```

```
import numpy as np

# fix random seed for reproducibility
seed = 7
np.random.seed(seed)

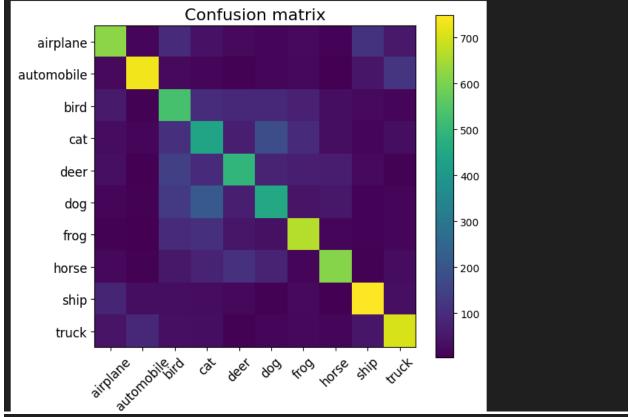
# summarize history for accuracy
plt.plot(hist.history['accuracy'])
plt.plot(hist.history['val_accuracy'])
plt.title("Accuracy by LeNet on CIFAR-10 Data")
plt.ylabel('accuracy')
plt.vlabel('accuracy')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
# summarize history for loss
plt.legend(['Train', 'Validation'], loc='upper left')
plt.plot(hist.history['val_loss'])
plt.title('Loss by LeNet on CIFAR-10 Data')
plt.ylabel('Loss')
plt.vlabel('Epochs')
plt.vlabel('Frain', 'Validation'])
plt.show()
```





```
from sklearn.metrics import confusion_matrix
   from sklearn.metrics import ConfusionMatrixDisplay
   y_predictions= lenet.predict(x_test)
   y predictions.reshape(-1,)
   y_predictions= np.argmax(y_predictions, axis=1)
   confusion_matrix(y_test, y_predictions)
313/313 [============ ] - 1s 2ms/step
array([[619,
              15, 91,
                        40,
                             22,
                                  14,
                                        21,
                                             11, 113,
                                                       54],
       [ 23, 731,
                   21,
                        16,
                              6,
                                  12,
                                        19,
                                             5,
                                                  48, 119],
       [ 57,
               6, 531,
                        97,
                             86,
                                  87,
                                             30,
                                                  21,
                                                       14],
                                        71,
       [ 27,
             12, 106, 439,
                             65, 179,
                                             32,
                                                  17,
                                        92,
                                                       31],
       [ 33,
               3, 143, 95, 493,
                                  73,
                                        66,
                                             64,
                                                  22,
                                                        8],
                             67, 453,
               8, 131, 211,
                                        41,
                                             50,
                                                  11,
       [ 13,
                                                       15],
               3,
          8,
                   92, 106,
                             48,
                                  36, 666,
                                             17,
                                                   9,
                                                       15],
               6,
                   50,
                        73, 110,
                                  78,
                                        17, 613,
       [ 19,
                                                   6,
                                                       28],
                                              4, 748,
              30,
                   30,
                        27,
                             19,
                                        21,
       [ 80,
                                   6,
                                                       35],
       [ 43,
              90,
                   34,
                        31,
                            7,
                                  14,
                                        18,
                                             14,
                                                 47, 702]])
```

```
# confusion matrix and accuracy
from sklearn.metrics import confusion_matrix, accuracy_score
plt.figure(figsize=(7, 6))
plt.title('Confusion matrix', fontsize=16)
plt.imshow(confusion_matrix(y_test, y_predictions))
plt.xticks(np.arange(10), classes, rotation=45, fontsize=12)
plt.yticks(np.arange(10), classes, fontsize=12)
plt.colorbar()
plt.show()
```

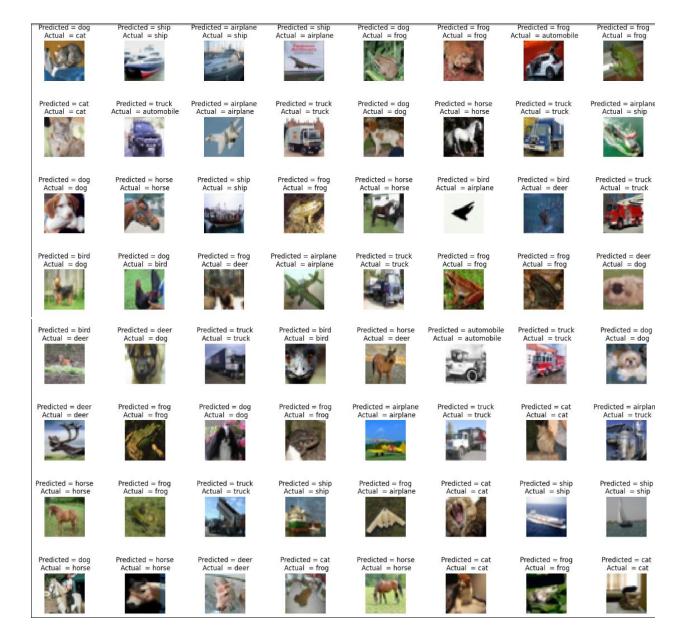


```
print("Test accuracy:", accuracy_score(y_test, y_predictions))

L = 8
W = 8
fig, axes = plt.subplots(L, W, figsize = (20,20))
axes = axes.ravel() #

for i in np.arange(0, L * W):
    axes[i].imshow(x_test[i])
    axes[i].set_title("Predicted = {}\n Actual = {}".format(classes[y_predictions[i]], classes[y_test[i]]))
    axes[i].axis('off')

plt.subplots_adjust(wspace=1)
```



```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv2D, Dropout, Flatten from tensorflow.keras.optimizers import SGD, Adam
from tensorflow.keras.layers import Convolution2D as Conv2D from tensorflow.keras.layers import MaxPooling2D
AlexNet = Sequential()
AlexNet.add(Conv2D(filters=16,kernel_size=(3,3),strides=(4,4),input_shape=(32,32,3), activation='relu'))
AlexNet.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
AlexNet.add(Conv2D(60,(5,5),padding='same',activation='relu'))
AlexNet.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
AlexNet.add(Conv2D(60,(3,3),padding='same',activation='relu'))
AlexNet.add(Conv2D(30,(3,3),padding='same',activation='relu'))
AlexNet.add(Conv2D(20,(3,3),padding='same',activation='relu'))
AlexNet.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
AlexNet.add(Flatten())
AlexNet.add(Dense(200, activation='relu'))
AlexNet.add(Dropout(0.1))
AlexNet.add(Dense(200, activation='relu'))
AlexNet.add(Dropout(0.1))
AlexNet.add(Dense(10,activation='softmax'))
AlexNet.compile(optimizer='SGD', loss=keras.losses.sparse_categorical_crossentropy, metrics=['accuracy'])
AlexNet.summary()
```

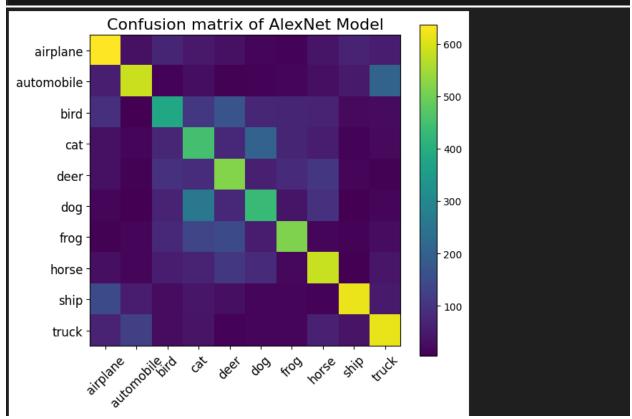
Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 8, 8, 16)	448
<pre>max_pooling2d (MaxPooling2 D)</pre>	(None, 4, 4, 16)	0
conv2d_4 (Conv2D)	(None, 4, 4, 60)	24060
<pre>max_pooling2d_1 (MaxPoolin g2D)</pre>	(None, 2, 2, 60)	0
conv2d_5 (Conv2D)	(None, 2, 2, 60)	32460
conv2d_6 (Conv2D)	(None, 2, 2, 30)	16230
conv2d_7 (Conv2D)	(None, 2, 2, 20)	5420
<pre>max_pooling2d_2 (MaxPoolin g2D)</pre>	(None, 1, 1, 20)	0
flatten_1 (Flatten)	(None, 20)	0
 Total params: 125028 (488.39 KB) Trainable params: 125028 (488.39 KB) Non-trainable params: 0 (0.00 Byte)		

```
history1 = AlexNet.fit(x_train, y_train, epochs=100, validation_data=(x_test, y_test),verbose=1)
Epoch 1/100
1563/1563 F=
                        1563/1563 F=
                                ==] - 9s 6ms/step - loss: 2.2379 - accuracy: 0.1729 - val_loss: 2.0964 - val_accuracy: 0.2019
Epoch 3/100
1563/1563 [==
                          =======] - 9s 6ms/step - loss: 2.0718 - accuracy: 0.2052 - val_loss: 2.0534 - val_accuracy: 0.2278
1563/1563 [=
                                ==] - 9s 6ms/step - loss: 1.9807 - accuracy: 0.2478 - val_loss: 2.0285 - val_accuracy: 0.2387
Epoch 5/100
                                ==] - 10s 6ms/step - loss: 1.8673 - accuracy: 0.2863 - val_loss: 1.7604 - val_accuracy: 0.3378
Epoch 6/100
1563/1563 [==
                                 =] - 9s 6ms/step - loss: 1.7570 - accuracy: 0.3271 - val_loss: 1.7866 - val_accuracy: 0.3321
Epoch 7/100
Epoch 8/100
                                 ==] - 9s 6ms/step - loss: 1.6125 - accuracy: 0.3900 - val_loss: 1.6049 - val_accuracy: 0.3961
Epoch 9/100
Epoch 10/100
                                 =] - 9s 5ms/step - loss: 1.4799 - accuracy: 0.4498 - val_loss: 1.6764 - val_accuracy: 0.3789
Epoch 11/100
                                ==] - 9s 6ms/step - loss: 1.4215 - accuracy: 0.4730 - val_loss: 1.3958 - val_accuracy: 0.4890
Epoch 12/100
1563/1563 [==
                         =======] - 9s 6ms/step - loss: 1.3713 - accuracy: 0.4935 - val_loss: 1.3535 - val_accuracy: 0.5073
Epoch 13/100
Epoch 99/100
1563/1563 [==
                              =====] - 9s 6ms/step - loss: 0.2739 - accuracy: 0.9039 - val loss: 2.5997 - val accuracy: 0.5227
Epoch 100/100
1563/1563 [==:
                               ===] - 9s 6ms/step - loss: 0.2681 - accuracy: 0.9057 - val_loss: 2.5864 - val_accuracy: 0.5327
     # summarize history for accuracy
     plt.plot(history1.history['accuracy'])
     plt.plot(history1.history['val_accuracy'])
     plt.title("Accuracy by AlexNet on CIFAR-10 Data")
     plt.ylabel('Accuracy')
     plt.xlabel('Epochs')
     plt.legend(['Train', 'Validation'], loc='upper left')
     plt.plot(history1.history['loss'])
     plt.plot(history1.history['val_loss'])
     plt.title('Loss by AlexNet on CIFAR-10 Data')
     plt.ylabel('Loss')
     plt.xlabel('Epochs')
     plt.legend(['Train', 'Validation'])
     plt.show()
     y_predictions1 = AlexNet.predict(x_test)
     y_predictions1.reshape(-1,)
     y_predictions1= np.argmax(y_predictions1, axis=1)
     confusion_matrix(y_test, y_predictions1)
```

```
313/313 [========== ] - 1s 2ms/step
array([[636, 32, 69, 48, 32, 13,
                                   9,
                                      41,
                                       31,
      [ 57, 585, 10, 28, 8, 11,
                                   15,
                                           50, 205],
             4, 381, 106, 169, 71,
      [ 90,
                                   70,
                                       66,
                                           21,
                                                22],
            16, 73, 449, 75, 202,
                                   70,
                                       53,
      [ 33,
                                           10,
                                                19],
                                           12,
      [ 32,
            8, 93, 83, 519, 59, 82, 105,
                                                 7],
      [ 14,
             6, 64, 257, 75, 429,
                                  40,
                                       95,
      [ 7, 12, 78, 136, 146, 53, 515,
                                       16,
                                           11,
      [ 31, 14, 54, 65, 107, 82, 17, 582,
                                            6,
                                                42],
      [147, 52, 26, 42, 30, 15, 13,
                                        9, 617, 49],
      [ 65, 124, 24, 37, 9, 16, 12, 62, 37, 614]])
```

```
# confusion matrix and accuracy
plt.figure(figsize=(7, 6))
plt.title('Confusion matrix of AlexNet Model', fontsize=16)
plt.imshow(confusion_matrix(y_test, y_predictions1))
plt.xticks(np.arange(10), classes, rotation=45, fontsize=12)
plt.yticks(np.arange(10), classes, fontsize=12)
plt.colorbar()
plt.show()
```



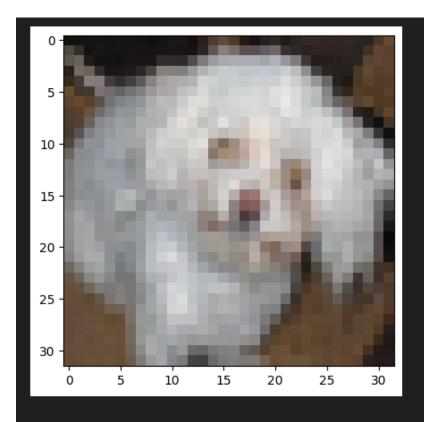
```
print("Test accuracy by AlexNet:", accuracy_score(y_test, y_predictions))
Test accuracy by AlexNet: 0.5995
                                                                                                            + Code
                                                                                                                          + Markdown
    L = 8
    W = 8
     fig, axes = plt.subplots(L, W, figsize = (20,20))
     axes = axes.ravel() #
     for i in np.arange(0, L * W):
           axes[i].imshow(x_test[i])
           axes[i].set_title("Predicted = {}\n Actual = {}".format(classes[y_predictions[i]], classes[y_test[i]]))
           axes[i].axis('off')
    plt.subplots_adjust(wspace=1)
                                                                                                                                                      Predicted = frog
Actual = automobile
 Predicted = dog
Actual = cat
                          Predicted = ship
                                                 Predicted = airplane
                                                                            Predicted = ship
                                                                                                     Predicted = dog
                                                                                                                              Predicted = frog
                                                                                                                                                                                 Predicted = frog
 Predicted = cat
Actual = cat
                          Predicted = truck
                                                 Predicted = airplane
Actual = airplane
                                                                           Predicted = truck
Actual = truck
                                                                                                     Predicted = dog
                                                                                                                             Predicted = horse
Actual = horse
                                                                                                                                                       Predicted = truck
Actual = truck
                                                                                                                                                                               Predicted = airplane
Actual = ship
                        Actual = automobile
                                                                                                       Actual = dog
 Predicted = dog
                         Predicted = horse
                                                   Predicted = ship
                                                                            Predicted = frog
                                                                                                     Predicted = horse
                                                                                                                              Predicted = bird
                                                                                                                                                        Predicted = bird
                                                                                                                                                                                Predicted = truck
   Actual = dog
                           Actual = horse
                                                     Actual = ship
                                                                              Actual = frog
                                                                                                      Actual = horse
                                                                                                                              Actual = airplane
                                                                                                                                                                                  Actual = truck
                                                                                                                                                                                Predicted = deer
 Predicted = bird
                          Predicted = dog
                                                   Predicted = frog
                                                                          Predicted = airplane
                                                                                                     Predicted = truck
                                                                                                                              Predicted = frog
                                                                                                                                                        Predicted = frog
                            Actual = bird
                                                                            Actual = airplane
                                                                                                                                Actual = frog
                                                                                                                                                          Actual = frog
   Actual = dog
                                                    Actual = deer
                                                                                                       Actual = truck
                                                                                                                                                                                   Actual = dog
Predicted = bird
                         Predicted = deer
                                                  Predicted = truck
                                                                           Predicted = bird
                                                                                                   Predicted = horse
                                                                                                                          Predicted = automobile
                                                                                                                                                      Predicted = truck
                                                                                                                                                                               Predicted = dog
  Actual = deer
                           Actual = dog
                                                    Actual = truck
                                                                             Actual = bird
                                                                                                     Actual = deer
                                                                                                                           Actual = automobile
                                                                                                                                                       Actual = truck
                                                                                                                                                                                 Actual = dog
                                                                                                                                                         : Milit
                         Predicted = frog
                                                                                                                                                                             Predicted = airplane
Actual = truck
Predicted = deer
                                                  Predicted = dog
                                                                           Predicted = frog
                                                                                                  Predicted = airplane
                                                                                                                            Predicted = truck
                                                                                                                                                      Predicted = cat
  Actual = deer
                            Actual = from
                                                    Actual = doc
                                                                                                    Actual = airplane
                                                                                                                                                         Actual = cat
Predicted = horse
Actual = horse
                         Predicted = frog
Actual = frog
                                                  Predicted = truck
Actual = truck
                                                                           Predicted = ship
Actual = ship
                                                                                                   Predicted = frog
Actual = airplane
                                                                                                                             Predicted = cat
Actual = cat
                                                                                                                                                      Predicted = ship
Actual = ship
                                                                                                                                                                               Predicted = ship
Actual = ship
                         Predicted = horse
Actual = horse
                                                                           Predicted = cat
Actual = frog
                                                                                                   Predicted = horse
Actual = horse
 Predicted = dog
                                                  Predicted = deer
                                                                                                                              Predicted = cat
                                                                                                                                                      Predicted = frog
                                                                                                                                                                                Predicted = cat
                                                    Actual = deer
                                                                                                                                                        Actual = frog
 Actual = horse
                                                                                                                                                                                 Actual
```

```
3.VGG 16
        import keras
from keras.models import Sequential
from keras.layers import Activation,Dense,Dropout,Conv2D,Flatten,MaxPooling2D
from keras.datasets import cifar10
from keras import optimizers
from matplotlib import pyplot as plt
         (x_train,y_train),(x_test,y_test) = cifar10.load_data()
        # config parameters
num_classes = 10
input_shape = x_train.shape[1:4]
optimizer = optimizers.Adam(lr=0.0003)
       # convert label to one-hot
one_hot_y_train = keras.utils.to_categorical(y_train,num_classes=num_classes)
one_hot_y_test = keras.utils.to_categorical(y_test,num_classes=num_classes)
       # check data
plt.imshow(x_train[1])
print(x_train[1].shape)
  (32, 32, 3)
       5
      10
      15
      20
      25
```

15

```
# build model(similar to VGG16, only change the input and output shape)
  model = Sequential()
  model.add(Conv2D(64,(3,3),activation='relu',input_shape=input_shape,padding='same'))
  model.add(Conv2D(64,(3,3),activation='relu',padding='same'))
  model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
  model.add(Conv2D(128,(3,3),activation='relu',padding='same'))
  model.add(Conv2D(128,(3,3),activation='relu',padding='same'))
  model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
  model.add(Conv2D(256,(3,3),activation='relu',padding='same'))
  model.add(Conv2D(256,(3,3),activation='relu',padding='same'))
  model.add(Conv2D(256,(3,3),activation='relu',padding='same'))
  model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
  model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
  model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
  model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
  model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
  model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
  model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
  model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
  model.add(Flatten())
  model.add(Dense(4096,activation='relu'))
  model.add(Dense(4096,activation='relu'))
  model.add(Dense(num_classes))
  model.add(Activation('softmax'))
   # config optimizer, loss, metrics
   model.compile(optimizer=optimizer,loss='categorical crossentropy',metrics=['accuracy'])
   # check model
   model.summary()
Model: "sequential_2"
 Layer (type)
                               Output Shape
                                                            Param #
 conv2d_8 (Conv2D)
                                (None, 32, 32, 64)
                                                            1792
 conv2d 9 (Conv2D)
                               (None, 32, 32, 64)
                                                            36928
 max_pooling2d_3 (MaxPoolin (None, 16, 16, 64)
 conv2d 10 (Conv2D)
                               (None, 16, 16, 128)
                                                            73856
 conv2d_11 (Conv2D)
                               (None, 16, 16, 128)
                                                            147584
 max_pooling2d_4 (MaxPoolin (None, 8, 8, 128)
                                                            0
 g2D)
 conv2d_12 (Conv2D)
                                (None, 8, 8, 256)
                                                            295168
```

```
conv2d 13 (Conv2D)
                                  (None, 8, 8, 256)
                                                                  590080
 conv2d 14 (Conv2D)
                                   (None, 8, 8, 256)
                                                                 590080
 max pooling2d 5 (MaxPoolin (None, 4, 4, 256)
                                                                 0
. . .
Total params: 33638218 (128.32 MB)
Trainable params: 33638218 (128.32 MB)
Non-trainable params: 0 (0.00 Byte)
   model.fit(x=x_train,y=one_hot_y_train,batch_size=128,epochs=10)
Epoch 1/10
391/391 [==
               Epoch 2/10
391/391 [==:
              -----] - 23s 59ms/step - loss: 2.3027 - accuracy: 0.0959
Epoch 3/10
391/391 [==
                     -----] - 23s 58ms/step - loss: 2.3027 - accuracy: 0.0961
Epoch 4/10
391/391 [===
                   Epoch 5/10
                    =======] - 23s 59ms/step - loss: 2.3027 - accuracy: 0.0969
391/391 [==
Epoch 6/10
391/391 [==:
                   ========] - 23s 59ms/step - loss: 2.3027 - accuracy: 0.0957
Epoch 7/10
391/391 [==:
                   -----] - 23s 58ms/step - loss: 2.3027 - accuracy: 0.0967
Epoch 8/10
391/391 [==
                   Epoch 9/10
391/391 [===
                    Epoch 10/10
391/391 [===
                    -----] - 23s 59ms/step - loss: 2.3027 - accuracy: 0.0981
   print(model.metrics_names)
   model.evaluate(x=x_test,y=one_hot_y_test,batch_size=512)
['loss', 'accuracy']
                    =======] - 7s 162ms/step - loss: 2.3026 - accuracy: 0.1000
20/20 [======
[2.3025965690612793, 0.10000000149011612]
   # predict
   plt.imshow(x_test[1000])
   result = model.predict(x test[1000:1001]).tolist()
   predict = 0
   expect = y_test[1000][0]
   for i,_ in enumerate(result[0]):
     if result[0][i] > result[0][predict]:
        predict = i
   print("predict class:",predict)
   print("expected class:",expect)
1/1 [=======] - 1s 640ms/step
predict class: 9
expected class: 5
```

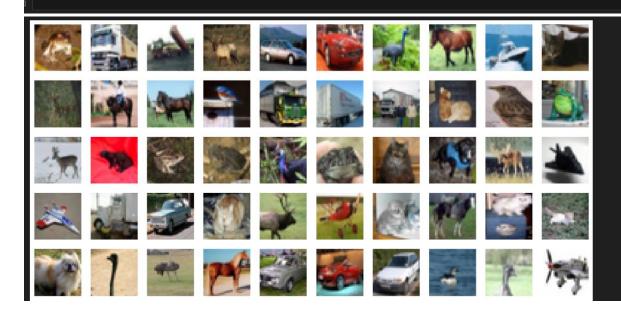


```
# save model
model.save("keras-VGG16-cifar10.h5")
```

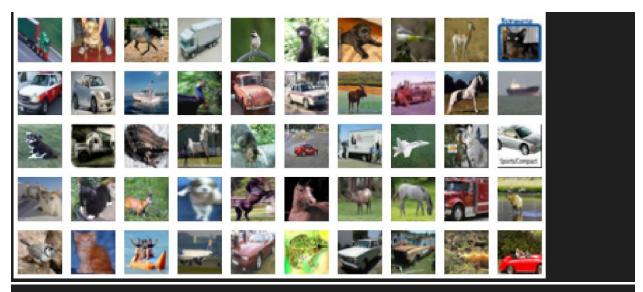
4.VGG19Model

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
import keras

from keras.datasets import cifar10
from tensorflow.keras.optimizers import RMSprop
from keras.preprocessing import image
from tensorflow.keras.preprocessing import image import ImageDataGenerator
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout, BatchNormalization
%matplotlib inline
```



plt.imshow(X_train[i], cmap = 'gray')



Training, Validating and Splitting trained and tested data

from sklearn.model_selection import train_test_split
x_train, x_val, y_train, y_val = train_test_split(X_train,Y_train,test_size=0.2)

from keras.utils import to_categorical
y_train = to_categorical(y_train, num_classes = 10)
y_val = to_categorical(y_val, num_classes = 10)

print(x_train.shape)
print(y_train.shape)
print(x_val.shape)
print(y_val.shape)
print(X_test.shape)
print(Y_test.shape)

(40000, 32, 32, 3) (40000, 10) (10000, 32, 32, 3) (10000, 10) (10000, 32, 32, 3) (10000, 1)

```
train datagen = ImageDataGenerator(
       preprocessing_function = tf.keras.applications.vgg19.preprocess_input,
       rotation_range=10,
       zoom_range = 0.1,
       width_shift_range = 0.1,
       height_shift_range = 0.1,
       shear_range = 0.1,
       horizontal_flip = True
    train_datagen.fit(x_train)
    val_datagen = ImageDataGenerator(preprocessing_function = tf.keras.applications.vgg19.preprocess_input)
    val_datagen.fit(x_val)
    from keras.callbacks import ReduceLROnPlateau
learning_rate_reduction = ReduceLROnPlateau(monitor='val_accuracy',
                                            patience=3,
                                            verbose=1,
                                            factor=0.5,
                                            min_lr=0.00001)
We have used only 16 layers out of 19 layers in the CNN
    vgg_model = tf.keras.applications.VGG19(
         include_top=False,
        weights="imagenet",
         input_shape=(32,32,3),
    vgg_model.summary()
Model: "vgg19"
                                Output Shape
 Layer (type)
                                                            Param #
  input_3 (InputLayer)
                                [(None, 32, 32, 3)]
  block1_conv1 (Conv2D)
                                (None, 32, 32, 64)
                                                            1792
  block1_conv2 (Conv2D)
                                (None, 32, 32, 64)
                                                            36928
  block1_pool (MaxPooling2D) (None, 16, 16, 64)
                                                            0
  block2_conv1 (Conv2D)
                                (None, 16, 16, 128)
                                                            73856
  block2_conv2 (Conv2D)
                                (None, 16, 16, 128)
                                                            147584
  block2_pool (MaxPooling2D) (None, 8, 8, 128)
  block3_conv1 (Conv2D)
                                (None, 8, 8, 256)
                                                            295168
  block3_conv2 (Conv2D)
                                      (None, 8, 8, 256)
                                                                      590080
  block3_conv3 (Conv2D)
                                      (None, 8, 8, 256)
                                                                      590080
  block3_conv4 (Conv2D)
                                      (None, 8, 8, 256)
                                                                      590080
 Total params: 20024384 (76.39 MB)
 Trainable params: 20024384 (76.39 MB)
 Non-trainable params: 0 (0.00 Byte)
```

```
model = tf.keras.Sequential()
    model.add(vgg_model)
    model.add(Flatten())
    model.add(Dense(1024, activation = 'relu'))
    model.add(Dense(1024, activation = 'relu'))
    model.add(Dense(256, activation = 'sigmoid'))
    model.add(Dense(10, activation = 'softmax'))
    model.summary()
Model: "sequential_3"
                                       Output Shape
 Layer (type)
                                                                           Param #
 vgg19 (Functional)
                                       (None, 1, 1, 512)
                                                                           20024384
 flatten_3 (Flatten)
                                       (None, 512)
                                                                           525312
 dense_10 (Dense)
                                       (None, 1024)
 dense_11 (Dense)
                                       (None, 1024)
                                                                           1049600
 dense_12 (Dense)
                                        (None, 256)
                                                                           262400
 dense_13 (Dense)
                                       (None, 10)
                                                                           2570
Total params: 21864266 (83.41 MB)
Trainable params: 21864266 (83.41 MB)
Non-trainable params: 0 (0.00 Byte)
  history = model.fit(
train_datagen.flow(x_train, y_train, batch_size = 128),
validation_data = val_datagen.flow(x_val,y_val, batch_size = 128),
       epochs = 10,
      verbose = 1,
callbacks = [learning_rate_reduction]
                              ======] - 38s 112ms/step - loss: 1.1032 - accuracy: 0.6178 - val_loss: 0.7488 - val_accuracy: 0.7486 - lr: 0.0010
Epoch 2/10
313/313 [===
Epoch 3/10
313/313 [===
Epoch 4/10
313/313 [===
Epoch 5/10
                               ======] - 34s 107ms/step - loss: 0.6273 - accuracy: 0.7884 - val loss: 0.6150 - val accuracy: 0.7950 - lr: 0.0010
                                =====] - 34s 107ms/step - loss: 0.5704 - accuracy: 0.8069 - val_loss: 0.5969 - val_accuracy: 0.7970 - lr: 0.0010
313/313 [==
Epoch 6/10
                            =======] - 34s 108ms/step - loss: 0.5160 - accuracy: 0.8231 - val_loss: 0.5143 - val_accuracy: 0.8258 - lr: 0.0010
313/313 [==
Epoch 7/10
313/313 [==
                           ========] - 34s 109ms/step - loss: 0.4794 - accuracy: 0.8351 - val_loss: 0.5276 - val_accuracy: 0.8218 - lr: 0.0010
                               =====] - 35s 112ms/step - loss: 0.4492 - accuracy: 0.8448 - val_loss: 0.5124 - val_accuracy: 0.8297 - lr: 0.0010
Epoch 8/10
                              ======] - 33s 106ms/step - loss: 0.4173 - accuracy: 0.8559 - val_loss: 0.4892 - val_accuracy: 0.8359 - lr: 0.0010
Epoch 9/10
313/313 [===
Epoch 10/10
313/313 [===
                           =======] - 33s 104ms/step - loss: 0.3871 - accuracy: 0.8678 - val_loss: 0.4836 - val_accuracy: 0.8373 - lr: 0.0010
                                  ===] - 33s 106ms/step - loss: 0.3677 - accuracy: 0.8744 - val_loss: 0.4372 - val_accuracy: 0.8516 - lr: 0.0010
```

```
loss = history.history['loss']
val_loss = history.history['val_loss']
 plt.plot(loss,color = 'green',label = 'Training Loss')
plt.plot(val_loss,color = 'red',label = 'Validation Loss')
<matplotlib.legend.Legend at 0x7f9ed55d68f0>
                                Training Loss
 1.1

    Validation Loss

 0.9
 0.8
 0.6
 0.5
     x test = tf.keras.applications.vgg19.preprocess input(X test)
     y_pred = np.argmax(model.predict(x_test), axis=-1)
     y_pred[:10]
313/313 [========== ] - 3s 9ms/step
array([3, 8, 8, 0, 6, 6, 1, 6, 3, 1])
     cm = confusion_matrix(Y_test, y_pred)
     CM
array([[892,
                     4,
                          19.
                                  5,
                                       10,
                                                2,
                                                      2,
                                                            12,
                                                                   36,
                                                                         18],
          [ 12, 885,
                           1,
                                  1,
                                         0,
                                                2,
                                                      З,
                                                             2,
                                                                   11,
                                                                         83],
                                                     35,
          [ 35,
                     1, 826,
                                 19.
                                       48,
                                              19,
                                                             9,
                                                                    5,
                                                                           3],
                          36, 700,
              5,
                     3,
                                       32, 145,
                                                     39,
                                                            19,
                                                                    6,
                                                                         15],
                                                     29,
          [ 12,
                     1,
                          37,
                                 27, 834,
                                              15,
                                                            40,
                                                                    4,
                                                                           1],
              3,
                                                     11,
                                                            34,
                                                                    1,
                          28, 105,
                                       22, 793,
                                                                           2],
                     1,
          [ 10,
                     2,
                          28,
                                 38,
                                       15,
                                              11, 884,
                                                             1,
                                                                    7,
                                                                           4],
                                              30,
              5,
                     Θ,
                          13.
                                 21,
                                       25.
                                                      1, 898,
                                                                           5],
                                               1,
                                                      0,
                                                             0, 923,
          [ 29,
                   15,
                           5,
                                 1,
                                         З,
                                                                         23],
                                 15,
                                                             7,
                                                                   12, 929]])
          [ 15,
                   16,
                           З,
                                         1,
                                                1,
                                                       1,
```

```
from sklearn.metrics import confusion_matrix, accuracy_score
print('Testing Accuarcy : ', accuracy_score(Y_test, y_pred))
```

Testing Accuarcy: 0.8564

```
import itertools
def plot_confusion_matrix(cm, classes,
                         normalize=False,
                         title='Confusion matrix',
                       cmap=plt.cm.Greens):
    Normalization can be applied by setting `normalize=True`.
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=30)
    plt.yticks(tick_marks, classes)
    if normalize:
       cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
       print("Normalized confusion matrix")
       print('Confusion matrix, without normalization')
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
       plt.text(j, i, cm[i, j],
           horizontalalignment="center",
            color="white" if cm[i, j] > thresh else "black")
```

```
plt.tight_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label')
```

