Name: Deekshitha, Gaddameedhi

GitHub link: https://github.com/deekshitha430/icp7 neural

ID: 700755765

Video Link: https://drive.google.com/file/d/117IP-

OCO\_VdnmXTnYWPMInPcxutW2769/view?usp=sharing

#### **Use Case Description:**

LeNet5, AlexNet, Vgg16, Vgg19

- 1. Training the model
- 2. Evaluating the model

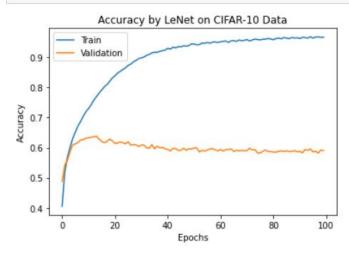
#### LeNEt5&AlexNet:

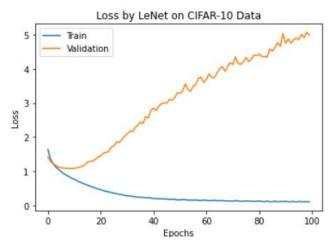
```
~
 In [2]: | import pandas as pd
            import numpy as np
            import matplotlib.pyplot as plt
            import tensorflow as tf
            from tensorflow import keras
            from tensorflow.keras.optimizers import RMSprop, Adam
            from sklearn.metrics import ConfusionMatrixDisplay
            from sklearn.metrics import classification_report, confusion_matrix
            import warnings
            warnings.filterwarnings("ignore")
 In [3]: M (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 [============ ] - 6s Ous/step
 In [4]: | classes = ["airplane", "automobile", "bird", "cat", "deer", "dog", "frog", "horse", "ship", "truck"]
 In [5]: y_train = y_train.reshape(-1,)
 In [6]: 

# Reshape converting 2D to 1D
            y_test = y_test.reshape(-1,)
            y_train = y_train.reshape(-1,)
 x_{train} = x_{train} / 255.0
```

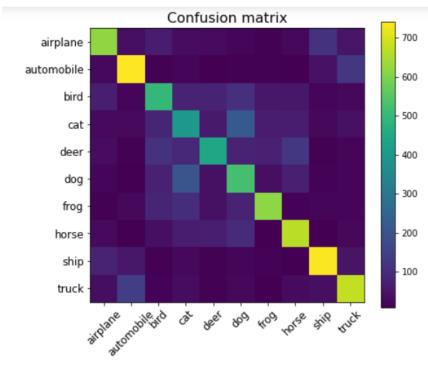
```
※ | 년 | 탄 || 不 | ♥ || ▶ KUN | ■ | Ե | 꺄 ||Code
                                                ~
        X^{ri.qTii} = X^{ri.qTii} / S^{ri.qTii}
         x_{test} = x_{test} / 255.0
[8]: ► x_train.shape
Out[8]: (50000, 32, 32, 3)
      I from tensorflow.keras import layers, models
         lenet = keras.models.Sequential([
             keras.layers.Conv2D(6, kernel_size=5, strides=1, activation='relu', input_shape=(32,32,3), padding='same'), #C1
             keras.layers.AveragePooling2D(), #S1
             keras.layers.Conv2D(16, kernel_size=5, strides=1, activation='relu', padding='valid'), #C2
             keras.layers.AveragePooling2D(), #S2
             keras.layers.Conv2D(120, kernel_size=5, strides=1, activation='relu', padding='valid'), #C3
            keras.layers.Flatten(), #Flatten
             keras.layers.Dense(84, activation='relu'), #F1
             keras.layers.Dense(10, activation='softmax') #Output layer
         ])
      ▶ lenet.summary()
[10]:
         Model: "sequential"
          Layer (type)
                                    Output Shape
                                                             Param #
         _____
          conv2d (Conv2D)
                                    (None, 32, 32, 6)
                                                             456
          average_pooling2d (AverageP (None, 16, 16, 6)
                                                             0
          ooling2D)
          conv2d_1 (Conv2D)
                                    (None, 12, 12, 16)
                                                             2416
          average_pooling2d_1 (Averag (None, 6, 6, 16)
          ePooling2D)
          conv2d_2 (Conv2D)
                                    (None, 2, 2, 120)
                                                             48120
          flatten (Flatten)
                                    (None, 480)
                                                             0
    In [10]: ▶ lenet.summary()
               Model: "sequential"
                Layer (type)
                                         Output Shape
                                                                Param #
               ______
                conv2d (Conv2D)
                                         (None, 32, 32, 6)
                                                                456
                average_pooling2d (AverageP (None, 16, 16, 6)
                ooling2D)
                conv2d_1 (Conv2D)
                                        (None, 12, 12, 16)
                                                                2416
                average_pooling2d_1 (Averag (None, 6, 6, 16)
                ePooling2D)
                conv2d_2 (Conv2D)
                                         (None, 2, 2, 120)
                                                                48120
                flatten (Flatten)
                                         (None, 480)
                dense (Dense)
                                                                40404
                                         (None, 84)
                                                                850
                dense_1 (Dense)
                                         (None, 10)
               _____
               Total params: 92,246
               Trainable params: 92,246
               Non-trainable params: 0
   In [11]: M lenet.compile(optimizer='adam', loss=keras.losses.sparse_categorical_crossentropy, metrics=['accuracy'])
```

```
In [12]: M hist = lenet.fit(x_train, y_train, epochs=100, validation_data=(x_test, y_test),verbose=1)
           Epoch 95/100
           1563/1563 [==
                               ==========] - 9s 6ms/step - loss: 0.0966 - accuracy: 0.9683 - val_loss: 4.9078 - val_accu
           acy: 0.5959
           Epoch 96/100
           1563/1563 [=
                               acy: 0.5863
           Epoch 97/100
           1563/1563 [==
                              ==========] - 8s 5ms/step - loss: 0.1035 - accuracy: 0.9671 - val_loss: 5.0162 - val_accu
           acy: 0.5881
           Epoch 98/100
           1563/1563 [=
                         acy: 0.5819
           Epoch 99/100
           1563/1563 [==
                              ==========] - 10s 6ms/step - loss: 0.1059 - accuracy: 0.9658 - val_loss: 5.0741 - val_acc
           racy: 0.5924
Epoch 100/100
           1563/1563 [==:
                       acy: 0.5902
In [13]: ▶ # 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.xlabel('Epochs')
           plt.legend(['Train', 'Validation'], loc='upper left')
          plt.show()
# summarize history for loss
plt.plot(hist.history['loss'])
plt.plot(hist.history['val_loss'])
           plt.title('Loss by LeNet on CIFAR-10 Data')
plt.ylabel('Loss')
plt.xlabel('Epochs')
           plt.legend(['Train', 'Validation'])
  plt.show()
                            ANTION TOU 1)
  plt.show()
```





```
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
   [ 25, 27, 83, 397, 61, 215, 67, 63, 23, 39], [ 32, 10, 114, 90, 441, 80, 75, 125, 12, 21], [ 18, 8, 75, 200, 39, 523, 38, 70, 13, 16], [ 12, 23, 82, 102, 40, 76, 615, 13, 21, 16], [ 25, 7, 37, 65, 68, 95, 8, 664, 8, 23], [ 77, 55, 11, 22, 12, 16, 14, 9, 737, 47], [ 33, 142, 13, 30, 11, 23, 9, 29, 38, 672]])
In [16]: ▶ # 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()
```

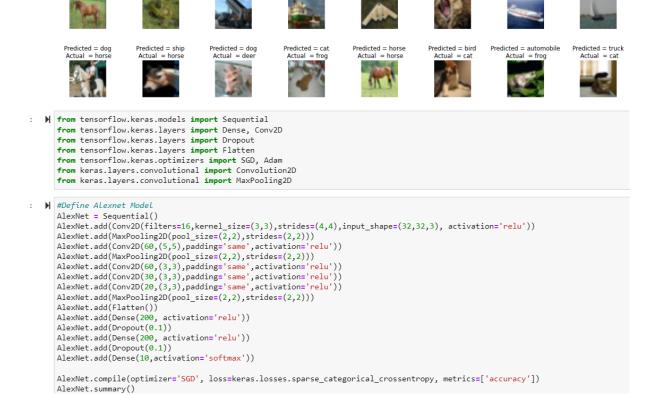


print("Test accuracy:", accuracy\_score(y\_test, y\_predictions))

Test accuracy: 0.5902

Predicted = horse Actual = horse Predicted = frog Actual = frog Predicted = truck Actual = truck

```
19]:
           H 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 = dog
Actual = cat
                                                Predicted = ship
Actual = ship
                                                                              Predicted = ship
Actual = ship
                                                                                                         Predicted = airplane
Actual = airplane
                                                                                                                                         Predicted = bird
Actual = frog
                                                                                                                                                                      Predicted = frog
Actual = frog
                                                                                                                                                                                                 Predicted = cat
Actual = automob
                                                                                                                                                                                                                                 Predicted = frog
Actual = frog
                    Predicted = cat
Actual = cat
                                                Predicted = truck
Actual = automobi
                                                                             Predicted = deer
Actual = airplane
                                                                                                           Predicted = truck
Actual = truck
                                                                                                                                         Predicted = dog
Actual = dog
                                                                                                                                                                     Predicted = horse
Actual = horse
                                                                                                                                                                                                   Predicted = truck
Actual = truck
                   Predicted = dog
Actual = dog
                                                Predicted = horse
Actual = horse
                                                                              Predicted = ship
Actual = ship
                                                                                                           Predicted = frog
Actual = frog
                                                                                                                                         Predicted = bird
Actual = horse
                                                                                                                                                                    Predicted = airplane
                                                                                                                                                                                                    Predicted = bird
                                                                                                                                                                                                    Predicted = cat
Actual = frog
                   Predicted = bird
Actual = dog
                                                Predicted = bird
Actual = bird
                                                                              Predicted = cat
Actual = deer
                                                                                                           Predicted = horse
Actual = airplane
                                                                                                                                        Predicted = truck
Actual = truck
                                                                                                                                                                                                                                 Predicted = dog
                                                                                                                                                                      Predicted = deer
                   Predicted = bird
                                                 Predicted = dog
                                                                             Predicted = truck
Actual = truck
                                                                                                       Predicted = automobile
Actual = bird
                                                                                                                                        Predicted = horse
                                                                                                                                                                    Predicted = airplane
                                                                                                                                                                                                   Predicted = truck
Actual = truck
                                                                                                                                                                                                                                 Predicted = dog
                                                   Actual = dog
                     Actual = deer
                                                                                                                                           Actual = deer
                                                                                                                                                                    Actual = automobile
                                                                                                                                                                                                                                    Actual = dog
                                                                                                                                                                                                         Militi
```



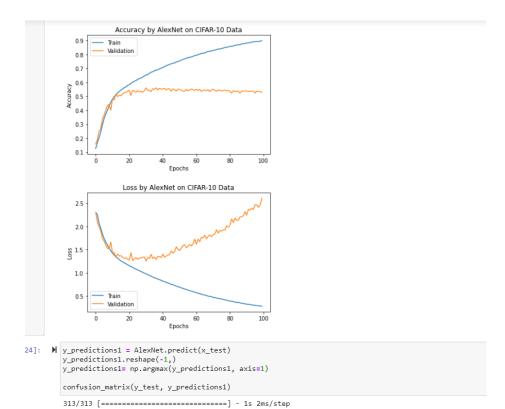
Predicted = ship Actual = ship Predicted = dog Actual = airplane Predicted = frog

Predicted = ship

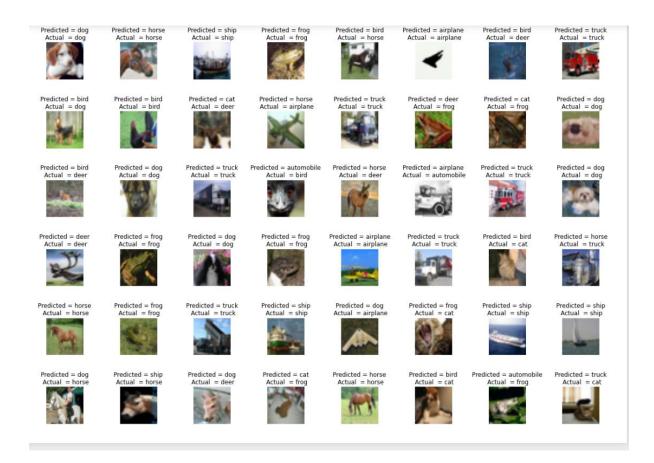
Predicted = ship Actual = ship

```
Model: "sequential_1"
Layer (type)
                           Output Shape
                                                   Param #
conv2d_3 (Conv2D)
                          (None, 8, 8, 16)
                                                   448
max_pooling2d (MaxPooling2D (None, 4, 4, 16)
conv2d_4 (Conv2D)
                           (None, 4, 4, 60)
                                                   24060
max_pooling2d_1 (MaxPooling (None, 2, 2, 60)
                                                   0
2D)
conv2d_5 (Conv2D)
                           (None, 2, 2, 60)
                                                   32460
conv2d_6 (Conv2D)
                           (None, 2, 2, 30)
                                                   16230
conv2d_7 (Conv2D)
                           (None, 2, 2, 20)
                                                   5420
max_pooling2d_2 (MaxPooling (None, 1, 1, 20)
                                                   0
2D)
flatten 1 (Flatten)
                           (None, 20)
                                                   0
dense_2 (Dense)
                           (None, 200)
                                                   4200
dropout (Dropout)
                           (None, 200)
dense_3 (Dense)
                           (None, 200)
                                                   40200
dropout_1 (Dropout)
                           (None, 200)
dense_4 (Dense)
                           (None, 10)
                                                   2010
_____
Total params: 125,028
Trainable params: 125,028
Non-trainable params: 0
```

```
[22]: M history1 = AlexNet.fit(x_train, y_train, epochs=100, validation_data=(x_test, y_test),verbose=1)
         racy: 0.5372
Epoch 95/100
         1563/1563 [==:
                        ============================== ] - 10s 6ms/step - loss: 0.3035 - accuracy: 0.8912 - val_loss: 2.3625 - val_accu
         racy: 0.5365
         Epoch 96/100
         1563/1563 「==
                         :=========================== ] - 10s 6ms/step - loss: 0.3017 - accuracy: 0.8921 - val_loss: 2.4652 - val_accu
         racy: 0.5241
Epoch 97/100
         racy: 0.5373
Epoch 98/100
                         1563/1563 [===
         racy: 0.5349
Epoch 99/100
         racy: 0.5338
Epoch 100/100
         1563/1563 [===
racy: 0.5287
                        # 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')
[23]:
         plt.xlabel('Epochs')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
          # summarize history for loss
         # Summarize in Early your toss
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'])
nlt chou()
```



Confusion matrix of AlexNet Model airplane 600 automobile bird 500 cat 400 deer dog 300 frog 200 horse 100 truck the working of the pay has take this trick



#### VGG16

```
import keras
  from keras.models import Sequential
  from keras.preprocessing import image
  from keras.layers import Activation, Dense, Dropout, Conv2D, Flatten, MaxPooling2D, BatchNormalization
  from keras.datasets import cifar10
  from keras import optimizers
  from matplotlib import pyplot as plt
  # generate cifar10 data
  (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)
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use the legacy optimizer,
e.g.,tf.keras.optimizers.legacy.Adam.
  # 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)
```

```
one_hot_y_test = keras.utils.to_categorical(y_test,num_classes=num_classes)
22]:
       # check data
       plt.imshow(x_train[1])
       print(x_train[1].shape)
     (32, 32, 3)
       5
     10
     15
     20
     25
     30
           0
                     5
                               10
                                          15
                                                    20
                                                               25
                                                                         30
  # 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'))
  \verb|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'])
```

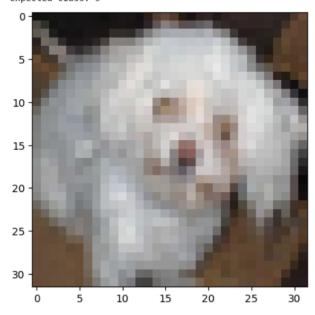
281.

```
27]: # train
   history=model.fit(x=x_train,y=one_hot_y_train,batch_size=128,epochs=10,validation_split=0.1)
  Epoch 1/10
  352/352 [============] - 25s 70ms/step - loss: 2.3027 - accuracy: 0.0997 - val_loss: 2.3027 - val_accuracy:
  Fnoch 2/10
  352/352 [============] - 22s 61ms/step - loss: 2.3027 - accuracy: 0.0993 - val_loss: 2.3027 - val_accuracy:
  Epoch 3/10
          352/352 [==
  0.0950
  352/352 [===========] - 22s 62ms/step - loss: 2.3027 - accuracy: 0.0993 - val loss: 2.3029 - val accuracy:
  Epoch 5/10
  352/352 [===========] - 22s 63ms/step - loss: 2.3027 - accuracy: 0.0965 - val_loss: 2.3029 - val_accuracy:
  0.0958
  Epoch 6/10
  Epoch 7/10
  352/352 [===========] - 22s 61ms/step - loss: 2.3027 - accuracy: 0.0990 - val_loss: 2.3029 - val_accuracy:
  0.0958
  Epoch 8/10
  0.1024
  352/352 [============] - 21s 61ms/step - loss: 2.3027 - accuracy: 0.0990 - val_loss: 2.3027 - val_accuracy:
  0.0976
  Epoch 10/10
  352/352 [===========] - 21s 61ms/step - loss: 2.3027 - accuracy: 0.0990 - val_loss: 2.3028 - val_accuracy:
  0.0976
```

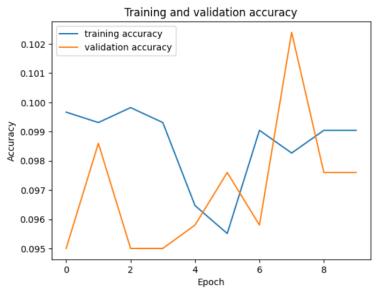
```
# predict
plt.imshow(x_test[1000])

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)
```

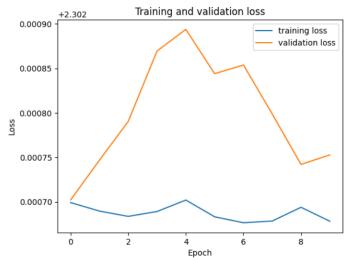
```
1/1 [======] - 0s 143ms/step predict class: 6 expected class: 5
```



```
plt.plot(history.history['accuracy'], label='training accuracy')
plt.plot(history.history['val_accuracy'], label='validation accuracy')
plt.title('Training and validation accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



```
plt.plot(history.history['loss'], label='training loss')
plt.plot(history.history['val_loss'], label='validation loss')
plt.title('Training and validation loss')
plt.ylabel('Epoch')
plt.ylabel('toss')
plt.legend()
plt.show()
```

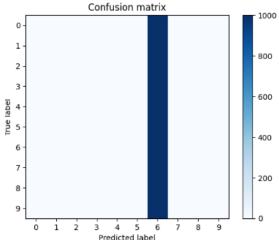


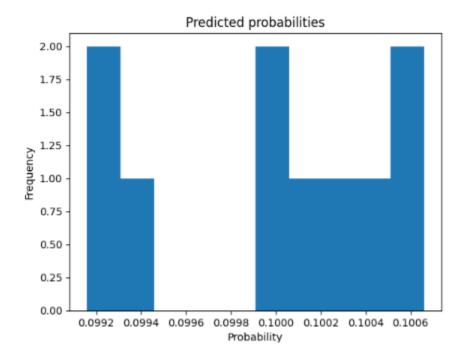
```
import numpy as np
from sklearn.metrics import confusion_matrix

# calculate the confusion matrix
y_pred = model.predict(x_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true = y_test.ravel()
cm = confusion_matrix(y_true, y_pred_classes)

# plot the confusion matrix
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion matrix')
plt.colorbar()
tick_marks = np.arange(num_classes)
plt.xtick(tick_marks, range(num_classes))
plt.xtick(tick_marks, range(num_classes))
plt.yticks(tick_marks, range(num_classes)
```







#### VGG19MODE\_CIFAR100:

Import libraries

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

from tensorflow.keras.optimizers import RMSprop

from keras.preprocessing import image

from tensorflow.keras.preprocessing.image import ImageDataGenerator

from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout, BatchNormalization

#### %matplotlib inline

Extract data and train and test dataset

```
\begin{split} & cifar 100 = tf.keras.datasets.cifar 100 \\ & (X\_train, Y\_train) \ , \ (X\_test, Y\_test) = cifar 10.load\_data() \\ & classes = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck'] \\ & Let's \ look \ into \ the \ dataset \ images \end{split}
```

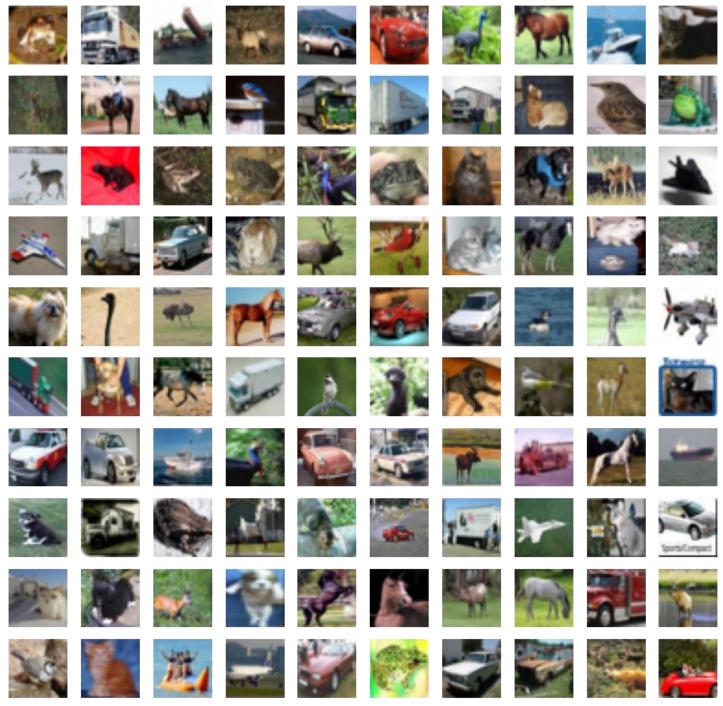
```
plt.figure(figsize = (16,16))
for i in range(100):
  plt.subplot(10,10,1+i)
  plt.axis('off')
  plt.imshow(X_train[i], cmap = 'gray')
```

In []:

In [ ]:

In [ ]:

In []:



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.np\_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)

In []:

In [ ]:

In [ ]:

```
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)
                                                                                                                     In [ ]:
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)
                                                                                                                     In [ ]:
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
                                                                                                                     In []:
vgg model = tf.keras.applications.VGG19(
  include_top=False,
  weights="imagenet",
  input_shape=(32,32,3),
)
vgg_model.summary()
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg19/vgg19_weights_tf_dim_ordering_tf_kern
els_notop.h5
Model: "vgg19"
Layer (type)
                    Output Shape
                                         Param #
input 1 (InputLayer)
                        [(None, 32, 32, 3)]
block1_conv1 (Conv2D)
                           (None, 32, 32, 64)
                                                1792
block1 conv2 (Conv2D)
                           (None, 32, 32, 64)
                                                36928
```

block2_conv1 (Conv2D) (None, 16, 16, 128) 73856  block2_conv2 (Conv2D) (None, 16, 16, 128) 147584  block2_pool (MaxPooling2D) (None, 8, 8, 128) 0  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  block3_conv4 (Conv2D) (None, 8, 8, 256) 590080  block3_pool (MaxPooling2D) (None, 4, 4, 256) 0  block4_conv1 (Conv2D) (None, 4, 4, 512) 1180160  block4_conv2 (Conv2D) (None, 4, 4, 512) 2359808  block4_conv3 (Conv2D) (None, 4, 4, 512) 2359808  block4_pool (MaxPooling2D) (None, 2, 2, 512) 0  block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv4 (Conv2D) (None, 2, 2, 512) 2359808	block1_pool (MaxPooling2D) (None, 16, 16, 64)	) 0
block2_pool (MaxPooling2D)         (None, 8, 8, 128)         0           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           block3_pool (MaxPooling2D)         (None, 4, 4, 256)         0           block4_conv1 (Conv2D)         (None, 4, 4, 512)         1180160           block4_conv2 (Conv2D)         (None, 4, 4, 512)         2359808           block4_conv3 (Conv2D)         (None, 4, 4, 512)         2359808           block4_pool (MaxPooling2D)         (None, 2, 2, 512)         2359808           block5_conv1 (Conv2D)         (None, 2, 2, 512)         2359808           block5_conv2 (Conv2D)         (None, 2, 2, 512)         2359808	block2_conv1 (Conv2D) (None, 16, 16, 128)	73856
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  block3_pool (MaxPooling2D) (None, 4, 4, 256) 0  block4_conv1 (Conv2D) (None, 4, 4, 512) 1180160  block4_conv2 (Conv2D) (None, 4, 4, 512) 2359808  block4_conv3 (Conv2D) (None, 4, 4, 512) 2359808  block4_conv4 (Conv2D) (None, 4, 4, 512) 2359808  block4_pool (MaxPooling2D) (None, 2, 2, 512) 0  block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block2_conv2 (Conv2D) (None, 16, 16, 128)	147584
block3_conv2 (Conv2D)         (None, 8, 8, 256)         590080           block3_conv3 (Conv2D)         (None, 8, 8, 256)         590080           block3_conv4 (Conv2D)         (None, 8, 8, 256)         590080           block3_pool (MaxPooling2D)         (None, 4, 4, 256)         0           block4_conv1 (Conv2D)         (None, 4, 4, 512)         1180160           block4_conv2 (Conv2D)         (None, 4, 4, 512)         2359808           block4_conv3 (Conv2D)         (None, 4, 4, 512)         2359808           block4_pool (MaxPooling2D)         (None, 2, 2, 512)         0           block5_conv1 (Conv2D)         (None, 2, 2, 512)         2359808           block5_conv2 (Conv2D)         (None, 2, 2, 512)         2359808           block5_conv3 (Conv2D)         (None, 2, 2, 512)         2359808	block2_pool (MaxPooling2D) (None, 8, 8, 128)	0
block3_conv3 (Conv2D) (None, 8, 8, 256) 590080  block3_conv4 (Conv2D) (None, 8, 8, 256) 590080  block3_pool (MaxPooling2D) (None, 4, 4, 256) 0  block4_conv1 (Conv2D) (None, 4, 4, 512) 1180160  block4_conv2 (Conv2D) (None, 4, 4, 512) 2359808  block4_conv3 (Conv2D) (None, 4, 4, 512) 2359808  block4_conv4 (Conv2D) (None, 4, 4, 512) 2359808  block4_pool (MaxPooling2D) (None, 2, 2, 512) 0  block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block3_conv1 (Conv2D) (None, 8, 8, 256)	295168
block3_conv4 (Conv2D) (None, 8, 8, 256) 590080  block3_pool (MaxPooling2D) (None, 4, 4, 256) 0  block4_conv1 (Conv2D) (None, 4, 4, 512) 1180160  block4_conv2 (Conv2D) (None, 4, 4, 512) 2359808  block4_conv3 (Conv2D) (None, 4, 4, 512) 2359808  block4_conv4 (Conv2D) (None, 4, 4, 512) 2359808  block4_pool (MaxPooling2D) (None, 2, 2, 512) 0  block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block3_conv2 (Conv2D) (None, 8, 8, 256)	590080
block3_pool (MaxPooling2D) (None, 4, 4, 256) 0 block4_conv1 (Conv2D) (None, 4, 4, 512) 1180160 block4_conv2 (Conv2D) (None, 4, 4, 512) 2359808 block4_conv3 (Conv2D) (None, 4, 4, 512) 2359808 block4_conv4 (Conv2D) (None, 4, 4, 512) 2359808 block4_pool (MaxPooling2D) (None, 2, 2, 512) 0 block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808 block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808 block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block3_conv3 (Conv2D) (None, 8, 8, 256)	590080
block4_conv1 (Conv2D) (None, 4, 4, 512) 1180160  block4_conv2 (Conv2D) (None, 4, 4, 512) 2359808  block4_conv3 (Conv2D) (None, 4, 4, 512) 2359808  block4_conv4 (Conv2D) (None, 4, 4, 512) 2359808  block4_pool (MaxPooling2D) (None, 2, 2, 512) 0  block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block3_conv4 (Conv2D) (None, 8, 8, 256)	590080
block4_conv2 (Conv2D)       (None, 4, 4, 512)       2359808         block4_conv3 (Conv2D)       (None, 4, 4, 512)       2359808         block4_conv4 (Conv2D)       (None, 4, 4, 512)       2359808         block4_pool (MaxPooling2D)       (None, 2, 2, 512)       0         block5_conv1 (Conv2D)       (None, 2, 2, 512)       2359808         block5_conv2 (Conv2D)       (None, 2, 2, 512)       2359808         block5_conv3 (Conv2D)       (None, 2, 2, 512)       2359808	block3_pool (MaxPooling2D) (None, 4, 4, 256)	0
block4_conv3 (Conv2D) (None, 4, 4, 512) 2359808  block4_conv4 (Conv2D) (None, 4, 4, 512) 2359808  block4_pool (MaxPooling2D) (None, 2, 2, 512) 0  block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block4_conv1 (Conv2D) (None, 4, 4, 512)	1180160
block4_conv4 (Conv2D) (None, 4, 4, 512) 2359808  block4_pool (MaxPooling2D) (None, 2, 2, 512) 0  block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808  block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block4_conv2 (Conv2D) (None, 4, 4, 512)	2359808
block4_pool (MaxPooling2D) (None, 2, 2, 512) 0 block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808 block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808 block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block4_conv3 (Conv2D) (None, 4, 4, 512)	2359808
block5_conv1 (Conv2D) (None, 2, 2, 512) 2359808 block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808 block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block4_conv4 (Conv2D) (None, 4, 4, 512)	2359808
block5_conv2 (Conv2D) (None, 2, 2, 512) 2359808 block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block4_pool (MaxPooling2D) (None, 2, 2, 512)	0
block5_conv3 (Conv2D) (None, 2, 2, 512) 2359808	block5_conv1 (Conv2D) (None, 2, 2, 512)	2359808
	block5_conv2 (Conv2D) (None, 2, 2, 512)	2359808
block5_conv4 (Conv2D) (None, 2, 2, 512) 2359808	block5_conv3 (Conv2D) (None, 2, 2, 512)	2359808
	block5_conv4 (Conv2D) (None, 2, 2, 512)	2359808
block5_pool (MaxPooling2D) (None, 1, 1, 512) 0	block5_pool (MaxPooling2D) (None, 1, 1, 512)	0

Total params: 20,024,384 Trainable params: 20,024,384

Non-trainable params: 0

```
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 = 'relu'))
model.add(Dense(10, activation = 'softmax'))
```

model.summary()

Model: "sequential"

Param #

In []:

Layer (type) Output Shape

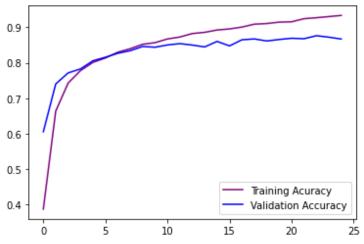
```
vgg19 (Functional)
                         (None, 1, 1, 512)
                                               20024384
flatten (Flatten)
                      (None, 512)
                                           0
dense (Dense)
                       (None, 1024)
                                             525312
dense_1 (Dense)
                        (None, 1024)
                                              1049600
dense 2 (Dense)
                        (None, 256)
                                             262400
dense_3 (Dense)
                        (None, 10)
                                             2570
Total params: 21,864,266
Trainable params: 21,864,266
Non-trainable params: 0
                                                                                                                             In [ ]:
optimizer = tf.keras.optimizers.SGD(lr = 0.001, momentum = 0.9)
model.compile(optimizer= optimizer,
       loss='categorical crossentropy',
       metrics=['accuracy'])
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/optimizer_v2/optimizer_v2.py:375: UserWarning: The `lr` argument is
deprecated, use `learning_rate` instead.
 "The `lr` argument is deprecated, use `learning_rate` instead.")
                                                                                                                              In [ ]:
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 = 25,
  verbose = 1,
  callbacks = [learning_rate_reduction]
Epoch 1/25
313/313 [=
                                      =======] - 84s 165ms/step - loss: 1.6671 - accuracy: 0.3875 - val_loss: 1.1241 - val_accur
acy: 0.6056
Epoch 2/25
313/313 [=
                                         ======] - 50s 159ms/step - loss: 0.9631 - accuracy: 0.6640 - val_loss: 0.7466 - val_accur
acy: 0.7404
Epoch 3/25
313/313 [=
                                          :=====] - 50s 160ms/step - loss: 0.7464 - accuracy: 0.7430 - val_loss: 0.6792 - val_accur
acy: 0.7716
Epoch 4/25
                                      =======] - 50s 160ms/step - loss: 0.6533 - accuracy: 0.7782 - val_loss: 0.6814 - val_accur
313/313 [=:
acy: 0.7829
Epoch 5/25
313/313 [==
                                         ======] - 50s 159ms/step - loss: 0.5779 - accuracy: 0.8013 - val loss: 0.5932 - val accur
acy: 0.8058
Epoch 6/25
                                         ======] - 50s 160ms/step - loss: 0.5369 - accuracy: 0.8136 - val_loss: 0.5455 - val_accur
313/313 [=:
acy: 0.8157
Epoch 7/25
                                      =======] - 50s 160ms/step - loss: 0.4925 - accuracy: 0.8299 - val_loss: 0.5119 - val_accur
313/313 [==
acy: 0.8269
Epoch 8/25
```

acc = history.history['accuracy']

```
=====] - 50s 160ms/step - loss: 0.4660 - accuracy: 0.8398 - val_loss: 0.5036 - val_accur
313/313 [=
acy: 0.8342
Epoch 9/25
313/313 [==
                                          ====] - 50s 160ms/step - loss: 0.4315 - accuracy: 0.8523 - val_loss: 0.4470 - val_accur
acy: 0.8461
Epoch 10/25
313/313 [==
                                      ======] - 50s 160ms/step - loss: 0.4110 - accuracy: 0.8569 - val loss: 0.4712 - val accur
acy: 0.8440
Epoch 11/25
313/313 [==
                                 ========] - 50s 159ms/step - loss: 0.3797 - accuracy: 0.8673 - val_loss: 0.4721 - val_accur
acy: 0.8504
Epoch 12/25
313/313 [==
                                    =======] - 50s 160ms/step - loss: 0.3641 - accuracy: 0.8728 - val loss: 0.4315 - val accur
acy: 0.8541
Epoch 13/25
313/313 [==
                                     ======] - 50s 159ms/step - loss: 0.3399 - accuracy: 0.8826 - val_loss: 0.4618 - val_accur
acy: 0.8501
Epoch 14/25
                                      ======] - 50s 159ms/step - loss: 0.3259 - accuracy: 0.8860 - val_loss: 0.4929 - val_accur
313/313 [==
acy: 0.8448
Epoch 15/25
acy: 0.8604
Epoch 16/25
313/313 [=====
                                ========] - 50s 159ms/step - loss: 0.2969 - accuracy: 0.8955 - val loss: 0.4943 - val accur
acy: 0.8477
Epoch 17/25
313/313 [==
                                    =======] - 50s 159ms/step - loss: 0.2805 - accuracy: 0.9008 - val_loss: 0.4315 - val_accur
acy: 0.8650
Epoch 18/25
313/313 [==
                                    =======] - 50s 159ms/step - loss: 0.2638 - accuracy: 0.9089 - val_loss: 0.4128 - val_accur
acy: 0.8674
Epoch 19/25
313/313 [==
                                       :=====] - 50s 159ms/step - loss: 0.2528 - accuracy: 0.9108 - val loss: 0.4517 - val accur
acy: 0.8616
Epoch 20/25
                                         ====] - 50s 159ms/step - loss: 0.2420 - accuracy: 0.9147 - val_loss: 0.4273 - val_accur
313/313 [==
acy: 0.8658
Epoch 21/25
                                    =======] - 50s 159ms/step - loss: 0.2311 - accuracy: 0.9158 - val loss: 0.4323 - val accur
313/313 [==
acy: 0.8693
Epoch 22/25
313/313 [==
                                 ========] - 50s 159ms/step - loss: 0.2142 - accuracy: 0.9244 - val loss: 0.4716 - val accur
acy: 0.8679
Epoch 23/25
313/313 [==
                                          ====] - 50s 159ms/step - loss: 0.2091 - accuracy: 0.9272 - val_loss: 0.4171 - val_accur
acy: 0.8765
Epoch 24/25
313/313 [==
                                         ====] - 50s 159ms/step - loss: 0.1964 - accuracy: 0.9304 - val_loss: 0.4461 - val_accur
acy: 0.8724
Epoch 25/25
                                    =======] - 50s 159ms/step - loss: 0.1879 - accuracy: 0.9337 - val_loss: 0.4827 - val_accur
313/313 [==
acy: 0.8671
                                                                                                                     In [ ]:
```

```
val_acc = history.history['val_accuracy']
plt.figure()
plt.plot(acc,color = 'purple',label = 'Training Acuracy')
plt.plot(val_acc,color = 'blue',label = 'Validation Accuracy')
plt.legend()
```

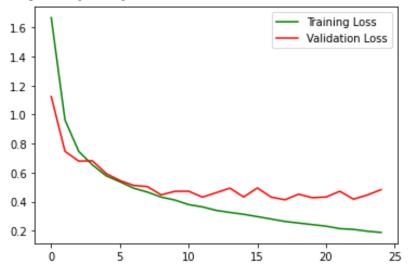
<matplotlib.legend.Legend at 0x7fc5601fe610>



loss = history.history['loss']
val\_loss = history.history['val\_loss']

plt.figure()
plt.plot(loss,color = 'green',label = 'Training Loss')
plt.plot(val\_loss,color = 'red',label = 'Validation Loss')
plt.legend()

<matplotlib.legend.Legend at 0x7fc5bd878ad0>



x\_test = tf.keras.applications.vgg19.preprocess\_input(X\_test)

y\_pred = model.predict\_classes(x\_test)

y\_pred[:10]

Out[]:

In []:

Out[]:

In []:

horizontalalignment="center",

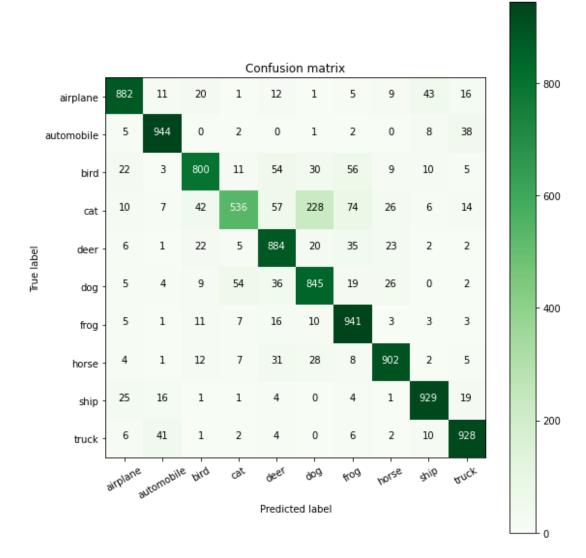
color="white" **if** cm[i, j] > thresh **else** "black")

/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/sequential.py:455: UserWarning: `model.predict\_classes()` is d eprecated and will be removed after 2021-01-01. Please use instead:\* `np.argmax(model.predict(x), axis=-1)`, if your model does mu lti-class classification (e.g. if it uses a `softmax` last-layer activation).\* `(model.predict(x) > 0.5).astype("int32")`, if your model doe s binary classification (e.g. if it uses a `sigmoid` last-layer activation). warnings.warn("model.predict\_classes()" is deprecated and ' Out[]: array([3, 8, 8, 0, 6, 6, 1, 6, 3, 1]) In [ ]: from sklearn.metrics import confusion\_matrix, accuracy\_score print('Testing Accuarcy : ', accuracy\_score(Y\_test, y\_pred)) Testing Accuarcy: 0.8591 In []: cm = confusion\_matrix(Y\_test, y\_pred) cm Out[]: array([[882, 11, 20, 1, 12, 1, 5, 9, 43, 16], [ 5, 944, 0, 2, 0, 1, 2, 0, 8, 38], [22, 3,800, 11, 54, 30, 56, 9, 10, 5], [10, 7, 42, 536, 57, 228, 74, 26, 6, 14], [ 6, 1, 22, 5, 884, 20, 35, 23, 2, 2], [ 5, 4, 9, 54, 36, 845, 19, 26, 0, 2], [ 5, 1, 11, 7, 16, 10, 941, 3, 3, 3], [ 4, 1, 12, 7, 31, 28, 8, 902, 2, 5], [25, 16, 1, 1, 4, 0, 4, 1, 929, 19], [ 6, 41, 1, 2, 4, 0, 6, 2, 10, 928]]) In [ ]: import itertools def plot\_confusion\_matrix(cm, classes, normalize=False, title='Confusion matrix', cmap=plt.cm.Greens): This function prints and plots the confusion matrix. 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") else: print('Confusion matrix, without normalization') #print(cm) 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],

plt.tight\_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label')

plt.figure(figsize=(8,8))
plot\_confusion\_matrix(cm,classes)

Confusion matrix, without normalization



In [ ]: