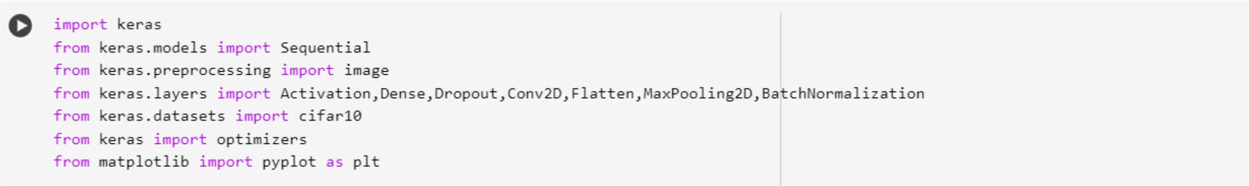
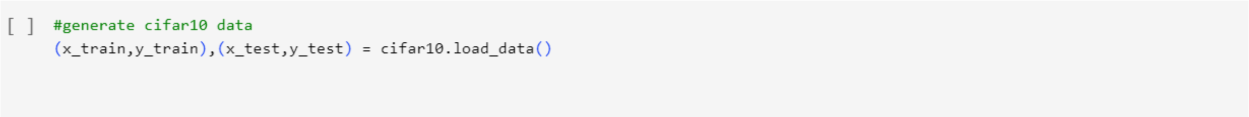
Spring 2024: CS5720 Neural Networks & Deep Learning - ICP-7
Assignment-7
NAME:Vinay Kumar Reddy Gunuguntla
STUDENT ID:700745726

Github Link: https://github.com/VinayGunuguntla/icp7.git

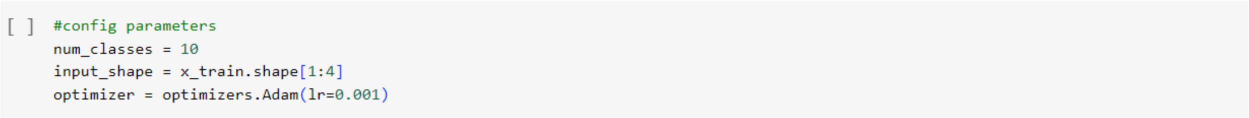
Video Link: NNDL_Assignment_7.mp4



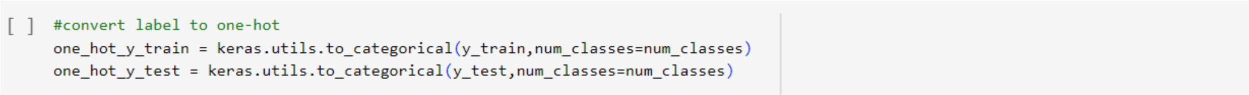
```
import keras
from keras.models import Sequential
from keras.preprocessing import image
from keras.layers import Activation,Dense,Dropout,Conv2D,Flatten,MaxPooling2D,BatchNormalization
from keras.datasets import cifar10
from keras import optimizers
from matplotlib import pyplot as plt
```



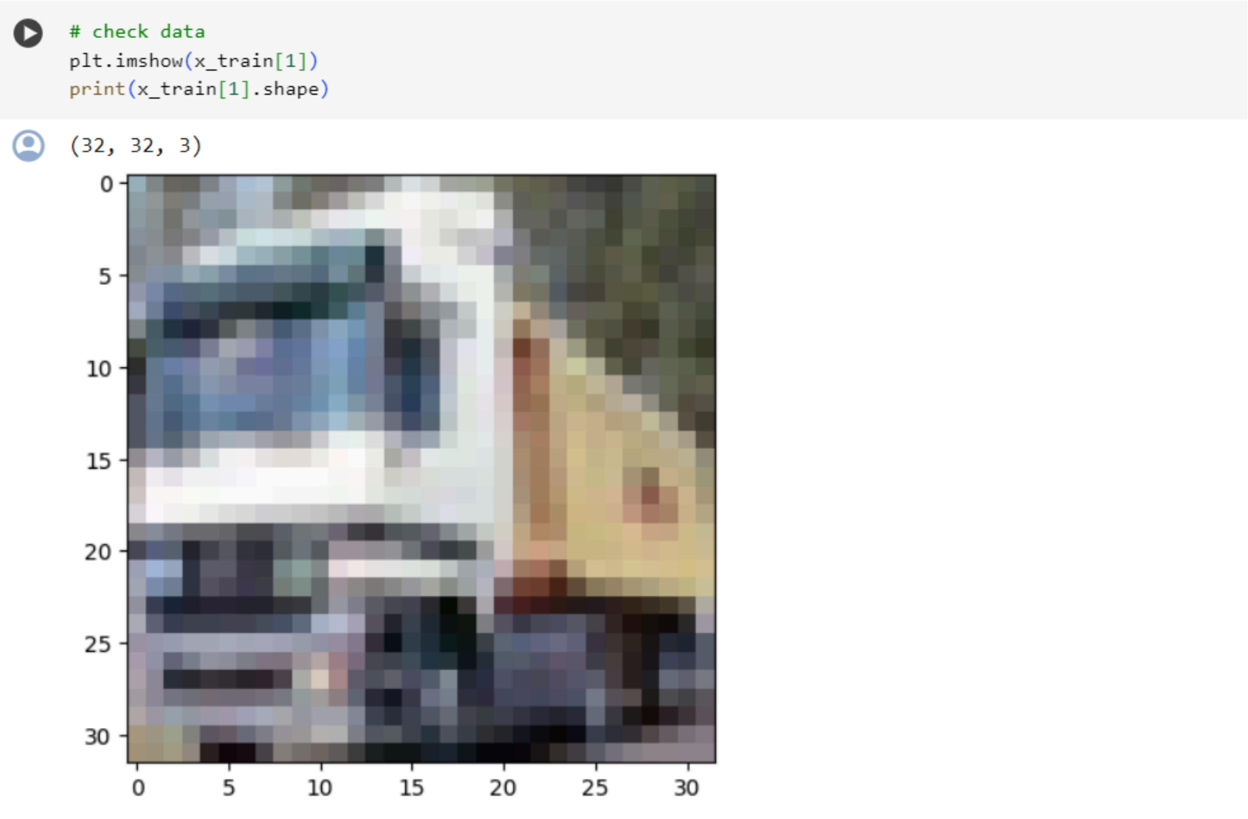
```
[ ] #generate cifar10 data
    (x_train,y_train),(x_test,y_test) = cifar10.load_data()
```



```
[ ] #config parameters
    num_classes = 10
    input_shape = x_train.shape[1:4]
    optimizer = optimizers.Adam(lr=0.001)
```

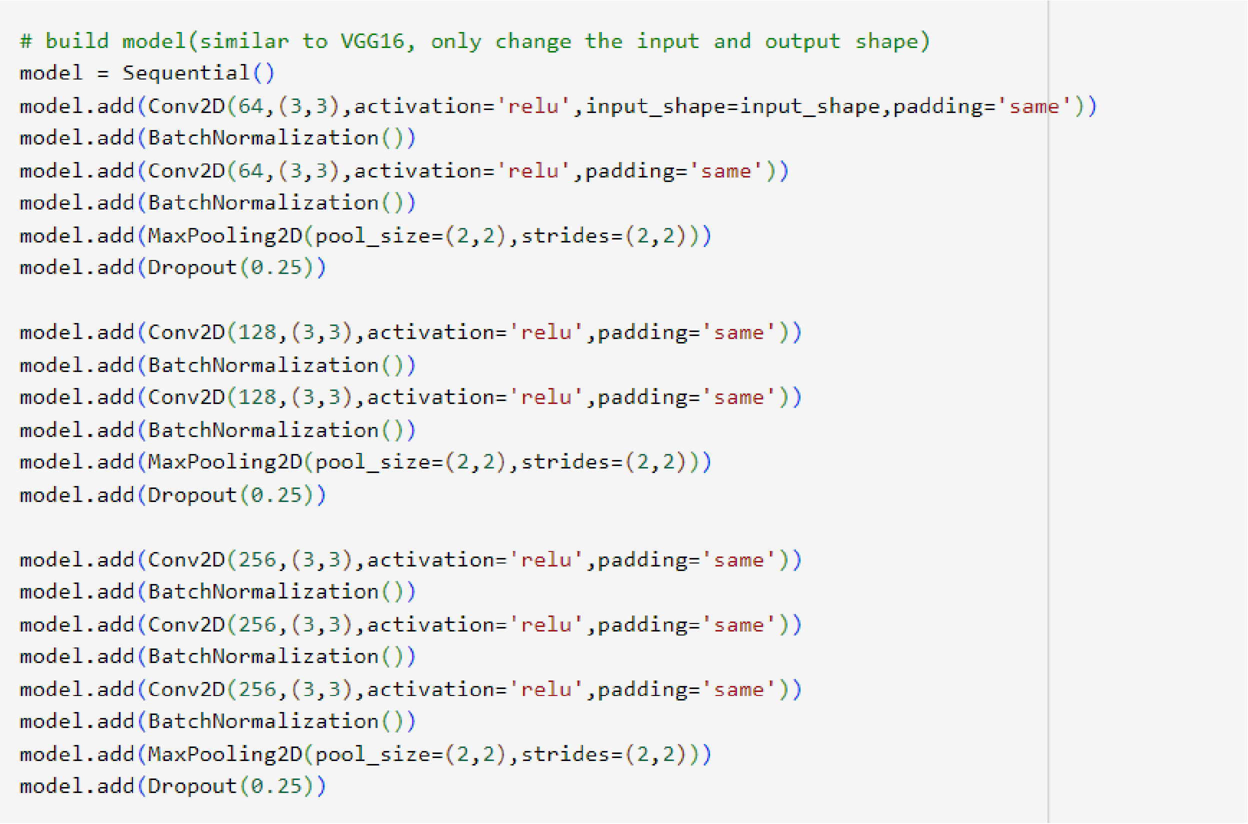


```
[ ] #convert label to one-hot
    one_hot_y_train = keras.utils.to_categorical(y_train,num_classes=num_classes)
    one_hot_y_test = keras.utils.to_categorical(y_test,num_classes=num_classes)
```

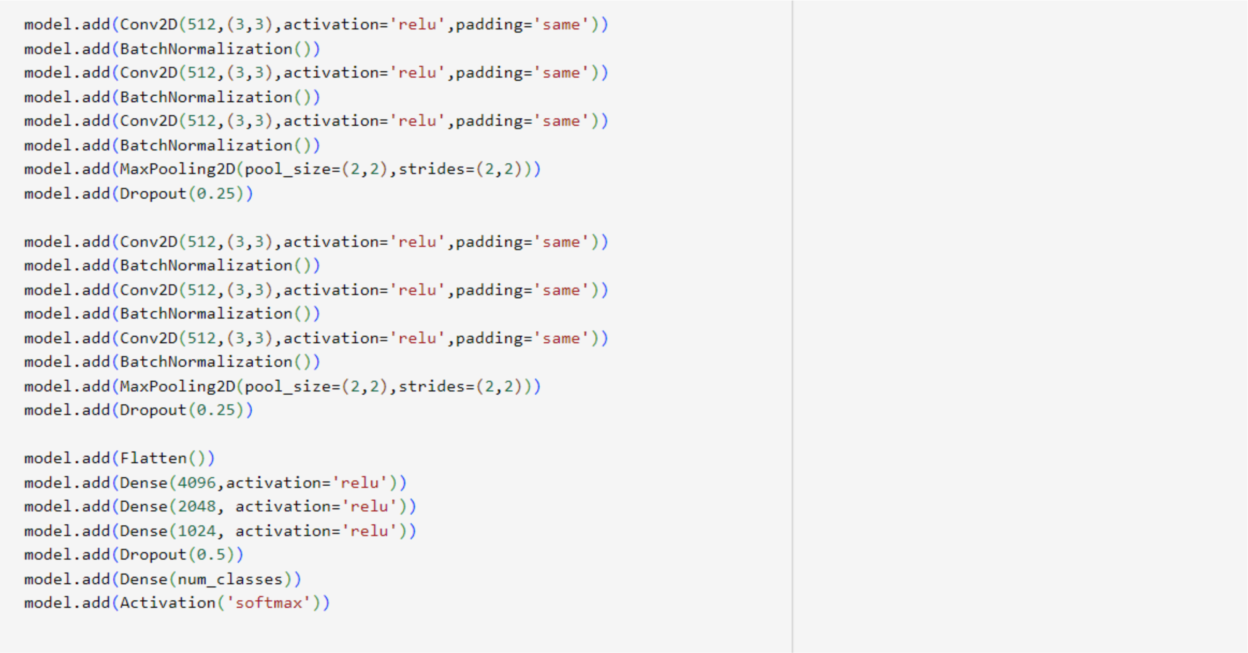


```
# check data
plt.imshow(x_train[1])
print(x_train[1].shape)
```

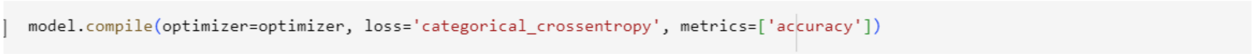
```
(32, 32, 3)
```



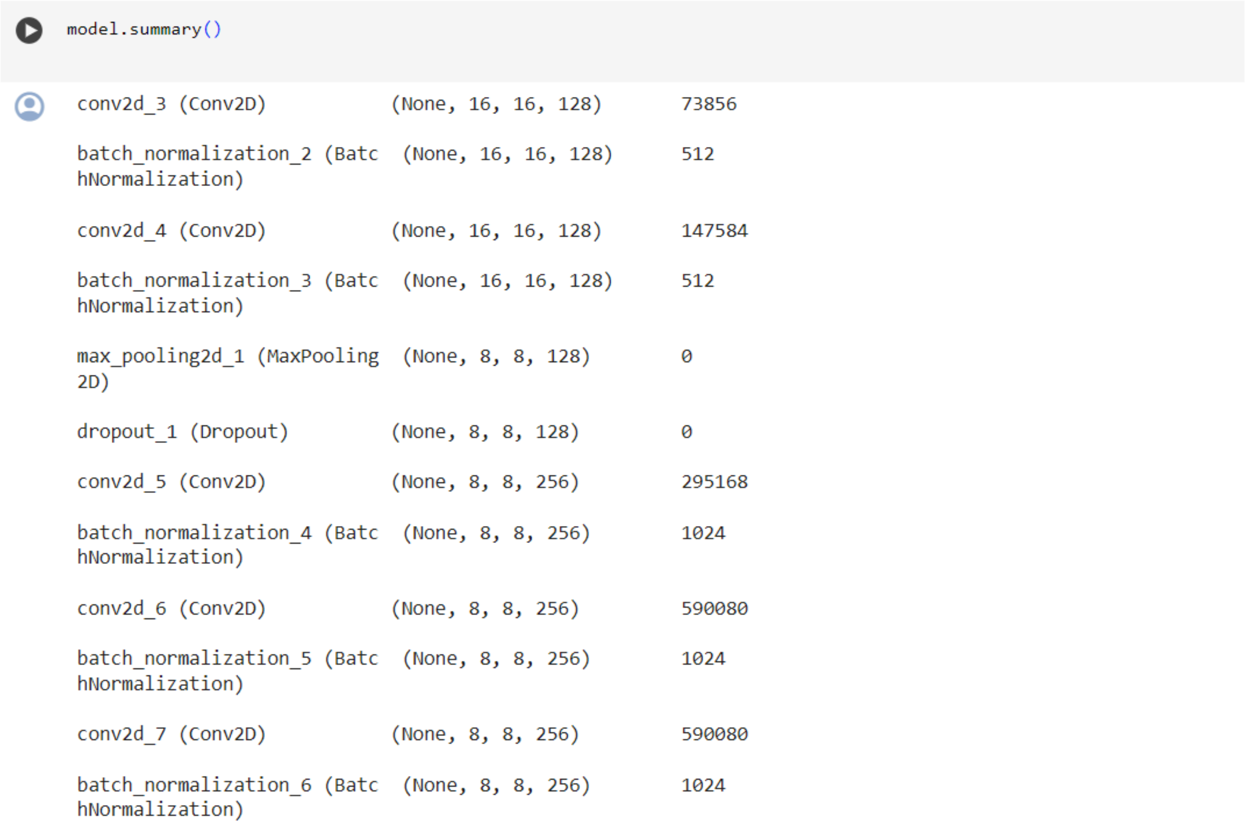
```
# build model(similar to VGG16, only change the input and output shape)
model = Sequential()
model.add(Conv2D(64,(3,3),activation='relu',input_shape=input_shape,padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(64,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
model.add(Dropout(0.25))

model.add(Conv2D(128,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(128,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
model.add(Dropout(0.25))

model.add(Conv2D(256,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(256,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(256,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
model.add(Dropout(0.25))
```



```
model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
model.add(Dropout(0.25))

model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(512,(3,3),activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(4096,activation='relu'))
model.add(Dense(2048, activation='relu'))
model.add(Dense(1024, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes))
model.add(Activation('softmax'))
```

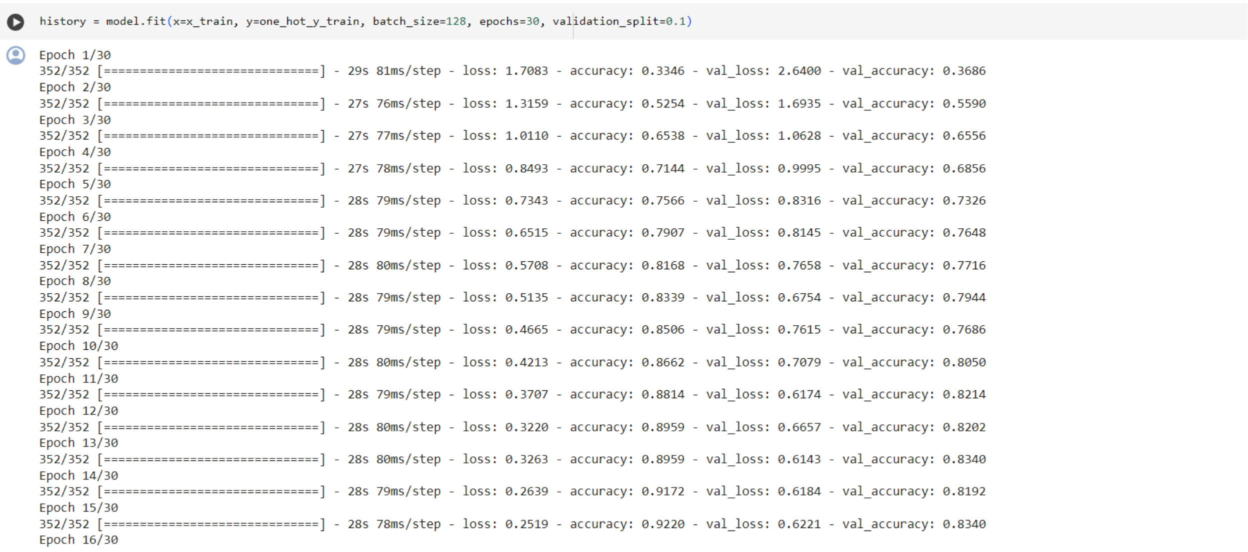


```
model.compile(optimizer=optimizer, loss='categorical_crossentropy', metrics=['accuracy'])
```



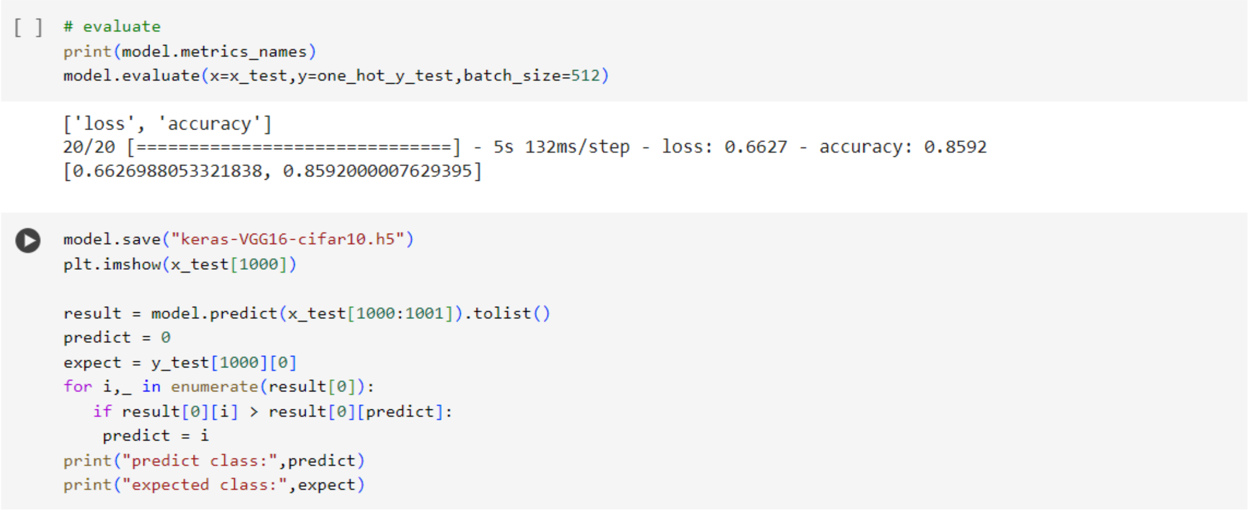
```
model.summary()
```

```
conv2d_3 (Conv2D)           (None, 16, 16, 128)       73856

batch_normalization_2 (Batc  (None, 16, 16, 128)      512
hNormalization)

conv2d_4 (Conv2D)           (None, 16, 16, 128)       147584

batch_normalization_3 (Batc  (None, 16, 16, 128)      512
hNormalization)

max_pooling2d_1 (MaxPooling  (None, 8, 8, 128)        0
2D)

dropout_1 (Dropout)         (None, 8, 8, 128)         0

conv2d_5 (Conv2D)           (None, 8, 8, 256)         295168

batch_normalization_4 (Batc  (None, 8, 8, 256)        1024
hNormalization)

conv2d_6 (Conv2D)           (None, 8, 8, 256)         590080

batch_normalization_5 (Batc  (None, 8, 8, 256)        1024
hNormalization)

conv2d_7 (Conv2D)           (None, 8, 8, 256)         590080

batch_normalization_6 (Batc  (None, 8, 8, 256)        1024
hNormalization)
```



```
history = model.fit(x=x_train, y=one_hot_y_train, batch_size=128, epochs=30, validation_split=0.1)
```

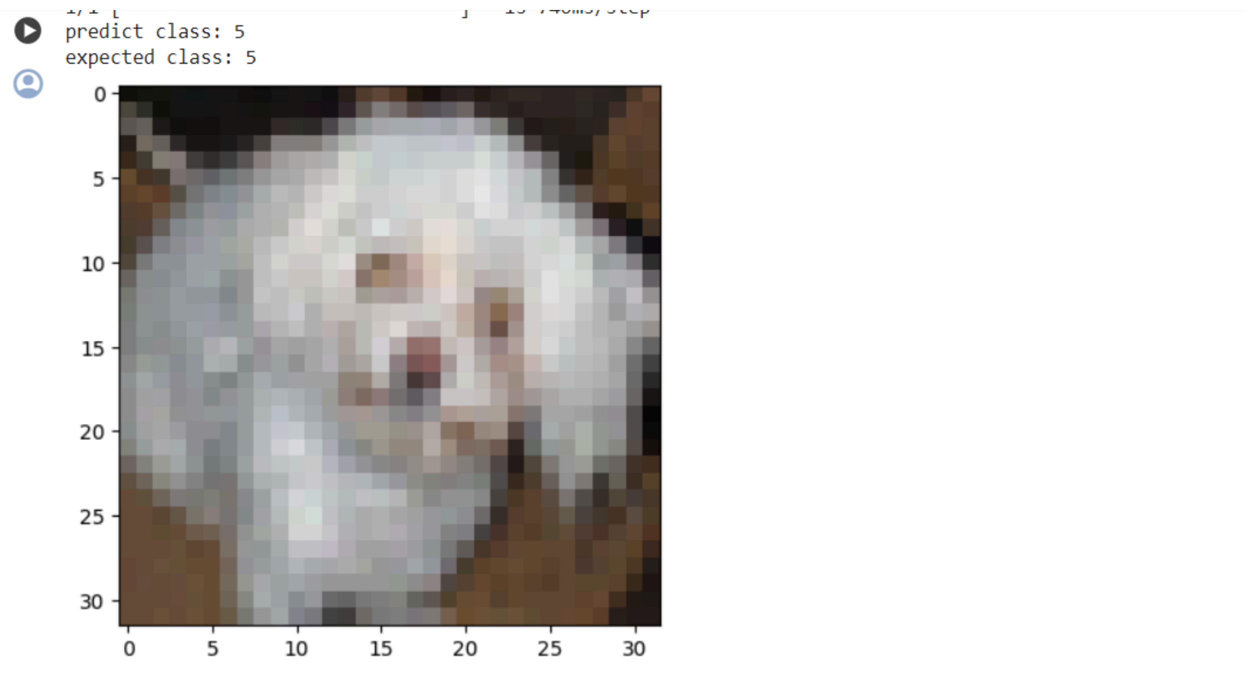
```
Epoch 1/30
352/352 [==============================] - 29s 81ms/step - loss: 1.7083 - accuracy: 0.3346 - val_loss: 2.6400 - val_accuracy: 0.3686
Epoch 2/30
352/352 [==============================] - 27s 76ms/step - loss: 1.3159 - accuracy: 0.5254 - val_loss: 1.6935 - val_accuracy: 0.5590
Epoch 3/30
352/352 [==============================] - 27s 77ms/step - loss: 1.0110 - accuracy: 0.6538 - val_loss: 1.0628 - val_accuracy: 0.6556
Epoch 4/30
352/352 [==============================] - 27s 78ms/step - loss: 0.8493 - accuracy: 0.7144 - val_loss: 0.9995 - val_accuracy: 0.6856
Epoch 5/30
352/352 [==============================] - 28s 79ms/step - loss: 0.7343 - accuracy: 0.7566 - val_loss: 0.8316 - val_accuracy: 0.7326
Epoch 6/30
352/352 [==============================] - 28s 79ms/step - loss: 0.6515 - accuracy: 0.7907 - val_loss: 0.8145 - val_accuracy: 0.7648
Epoch 7/30
352/352 [==============================] - 28s 80ms/step - loss: 0.5708 - accuracy: 0.8168 - val_loss: 0.7658 - val_accuracy: 0.7716
Epoch 8/30
352/352 [==============================] - 28s 79ms/step - loss: 0.5135 - accuracy: 0.8339 - val_loss: 0.6754 - val_accuracy: 0.7944
Epoch 9/30
352/352 [==============================] - 28s 79ms/step - loss: 0.4665 - accuracy: 0.8506 - val_loss: 0.7615 - val_accuracy: 0.7686
Epoch 10/30
352/352 [==============================] - 28s 80ms/step - loss: 0.4213 - accuracy: 0.8662 - val_loss: 0.7079 - val_accuracy: 0.8050
Epoch 11/30
352/352 [==============================] - 28s 79ms/step - loss: 0.3707 - accuracy: 0.8814 - val_loss: 0.6174 - val_accuracy: 0.8214
Epoch 12/30
352/352 [==============================] - 28s 80ms/step - loss: 0.3220 - accuracy: 0.8959 - val_loss: 0.6657 - val_accuracy: 0.8202
Epoch 13/30
352/352 [==============================] - 28s 80ms/step - loss: 0.3263 - accuracy: 0.8959 - val_loss: 0.6143 - val_accuracy: 0.8340
Epoch 14/30
352/352 [==============================] - 28s 79ms/step - loss: 0.2639 - accuracy: 0.9172 - val_loss: 0.6184 - val_accuracy: 0.8192
Epoch 15/30
352/352 [==============================] - 28s 78ms/step - loss: 0.2519 - accuracy: 0.9220 - val_loss: 0.6221 - val_accuracy: 0.8340
Epoch 16/30
```



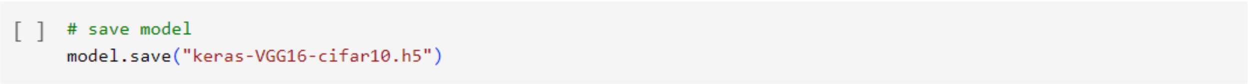
```
[ ]  # evaluate
     print(model.metrics_names)
     model.evaluate(x=x_test,y=one_hot_y_test,batch_size=512)
```

```
['loss', 'accuracy']
20/20 [==============================] - 5s 132ms/step - loss: 0.6627 - accuracy: 0.8592
[0.6626988053321838, 0.8592000007629395]
```

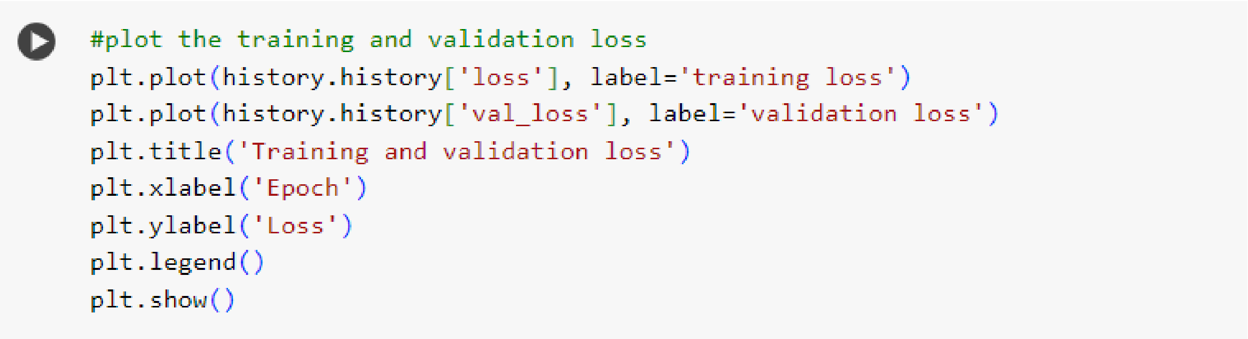
```
model.save("keras-VGG16-cifar10.h5")
plt.imshow(x_test[1000])

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)
```



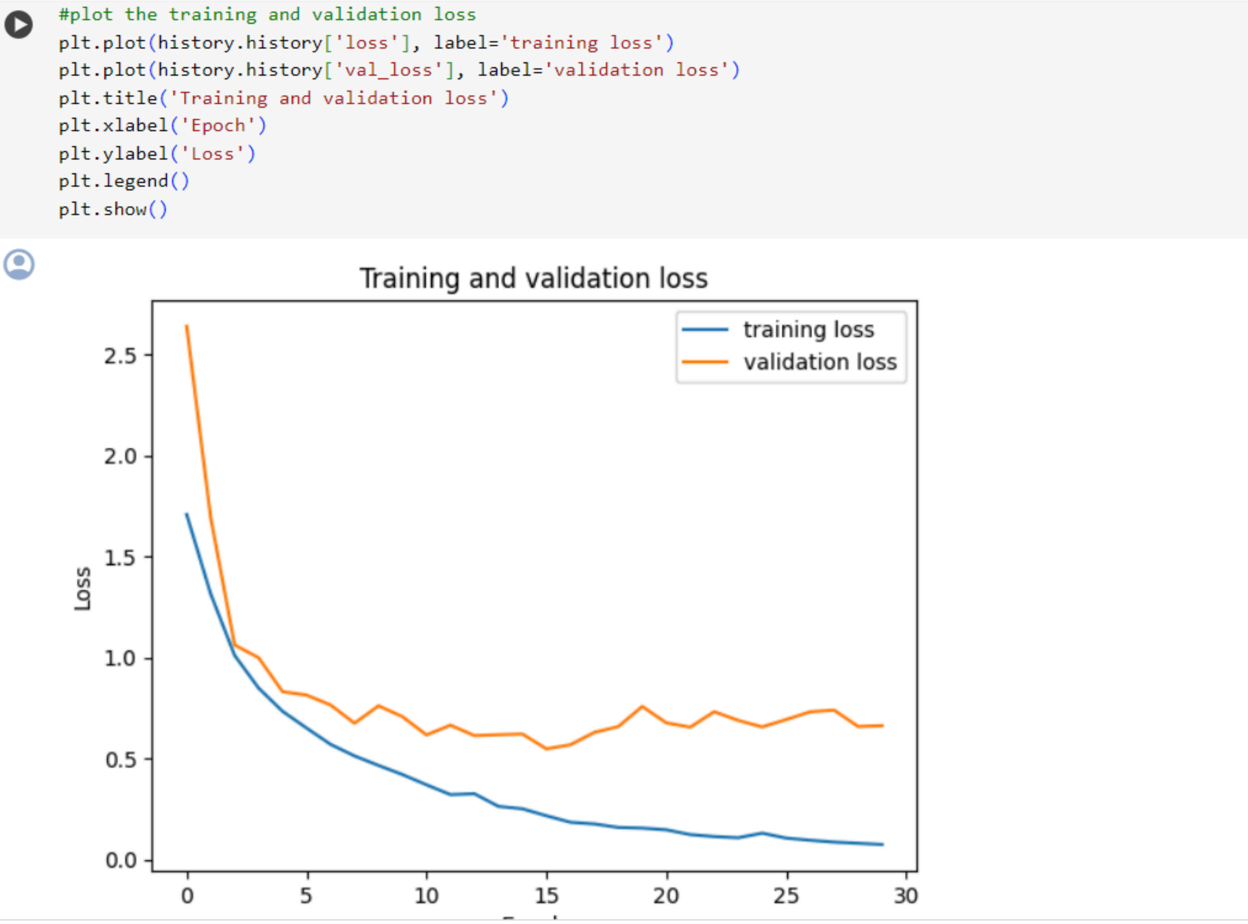
```
1/1 [                              ] - 1s 740ms/step
predict class: 5
expected class: 5
```



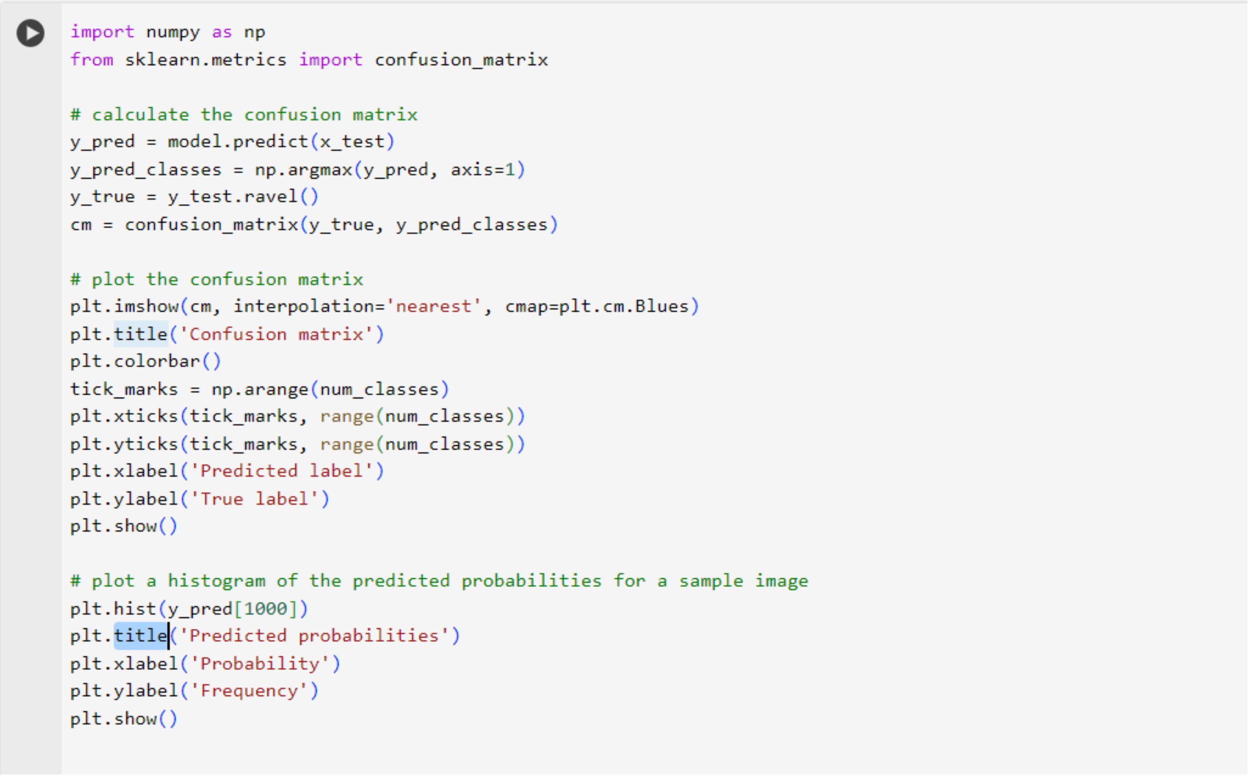
```
# save model
model.save("keras-VGG16-cifar10.h5")
```



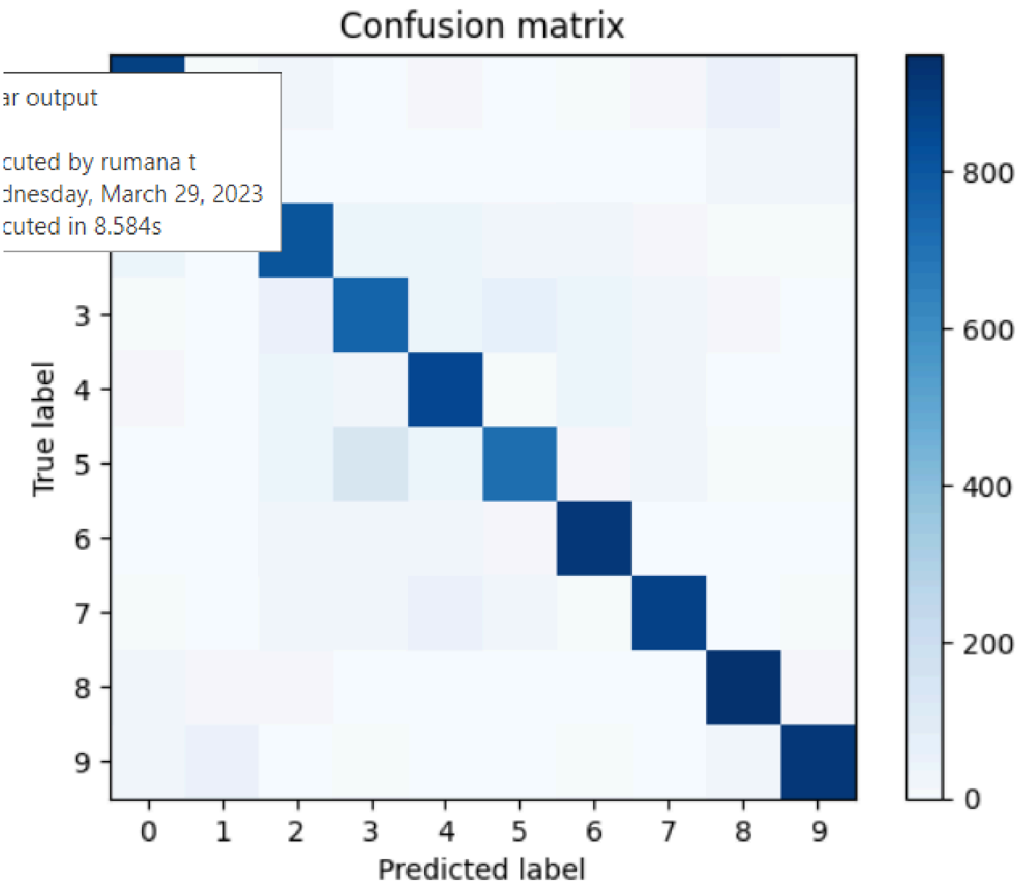
```
#plot the training and validation loss
plt.plot(history.history['loss'], label='training loss')
plt.plot(history.history['val_loss'], label='validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



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

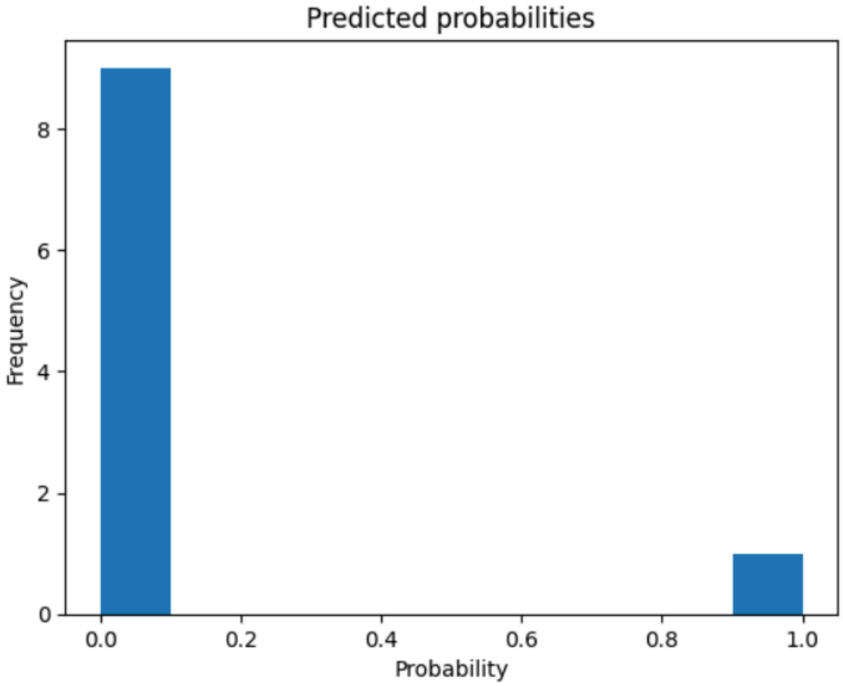


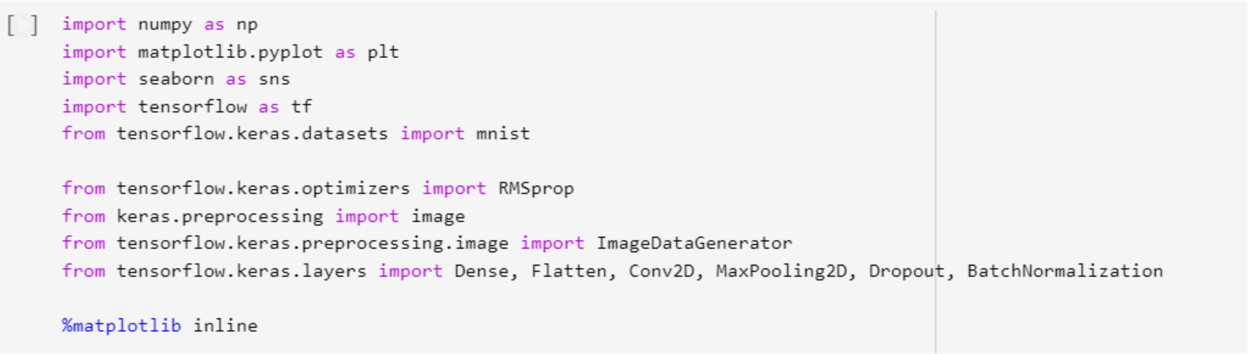
```
import numpy as np
from sklearn.metrics import confusion_matrix

# 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.xticks(tick_marks, range(num_classes))
plt.yticks(tick_marks, range(num_classes))
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.show()

# plot a histogram of the predicted probabilities for a sample image
plt.hist(y_pred[1000])
plt.title('Predicted probabilities')
plt.xlabel('Probability')
plt.ylabel('Frequency')
plt.show()
```



ar output

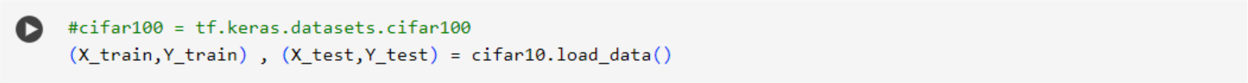
cuted by rumana t
dnesday, March 29, 2023
cuted in 8.584s



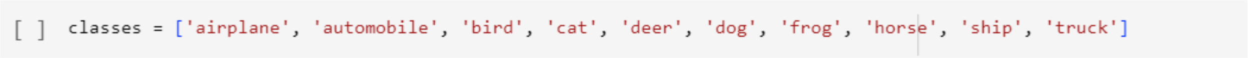


```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from tensorflow.keras.datasets import mnist

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

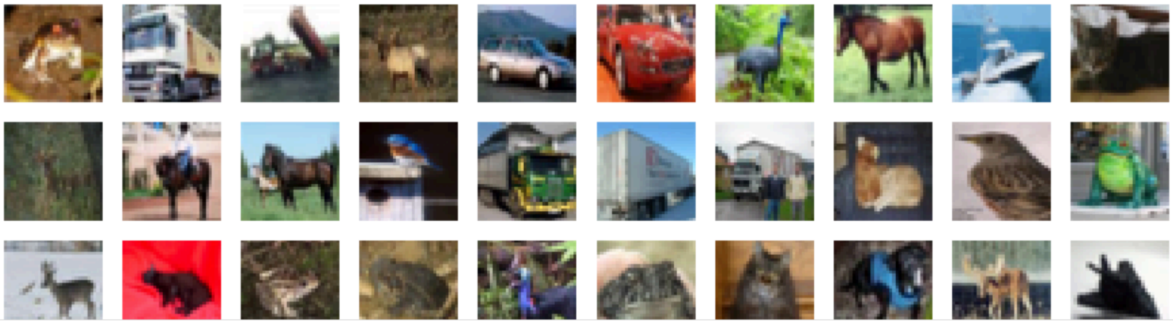


```
#cifar100 = tf.keras.datasets.cifar100
(X_train,Y_train) , (X_test,Y_test) = cifar10.load_data()
```



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

```
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')
```



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)
```

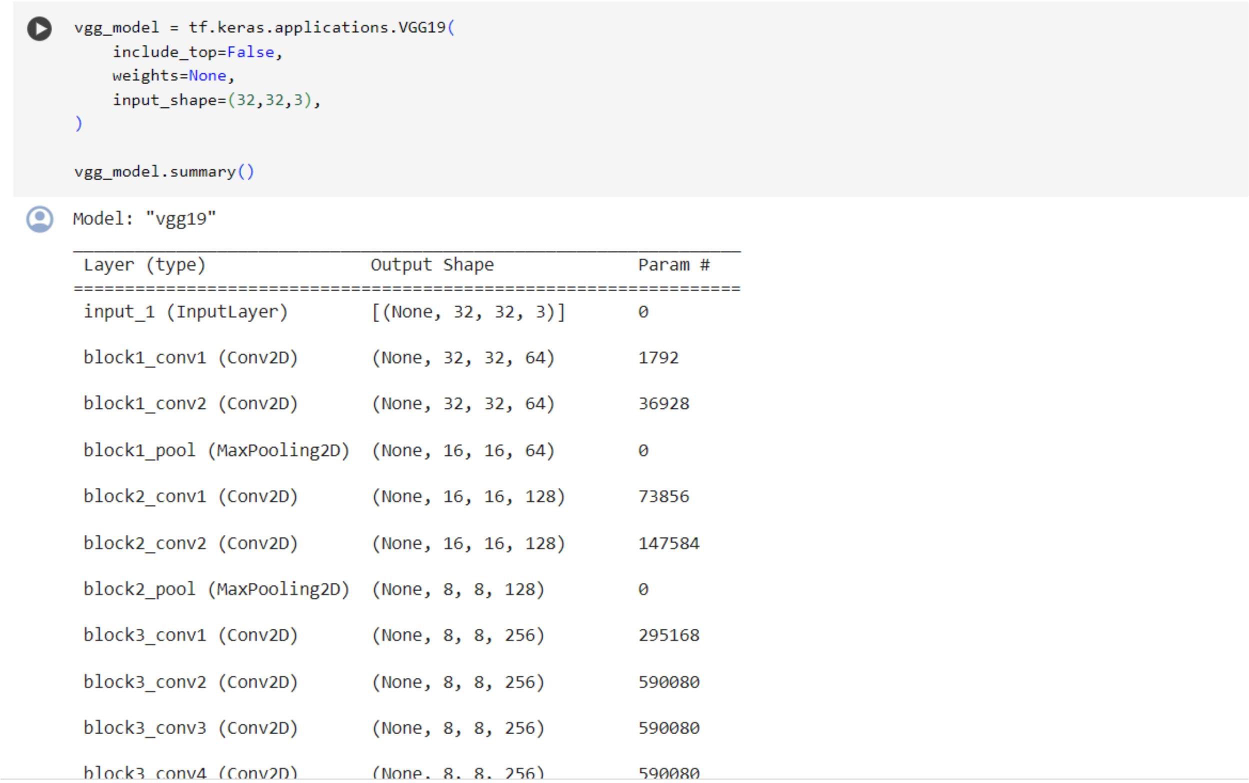
```
print(x_train.shape)
print(y_train.shape)
print(x_val.shape)
print(y_val.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(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)
```

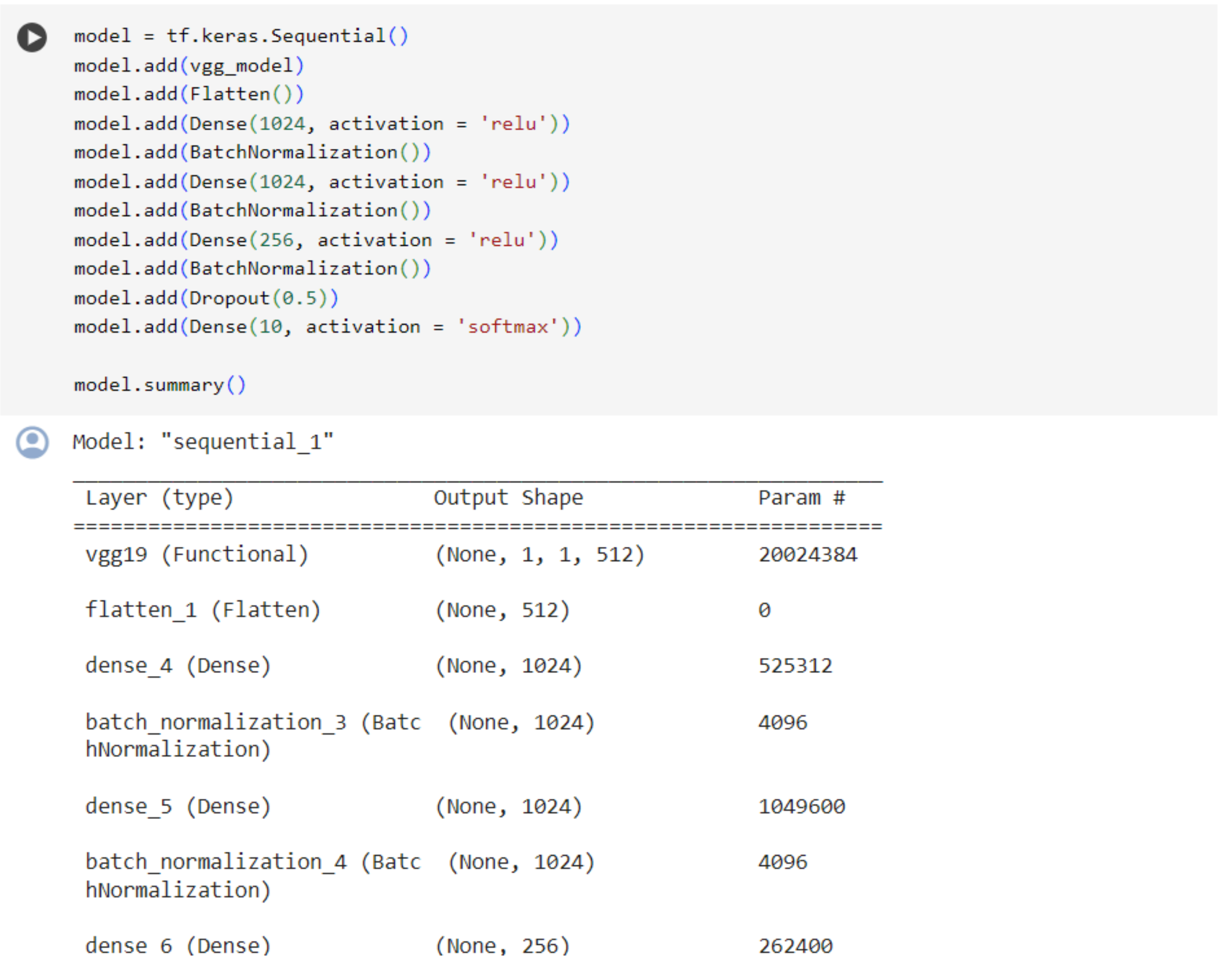
```
from keras.callbacks import ReduceLROnPlateau
learning_rate_reduction = ReduceLROnPlateau(monitor='val_accuracy',
                                            patience=3,
                                            verbose=1,
                                            factor=0.5,
                                            min_lr=0.00001)
```

We have used only 16 layers out of 19 layers in the CNN



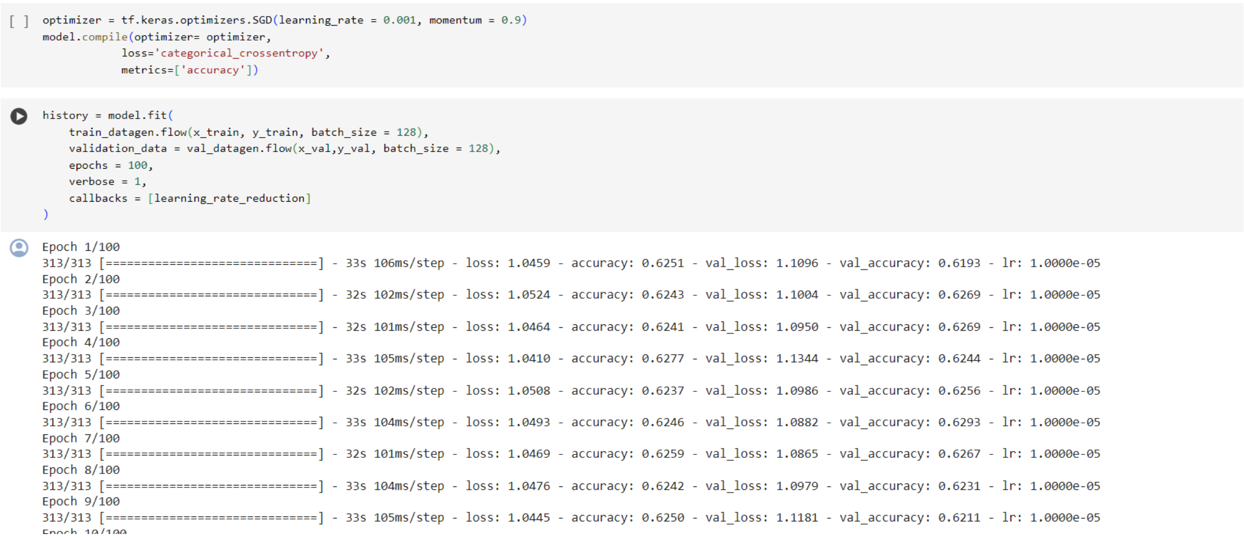
```
vgg_model = tf.keras.applications.VGG19(
    include_top=False,
    weights=None,
    input_shape=(32,32,3),
)

vgg_model.summary()
```

```
Model: "vgg19"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_1 (InputLayer)        [(None, 32, 32, 3)]       0         
                                                                 
 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)         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    
```



```
model = tf.keras.Sequential()
model.add(vgg_model)
model.add(Flatten())
model.add(Dense(1024, activation = 'relu'))
model.add(BatchNormalization())
model.add(Dense(1024, activation = 'relu'))
model.add(BatchNormalization())
model.add(Dense(256, activation = 'relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(10, activation = 'softmax'))

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg19 (Functional)          (None, 1, 1, 512)         20024384

 flatten_1 (Flatten)         (None, 512)               0

 dense_4 (Dense)             (None, 1024)              525312

 batch_normalization_3 (Batc  (None, 1024)             4096
 hNormalization)

 dense_5 (Dense)             (None, 1024)              1049600

 batch_normalization_4 (Batc  (None, 1024)             4096
 hNormalization)

 dense 6 (Dense)             (None, 256)               262400
```



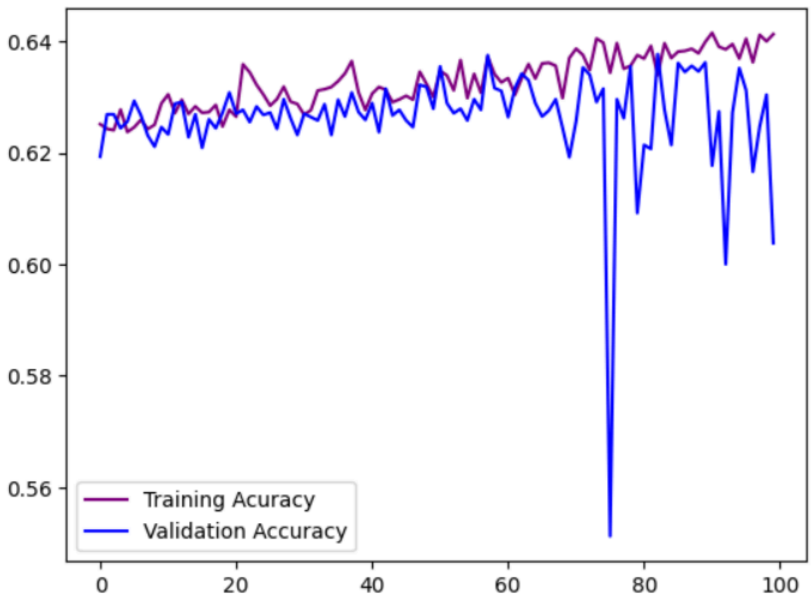
```
optimizer = tf.keras.optimizers.SGD(learning_rate = 0.001, momentum = 0.9)
model.compile(optimizer= optimizer,
            loss='categorical_crossentropy',
            metrics=['accuracy'])
```

```
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 = 100,
    verbose = 1,
    callbacks = [learning_rate_reduction]
)
```

```
Epoch 1/100
313/313 [==============================] - 33s 106ms/step - loss: 1.0459 - accuracy: 0.6251 - val_loss: 1.1096 - val_accuracy: 0.6193 - lr: 1.0000e-05
Epoch 2/100
313/313 [==============================] - 32s 102ms/step - loss: 1.0524 - accuracy: 0.6243 - val_loss: 1.1004 - val_accuracy: 0.6269 - lr: 1.0000e-05
Epoch 3/100
313/313 [==============================] - 32s 101ms/step - loss: 1.0464 - accuracy: 0.6241 - val_loss: 1.0950 - val_accuracy: 0.6269 - lr: 1.0000e-05
Epoch 4/100
313/313 [==============================] - 33s 105ms/step - loss: 1.0410 - accuracy: 0.6277 - val_loss: 1.1344 - val_accuracy: 0.6244 - lr: 1.0000e-05
Epoch 5/100
313/313 [==============================] - 32s 102ms/step - loss: 1.0508 - accuracy: 0.6237 - val_loss: 1.0986 - val_accuracy: 0.6256 - lr: 1.0000e-05
Epoch 6/100
313/313 [==============================] - 33s 104ms/step - loss: 1.0493 - accuracy: 0.6246 - val_loss: 1.0882 - val_accuracy: 0.6293 - lr: 1.0000e-05
Epoch 7/100
313/313 [==============================] - 32s 101ms/step - loss: 1.0469 - accuracy: 0.6259 - val_loss: 1.0865 - val_accuracy: 0.6267 - lr: 1.0000e-05
Epoch 8/100
313/313 [==============================] - 33s 104ms/step - loss: 1.0476 - accuracy: 0.6242 - val_loss: 1.0979 - val_accuracy: 0.6231 - lr: 1.0000e-05
Epoch 9/100
313/313 [==============================] - 33s 105ms/step - loss: 1.0445 - accuracy: 0.6250 - val_loss: 1.1181 - val_accuracy: 0.6211 - lr: 1.0000e-05
Epoch 10/100
```

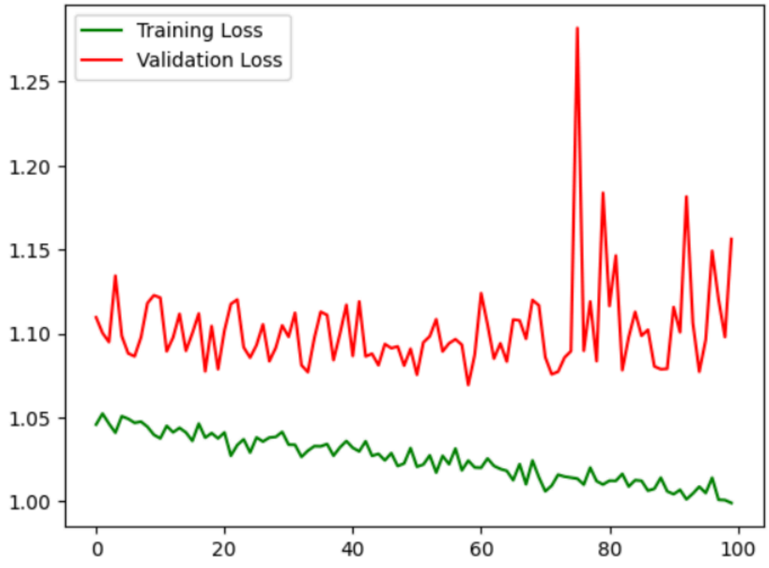
```python
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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

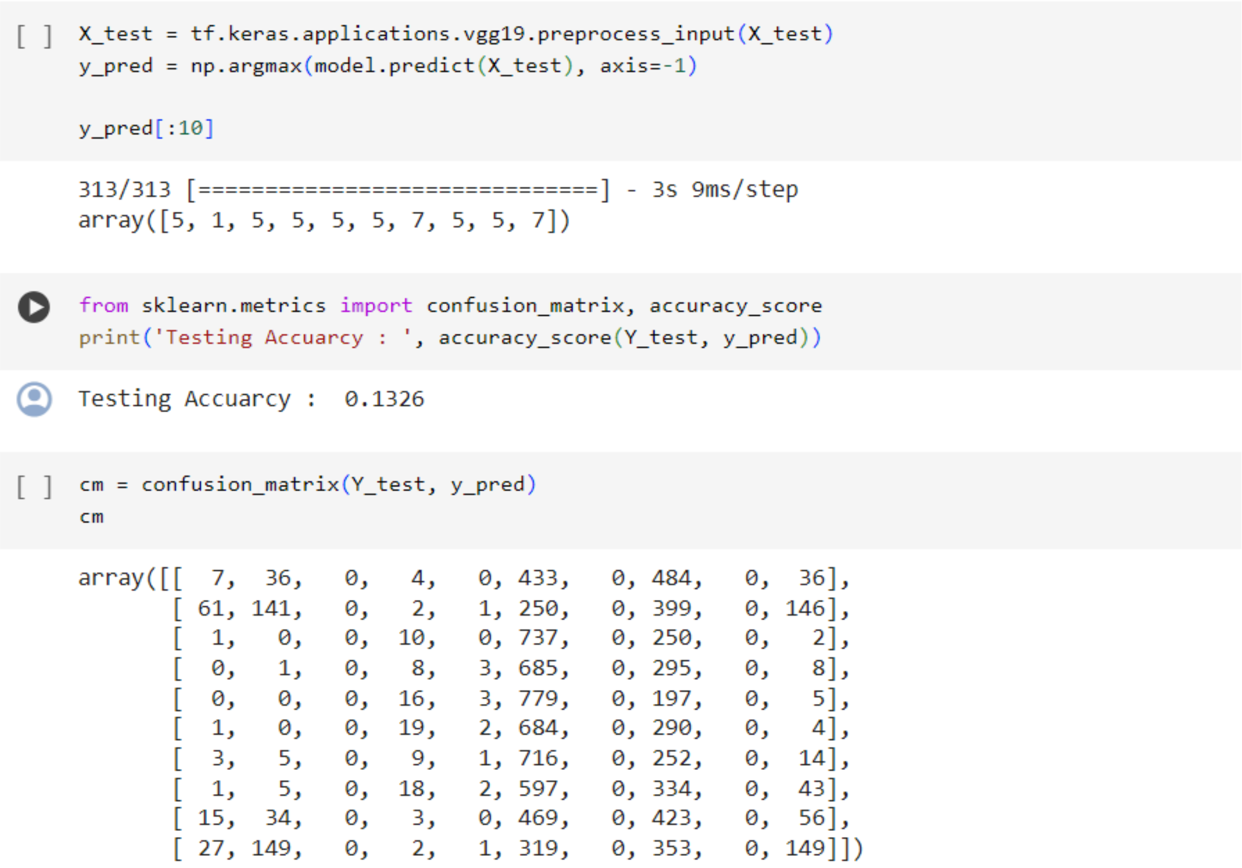
```
<matplotlib.legend.Legend at 0x7f75101e8160>
```



```python
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 0x7f75101e8d30>
```





```
X_test = tf.keras.applications.vgg19.preprocess_input(X_test)
y_pred = np.argmax(model.predict(X_test), axis=-1)

y_pred[:10]
```

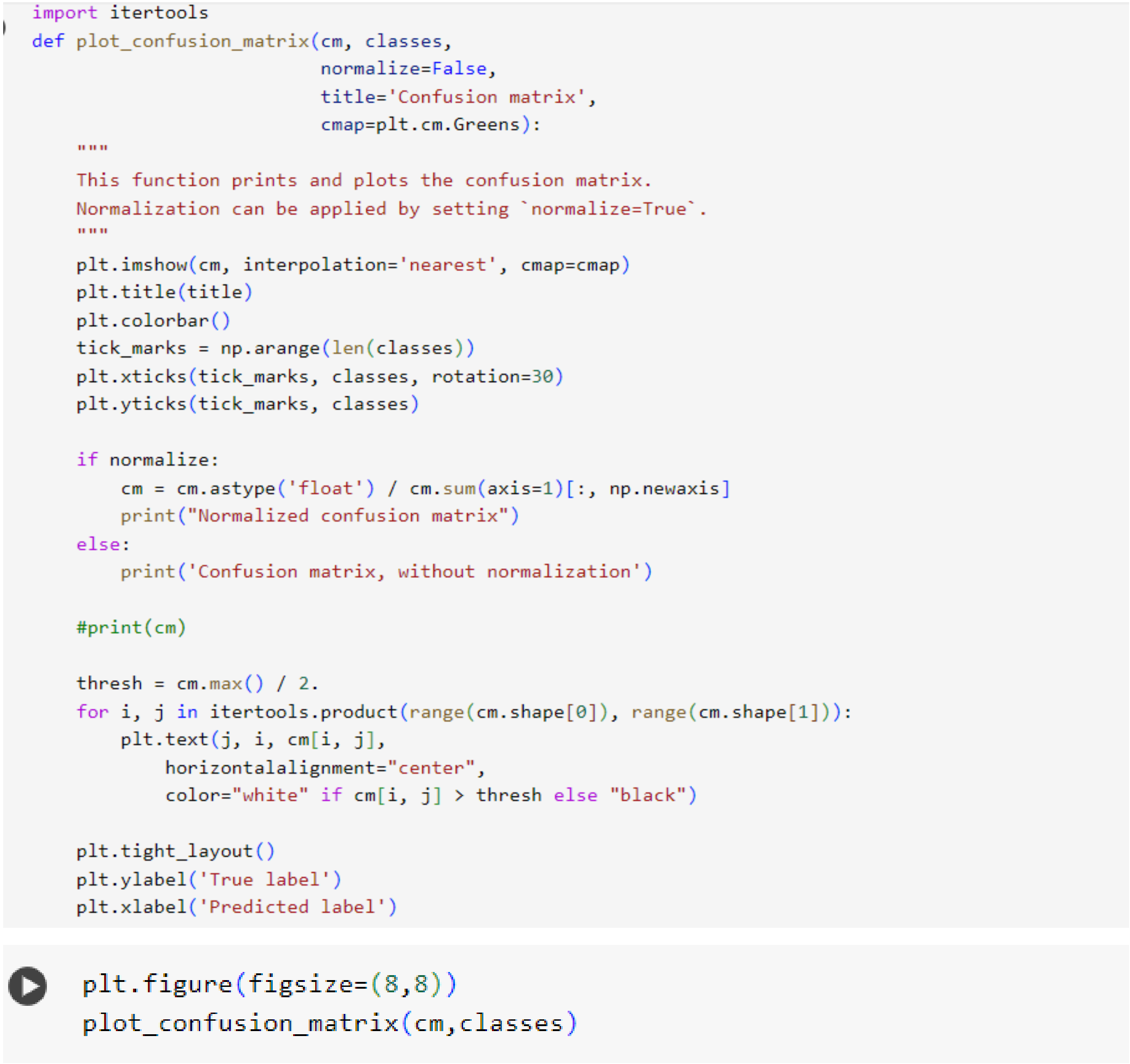
```
313/313 [==============================] - 3s 9ms/step
array([5, 1, 5, 5, 5, 5, 7, 5, 5, 7])
```

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

```
Testing Accuarcy :  0.1326
```

```
cm = confusion_matrix(Y_test, y_pred)
cm
```

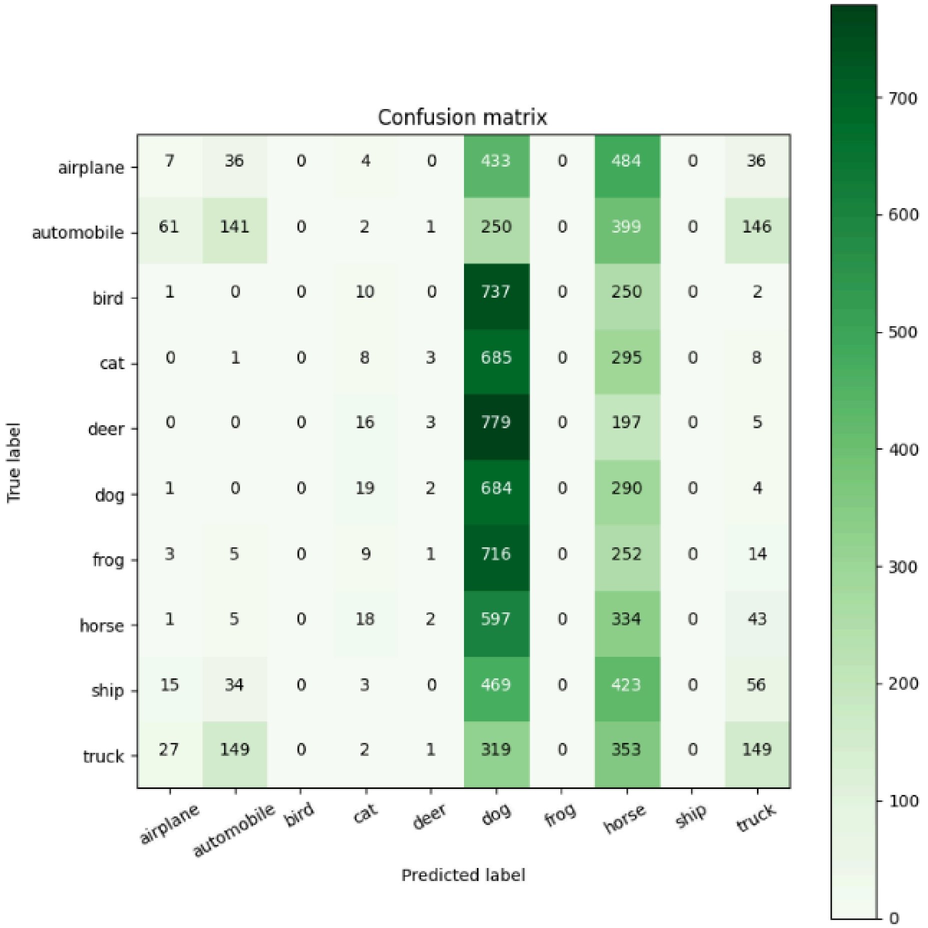
```
array([[  7,  36,   0,   4,   0, 433,   0, 484,   0,  36],
       [ 61, 141,   0,   2,   1, 250,   0, 399,   0, 146],
       [  1,   0,   0,  10,   0, 737,   0, 250,   0,   2],
       [  0,   1,   0,   8,   3, 685,   0, 295,   0,   8],
       [  0,   0,   0,  16,   3, 779,   0, 197,   0,   5],
       [  1,   0,   0,  19,   2, 684,   0, 290,   0,   4],
       [  3,   5,   0,   9,   1, 716,   0, 252,   0,  14],
       [  1,   5,   0,  18,   2, 597,   0, 334,   0,  43],
       [ 15,  34,   0,   3,   0, 469,   0, 423,   0,  56],
       [ 27, 149,   0,   2,   1, 319,   0, 353,   0, 149]])
```



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

    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
```



Confusion matrix

True label \ Predicted label	airplane	automobile	bird	cat	deer	dog	frog	horse	ship	truck
airplane	7	36	0	4	0	433	0	484	0	36
automobile	61	141	0	2	1	250	0	399	0	146
bird	1	0	0	10	0	737	0	250	0	2
cat	0	1	0	8	3	685	0	295	0	8
deer	0	0	0	16	3	779	0	197	0	5
dog	1	0	0	19	2	684	0	290	0	4
frog	3	5	0	9	1	716	0	252	0	14
horse	1	5	0	18	2	597	0	334	0	43
ship	15	34	0	3	0	469	0	423	0	56
truck	27	149	0	2	1	319	0	353	0	149