Practical 3

Aim: Implement deep learning for recognizing classes for datasets like CIFAR-10 images for previously unseen images and assign them to one of the 10 classes.

Code:

Loading and preparing Cifar10 dataset

```
import tensorflow as tf

# other imports
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.layers import Input, Conv2D, Dense, Flatten,
Dropout
from tensorflow.keras.layers import GlobalMaxPooling2D, MaxPooling2D
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.models import Model

# Load in the data
cifar10 = tf.keras.datasets.cifar10

# Distribute it to train and test set
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
print(x_train.shape, y_train.shape, x_test.shape, y_test.shape)

# Reduce pixel values
x_train, x_test = x_train / 255.0, x_test / 255.0

# flatten the label values
y_train, y_test = y_train.flatten(), y_test.flatten()

# visualize data by plotting images
fig, ax = plt.subplots(5, 5)
k = 0

for i in range(5):
  for j in range(5):
    ax[i][j].imshow(x_train[k], aspect='auto')
    k += 1

plt.show()
```

```
# number of classes
K = len(set(y_train))

# calculate total number of classes
# for output layer
print("number of classes:", K)
```

Output:

Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 6s 0us/step
(50000, 32, 32, 3) (50000, 1) (10000, 32, 32, 3) (10000, 1)

number of classes: 10

Model Definition and Building

```
# Build the model using the functional API
# input layer
i = Input(shape=x_train[0].shape)
x = Conv2D(32, (3, 3), activation='relu', padding='same')(i)
x = BatchNormalization()(x)
x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
x = BatchNormalization()(x)
x = MaxPooling2D((2, 2))(x)

x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
x = BatchNormalization()(x)
x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
x = BatchNormalization()(x)
```

```
x = MaxPooling2D((2, 2))(x)

x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)
x = BatchNormalization()(x)
x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)
x = BatchNormalization()(x)
x = MaxPooling2D((2, 2))(x)

x = Flatten()(x)
x = Dropout(0.2)(x)

# Hidden layer
x = Dense(1024, activation='relu')(x)
x = Dropout(0.2)(x)

# last hidden layer i.e.. output layer
x = Dense(K, activation='softmax')(x)

model = Model(i, x)

# model description
model.summary()

# Compile
model.compile(optimizer='adam',loss='sparse_categorical_crossentropy',m
etrics=['accuracy'])
# Fit
r = model.fit(x_train, y_train, validation_data=(x_test, y_test),
epochs=5)
```

Output:

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

 conv2d (Conv2D)             (None, 32, 32, 32)        896

 batch_normalization (Batch  (None, 32, 32, 32)        128
 Normalization)

 conv2d_1 (Conv2D)           (None, 32, 32, 32)        9248

 batch_normalization_1 (Bat  (None, 32, 32, 32)        128
```

```
 chNormalization)

 max_pooling2d (MaxPooling2  (None, 16, 16, 32)        0
 D)

 conv2d_2 (Conv2D)           (None, 16, 16, 64)        18496

 batch_normalization_2 (Bat  (None, 16, 16, 64)        256
 chNormalization)

 conv2d_3 (Conv2D)           (None, 16, 16, 64)        36928

 batch_normalization_3 (Bat  (None, 16, 16, 64)        256
 chNormalization)

 max_pooling2d_1 (MaxPoolin  (None, 8, 8, 64)          0
 g2D)

 conv2d_4 (Conv2D)           (None, 8, 8, 128)         73856

 batch_normalization_4 (Bat  (None, 8, 8, 128)         512
 chNormalization)

 conv2d_5 (Conv2D)           (None, 8, 8, 128)         147584

 batch_normalization_5 (Bat  (None, 8, 8, 128)         512
 chNormalization)

 max_pooling2d_2 (MaxPoolin  (None, 4, 4, 128)         0
 g2D)

 flatten (Flatten)           (None, 2048)              0

 dropout (Dropout)           (None, 2048)              0

 dense (Dense)               (None, 1024)              2098176

 dropout_1 (Dropout)         (None, 1024)              0

 dense_1 (Dense)             (None, 10)                10250

=================================================================
Total params: 2397226 (9.14 MB)
Trainable params: 2396330 (9.14 MB)
Non-trainable params: 896 (3.50 KB)
_________________________________________________________________
```

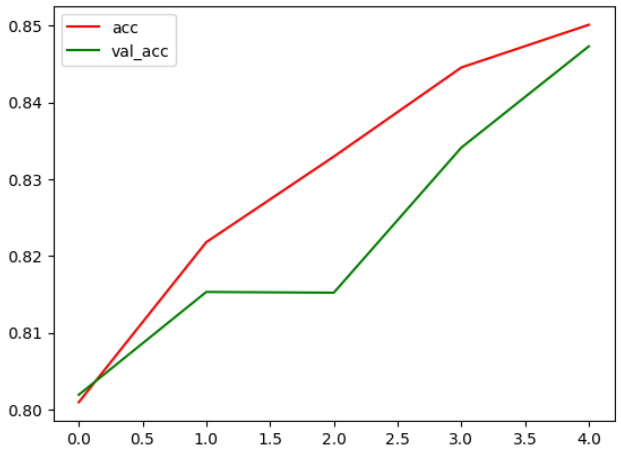
Training the model

```
# Fit with data augmentation
# Note: if you run this AFTER calling
```

```
# the previous model.fit()
# it will CONTINUE training where it left off
batch_size = 32
data_generator =
tf.keras.preprocessing.image.ImageDataGenerator(width_shift_range=0.1,
height_shift_range=0.1, horizontal_flip=True)

train_generator = data_generator.flow(x_train, y_train, batch_size)
steps_per_epoch = x_train.shape[0] // batch_size

r = model.fit(train_generator, validation_data=(x_test,
y_test),steps_per_epoch=steps_per_epoch, epochs=5)

# Plot accuracy per iteration
plt.plot(r.history['accuracy'], label='acc', color='red')
plt.plot(r.history['val_accuracy'], label='val_acc', color='green')
plt.legend()
```

Output:

Epoch 1/5
1562/1562 [==============================] - 42s 26ms/step - loss: 0.6071 - accuracy: 0.8009 - val_loss: 0.6268 - val_accuracy: 0.8019
Epoch 2/5
1562/1562 [==============================] - 39s 25ms/step - loss: 0.5292 - accuracy: 0.8218 - val_loss: 0.5791 - val_accuracy: 0.8153
Epoch 3/5
1562/1562 [==============================] - 41s 26ms/step - loss: 0.4966 - accuracy: 0.8329 - val_loss: 0.5649 - val_accuracy: 0.8152
Epoch 4/5
1562/1562 [==============================] - 39s 25ms/step - loss: 0.4631 - accuracy: 0.8445 - val_loss: 0.4867 - val_accuracy: 0.8341
Epoch 5/5
1562/1562 [==============================] - 39s 25ms/step - loss: 0.4390 - accuracy: 0.8501 - val_loss: 0.4518 - val_accuracy: 0.8473



Testing the model

```
# label mapping

labels = '''airplane automobile bird cat deer dog frog horse ship
truck'''.split()

# select the image from our test dataset
image_number = 1
# display the image
plt.imshow(x_test[image_number])

# load the image in an array
n = np.array(x_test[image_number])

# reshape it
p = n.reshape(1, 32, 32, 3)
# pass in the network for prediction and
# save the predicted label
print(model.predict(p).argmax())
predicted_label = labels[model.predict(p).argmax()]
# load the original label
original_label = labels[y_test[image_number]]
# display the result
print("Original label is {} and predicted label is
{}".format(original_label, predicted_label))
```

Output:

```
1/1 [==============================] - 0s 27ms/step
8
1/1 [==============================] - 0s 17ms/step
Original label is ship and predicted label is ship
```