Data Description:

You are provided with a dataset of images of plant seedlings at various stages of grown. Each image has a filename that is its unique id. The dataset comprises 12 plant species. The goal of the project is to create a classifier capable of determining a plant's species from a photo.

Dataset:

The dataset can be download from Olympus.
The data file names are:
images.npy.
Label.csv.

Context:

Can you differentiate a weed from a crop seedling?
The ability to do so effectively can mean better crop yields and better stewardship of the environment.
The Aarhus University Signal Processing group, in collaboration with University of Southern Denmark, has recently released a dataset containing images of unique plants belonging to 12 species at several growth stages

Objective:

1. Import the libraries, load dataset, print shape of data, visualize the images in dataset. (5 Marks)

In [1]:
```
# Import necessary libraries.

import warnings
warnings.filterwarnings('ignore')
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import os

from sklearn.metrics import confusion_matrix, classification_report
from sklearn import preprocessing
from sklearn.model_selection import train_test_split

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten,
GlobalAveragePooling2D
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from keras.optimizers import Adam ,RMSprop

import cv2
from google.colab.patches import cv2_imshow
from google.colab import drive
```

In [2]:
```
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remoun
t, call drive.mount("/content/drive", force_remount=True).
```

In [3]:
```
#labelsData
imagesData = np.load('/content/drive/My Drive/projectcnn/images.npy')
labels=pd.read_csv('/content/drive/My Drive/projectcnn/Labels.csv')
```

In [4]:
```
imagesData.shape
```

Out[4]:
```
(4750, 128, 128, 3)
```

In [5]:
```
labels.shape
```

Out[5]:
```
(4750, 1)
```

In [6]:
```
labels['Label'].unique()
```

Out[6]:
```
array(['Small-flowered Cranesbill', 'Fat Hen', 'Shepherds Purse',
       'Common wheat', 'Common Chickweed', 'Charlock', 'Cleavers',
       'Scentless Mayweed', 'Sugar beet', 'Maize', 'Black-grass',
       'Loose Silky-bent'], dtype=object)
```

In [7]:
```
labels.head()
```

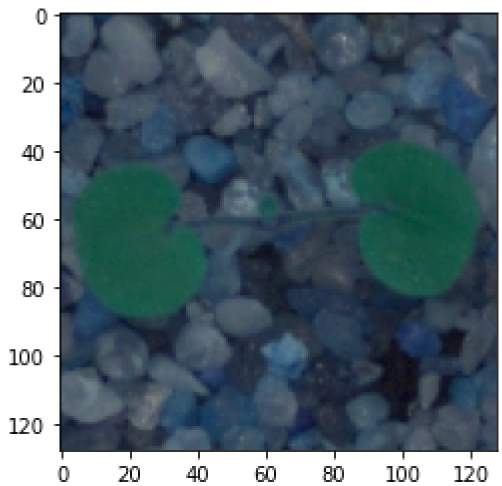
Out[7]:

	Label
0	Small-flowered Cranesbill
1	Small-flowered Cranesbill
2	Small-flowered Cranesbill
3	Small-flowered Cranesbill
4	Small-flowered Cranesbill

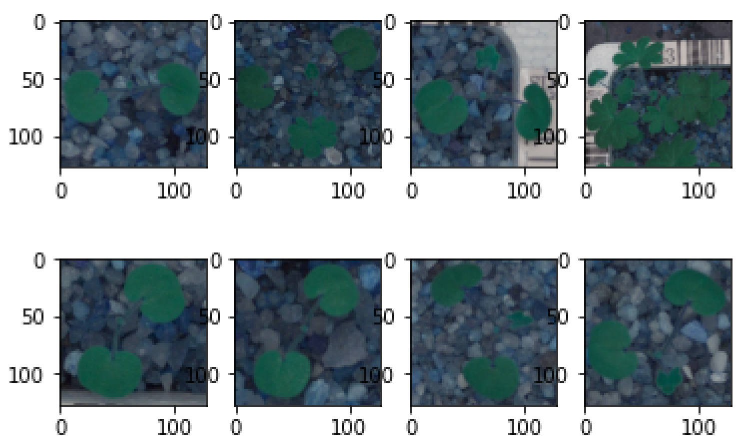
In [8]:
```
labels['Label'][0]
```

Out[8]: 'Small-flowered Cranesbill'

In [9]:
```
plt.imshow(imagesData[0]);
```



In [10]:
```
# Show some example images
for i in range(8):
    plt.subplot(2, 4, i + 1)
    plt.imshow(imagesData[i])
```



In [11]:
```
labels['Label'][33]
```

Out[11]:
```
'Small-flowered Cranesbill'
```

2. Data Pre-processing: (15 Marks)

a. Normalization.
b. Gaussian Blurring.
c. Visualize data after pre-processing.

In [11]:
```

```

In [11]:
```

```

In [11]:
```

```

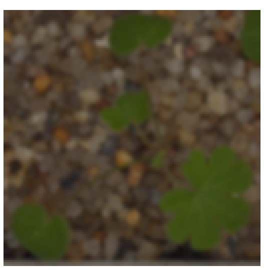
In [12]:
```
imagesData[33].shape
```

Out[12]:
```
(128, 128, 3)
```

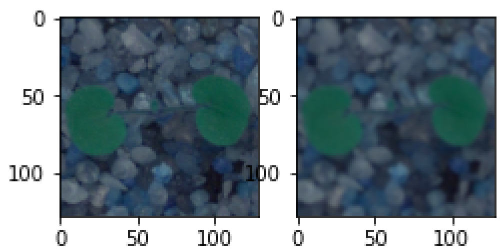
In [13]:
```
testImage=imagesData[33].astype('float32')

Gaussian1 = cv2.GaussianBlur(testImage, (5, 5), 0)
print('Original Image:\n')
cv2_imshow(imagesData[33])

cv2_imshow(testImage)
print('\n Output after first gaussian blurring: \n')
cv2_imshow(Gaussian1)
```

```
Original Image:
```

```
 Output after first gaussian blurring:
```



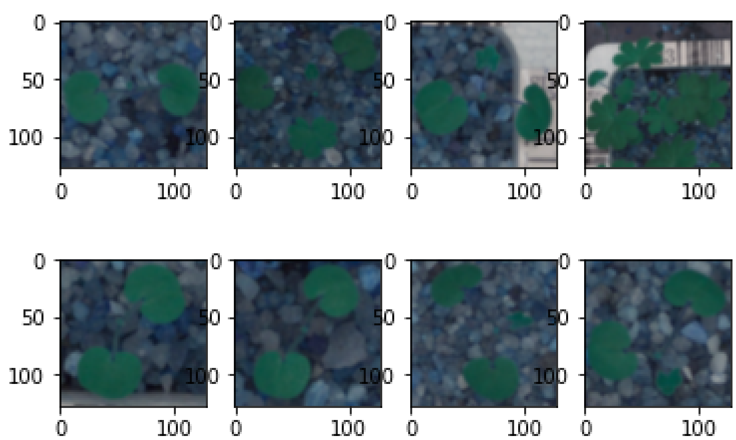
In [14]:
```
# Gaussian Blurring.
blurTrainImg = []
showEx = True
for img in imagesData:
    # Use gaussian blur
    blurImg = cv2.GaussianBlur(img, (5, 5), 0)



    blurTrainImg.append(blurImg)  # Append image without backgroung

    # Show examples
    if showEx:
        plt.subplot(2, 3, 1); plt.imshow(img)  # Show the original image
        plt.subplot(2, 3, 2); plt.imshow(blurImg)  # Blur image
        showEx = False

blurTrainImg = np.asarray(blurTrainImg)
```



In [15]:
```
blurTrainImg.shape
```

Out[15]: (4750, 128, 128, 3)

In [16]:
```
# Visualize data after pre-processing.
for i in range(8):
    plt.subplot(2, 4, i + 1)
    plt.imshow(blurTrainImg[i])
```



In [17]:
```
#Normalize input

blurTrainImg = blurTrainImg / 255
```

3. Make data compatible: (10 Marks)

a. Convert labels to one-hot-vectors.
b. Print the label for y_train[0].
c. Split the dataset into training, testing, and validation set.
(Hint: First split images and labels into training and testing set with test_size = 0.3. Then further split test data into test and validation set with test_size = 0.5)
d. Check the shape of data, Reshape data into shapes compatible with Keras models if it's not already. If it's already in the compatible shape, then comment in the notebook that it's already in compatible shape.

In [18]:
```
#Convert labels to one-hot-vectors.
#Label encoding target variable
species = labels['Label'].unique()

labelencoder = preprocessing.LabelEncoder()
labelencoder.fit(species)
encodedlabels = labelencoder.transform( labels['Label'])
print('\n')
print('Classes'+str(labelencoder.classes_))


# One Hot Encoding
onehotencoded_labels = keras.utils.to_categorical(encodedlabels)
```

```
Classes['Black-grass' 'Charlock' 'Cleavers' 'Common Chickweed' 'Common wheat'
 'Fat Hen' 'Loose Silky-bent' 'Maize' 'Scentless Mayweed'
 'Shepherds Purse' 'Small-flowered Cranesbill' 'Sugar beet']
```

In [19]:
```
species
```

Out[19]:
```
array(['Small-flowered Cranesbill', 'Fat Hen', 'Shepherds Purse',
       'Common wheat', 'Common Chickweed', 'Charlock', 'Cleavers',
       'Scentless Mayweed', 'Sugar beet', 'Maize', 'Black-grass',
       'Loose Silky-bent'], dtype=object)
```

In [20]:
```
onehotencoded_labels.shape
```

Out[20]:
```
(4750, 12)
```

In [20]:

In [20]:

In [21]:
```
#Split the dataset into training, testing, and validation set.
# create training and testing vars using blurTrainImg
X_train, X_test1, y_train, y_test1 = train_test_split(blurTrainImg, oneh
otencoded_labels, test_size=0.3)
print (X_train.shape,y_train.shape)
print (X_test1.shape, y_test1.shape)
```

```
(3325, 128, 128, 3) (3325, 12)
(1425, 128, 128, 3) (1425, 12)
```

In [22]:
```
X_test, X_valid, y_test, y_valid= train_test_split(X_test1, y_test1, tes
t_size=0.5)
print (X_test.shape,y_test.shape)
print (X_valid.shape, y_valid.shape)
```

```
(712, 128, 128, 3) (712, 12)
(713, 128, 128, 3) (713, 12)
```

In [23]:
```
y_train[0]
```

Out[23]:
```
array([0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.], dtype=float32)
```

In [24]:
```
X_test[0]
```

Out[24]:
```
array([[[0.38431373, 0.4627451 , 0.50196078],
        [0.38431373, 0.4627451 , 0.49803922],
        [0.37647059, 0.45490196, 0.49019608],
        ...,
        [0.17647059, 0.21176471, 0.28627451],
        [0.16862745, 0.20784314, 0.27843137],
        [0.16862745, 0.20784314, 0.27843137]],

       [[0.38823529, 0.47058824, 0.50980392],
        [0.38823529, 0.46666667, 0.50588235],
        [0.38039216, 0.4627451 , 0.49411765],
        ...,
        [0.17254902, 0.21176471, 0.28235294],
        [0.16862745, 0.20784314, 0.27843137],
        [0.16470588, 0.20784314, 0.2745098 ]],

       [[0.4       , 0.48235294, 0.52156863],
        [0.39607843, 0.47843137, 0.51764706],
        [0.38823529, 0.47058824, 0.50588235],
        ...,
        [0.16862745, 0.20784314, 0.27843137],
        [0.16470588, 0.20392157, 0.2745098 ],
        [0.16078431, 0.20392157, 0.2745098 ]],

       ...,

       [[0.2       , 0.26666667, 0.35294118],
        [0.2       , 0.26666667, 0.34901961],
        [0.2       , 0.26666667, 0.34901961],
        ...,
        [0.16078431, 0.22352941, 0.29411765],
        [0.16078431, 0.21960784, 0.28627451],
        [0.15686275, 0.21568627, 0.28235294]],

       [[0.19607843, 0.2627451 , 0.34901961],
        [0.2       , 0.26666667, 0.34901961],
        [0.2       , 0.27058824, 0.34901961],
        ...,
        [0.16078431, 0.22352941, 0.29019608],
        [0.15686275, 0.21568627, 0.28627451],
        [0.15686275, 0.21568627, 0.28235294]],

       [[0.19607843, 0.2627451 , 0.34901961],
        [0.2       , 0.26666667, 0.34901961],
        [0.20392157, 0.27058824, 0.34901961],
        ...,
        [0.16078431, 0.21960784, 0.29019608],
        [0.15686275, 0.21568627, 0.28235294],
        [0.15294118, 0.21568627, 0.27843137]]])
```

In [25]:
```
#compatible with keras
```

4. Building CNN: (15 Marks)

a. Define layers. b. Set optimizer and loss function. (Use Adam optimizer and categorical crossentropy.)

In [26]:

```
num_classes=12
# Create the model
model = Sequential()
model.add(Conv2D(32, (3, 3), padding='same',
                 input_shape=X_train.shape[1:]))
model.add(Activation('relu'))
model.add(Conv2D(32, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes))
model.add(Activation('softmax'))


# initiate Adam optimizer
opt = keras.optimizers.Adam(learning_rate=0.0001)

# Let's train the model using RMSprop
model.compile(loss='categorical_crossentropy',
              optimizer=opt,
              metrics=['accuracy'])

# Network structure is summarized which confirms our design was implemen
ted correctly.
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 128, 128, 32)      896       
_________________________________________________________________
activation (Activation)      (None, 128, 128, 32)      0         
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 126, 126, 32)      9248      
_________________________________________________________________
activation_1 (Activation)    (None, 126, 126, 32)      0         
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 63, 63, 32)        0         
_________________________________________________________________
dropout (Dropout)            (None, 63, 63, 32)        0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 63, 63, 64)        18496     
_________________________________________________________________
activation_2 (Activation)    (None, 63, 63, 64)        0         
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 61, 61, 64)        36928     
_________________________________________________________________
activation_3 (Activation)    (None, 61, 61, 64)        0         
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 30, 30, 64)        0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 30, 30, 64)        0         
_________________________________________________________________
flatten (Flatten)            (None, 57600)             0         
_________________________________________________________________
dense (Dense)                (None, 512)               29491712  
_________________________________________________________________
activation_4 (Activation)    (None, 512)               0         
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 12)                6156      
_________________________________________________________________
activation_5 (Activation)    (None, 12)                0         
=================================================================
Total params: 29,563,436
Trainable params: 29,563,436
Non-trainable params: 0
_________________________________________________________________
```

5. Fit and evaluate model and print confusion matrix. (10 Marks)

In [27]:

```
#Adding Early stopping callback to the fit function is going to stop the training,
#if the val_loss is not going to change even '0.001' for more than 10 continous epochs
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping

early_stopping = EarlyStopping(monitor='val_loss', min_delta=0.001, patience=10)

#Adding Model Checkpoint callback to the fit function is going to save the weights whenever val_loss achieves a new low value.
#Hence saving the best weights occurred during training

model_checkpoint =  ModelCheckpoint('cifar_cnn_checkpoint_{epoch:02d}_loss{val_loss:.4f}.h5',
                                                           monitor='val_loss',
                                                           verbose=1,
                                                           save_best_only=True,
                                                           save_weights_only=True,
                                                           mode='auto',
                                                           period=1)
```

```
WARNING:tensorflow:`period` argument is deprecated. Please use `save_freq` to specify the frequency in number of batches seen.
```

In [28]:
```
# Set the batch size, number of epochs.
batch_size = 64
epochs = 30

model.fit(X_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          validation_data=(X_valid, y_valid),
          shuffle=True,
          verbose=1,
          callbacks=[early_stopping,model_checkpoint])
```

```
Epoch 1/30
52/52 [==============================] - ETA: 0s - loss: 2.4105 - accur
acy: 0.1588
Epoch 00001: val_loss improved from inf to 2.34754, saving model to cif
ar_cnn_checkpoint_01_loss2.3475.h5
52/52 [==============================] - 5s 98ms/step - loss: 2.4105 -
accuracy: 0.1588 - val_loss: 2.3475 - val_accuracy: 0.1865
Epoch 2/30
52/52 [==============================] - ETA: 0s - loss: 2.1004 - accur
acy: 0.2986
Epoch 00002: val_loss improved from 2.34754 to 1.93195, saving model to
cifar_cnn_checkpoint_02_loss1.9319.h5
52/52 [==============================] - 4s 78ms/step - loss: 2.1004 -
accuracy: 0.2986 - val_loss: 1.9319 - val_accuracy: 0.3548
Epoch 3/30
52/52 [==============================] - ETA: 0s - loss: 1.7846 - accur
acy: 0.3835
Epoch 00003: val_loss improved from 1.93195 to 1.66868, saving model to
cifar_cnn_checkpoint_03_loss1.6687.h5
52/52 [==============================] - 4s 78ms/step - loss: 1.7846 -
accuracy: 0.3835 - val_loss: 1.6687 - val_accuracy: 0.4250
Epoch 4/30
52/52 [==============================] - ETA: 0s - loss: 1.5528 - accur
acy: 0.4647
Epoch 00004: val_loss improved from 1.66868 to 1.50225, saving model to
cifar_cnn_checkpoint_04_loss1.5023.h5
52/52 [==============================] - 4s 78ms/step - loss: 1.5528 -
accuracy: 0.4647 - val_loss: 1.5023 - val_accuracy: 0.4867
Epoch 5/30
52/52 [==============================] - ETA: 0s - loss: 1.3998 - accur
acy: 0.5212
Epoch 00005: val_loss improved from 1.50225 to 1.36696, saving model to
cifar_cnn_checkpoint_05_loss1.3670.h5
52/52 [==============================] - 4s 78ms/step - loss: 1.3998 -
accuracy: 0.5212 - val_loss: 1.3670 - val_accuracy: 0.5007
Epoch 6/30
52/52 [==============================] - ETA: 0s - loss: 1.2982 - accur
acy: 0.5621
Epoch 00006: val_loss improved from 1.36696 to 1.29464, saving model to
cifar_cnn_checkpoint_06_loss1.2946.h5
52/52 [==============================] - 4s 78ms/step - loss: 1.2982 -
accuracy: 0.5621 - val_loss: 1.2946 - val_accuracy: 0.5456
Epoch 7/30
52/52 [==============================] - ETA: 0s - loss: 1.1735 - accur
acy: 0.6066
Epoch 00007: val_loss improved from 1.29464 to 1.17734, saving model to
cifar_cnn_checkpoint_07_loss1.1773.h5
52/52 [==============================] - 4s 78ms/step - loss: 1.1735 -
accuracy: 0.6066 - val_loss: 1.1773 - val_accuracy: 0.5989
Epoch 8/30
52/52 [==============================] - ETA: 0s - loss: 1.0504 - accur
acy: 0.6400
Epoch 00008: val_loss improved from 1.17734 to 1.16321, saving model to
cifar_cnn_checkpoint_08_loss1.1632.h5
52/52 [==============================] - 4s 79ms/step - loss: 1.0504 -
accuracy: 0.6400 - val_loss: 1.1632 - val_accuracy: 0.5961
Epoch 9/30
```

```
52/52 [==============================] - ETA: 0s - loss: 1.0034 - accur
acy: 0.6659
Epoch 00009: val_loss improved from 1.16321 to 1.12859, saving model to
cifar_cnn_checkpoint_09_loss1.1286.h5
52/52 [==============================] - 4s 79ms/step - loss: 1.0034 -
accuracy: 0.6659 - val_loss: 1.1286 - val_accuracy: 0.6227
Epoch 10/30
52/52 [==============================] - ETA: 0s - loss: 0.9365 - accur
acy: 0.6770
Epoch 00010: val_loss improved from 1.12859 to 1.07272, saving model to
cifar_cnn_checkpoint_10_loss1.0727.h5
52/52 [==============================] - 4s 79ms/step - loss: 0.9365 -
accuracy: 0.6770 - val_loss: 1.0727 - val_accuracy: 0.6508
Epoch 11/30
52/52 [==============================] - ETA: 0s - loss: 0.8793 - accur
acy: 0.7017
Epoch 00011: val_loss improved from 1.07272 to 1.05517, saving model to
cifar_cnn_checkpoint_11_loss1.0552.h5
52/52 [==============================] - 4s 79ms/step - loss: 0.8793 -
accuracy: 0.7017 - val_loss: 1.0552 - val_accuracy: 0.6522
Epoch 12/30
52/52 [==============================] - ETA: 0s - loss: 0.8097 - accur
acy: 0.7245
Epoch 00012: val_loss did not improve from 1.05517
52/52 [==============================] - 4s 74ms/step - loss: 0.8097 -
accuracy: 0.7245 - val_loss: 1.0587 - val_accuracy: 0.6480
Epoch 13/30
52/52 [==============================] - ETA: 0s - loss: 0.7690 - accur
acy: 0.7329
Epoch 00013: val_loss improved from 1.05517 to 1.03003, saving model to
cifar_cnn_checkpoint_13_loss1.0300.h5
52/52 [==============================] - 4s 79ms/step - loss: 0.7690 -
accuracy: 0.7329 - val_loss: 1.0300 - val_accuracy: 0.6662
Epoch 14/30
52/52 [==============================] - ETA: 0s - loss: 0.7372 - accur
acy: 0.7489
Epoch 00014: val_loss improved from 1.03003 to 0.96747, saving model to
cifar_cnn_checkpoint_14_loss0.9675.h5
52/52 [==============================] - 4s 79ms/step - loss: 0.7372 -
accuracy: 0.7489 - val_loss: 0.9675 - val_accuracy: 0.6592
Epoch 15/30
52/52 [==============================] - ETA: 0s - loss: 0.6736 - accur
acy: 0.7600
Epoch 00015: val_loss did not improve from 0.96747
52/52 [==============================] - 4s 74ms/step - loss: 0.6736 -
accuracy: 0.7600 - val_loss: 0.9730 - val_accuracy: 0.6774
Epoch 16/30
52/52 [==============================] - ETA: 0s - loss: 0.6390 - accur
acy: 0.7808
Epoch 00016: val_loss did not improve from 0.96747
52/52 [==============================] - 4s 74ms/step - loss: 0.6390 -
accuracy: 0.7808 - val_loss: 0.9974 - val_accuracy: 0.6634
Epoch 17/30
52/52 [==============================] - ETA: 0s - loss: 0.6024 - accur
acy: 0.7985
Epoch 00017: val_loss improved from 0.96747 to 0.94588, saving model to
cifar_cnn_checkpoint_17_loss0.9459.h5
```

```
52/52 [==============================] - 4s 80ms/step - loss: 0.6024 -
accuracy: 0.7985 - val_loss: 0.9459 - val_accuracy: 0.6872
Epoch 18/30
52/52 [==============================] - ETA: 0s - loss: 0.5629 - accur
acy: 0.8120
Epoch 00018: val_loss did not improve from 0.94588
52/52 [==============================] - 4s 75ms/step - loss: 0.5629 -
accuracy: 0.8120 - val_loss: 0.9780 - val_accuracy: 0.6886
Epoch 19/30
52/52 [==============================] - ETA: 0s - loss: 0.5410 - accur
acy: 0.8177
Epoch 00019: val_loss improved from 0.94588 to 0.92973, saving model to
cifar_cnn_checkpoint_19_loss0.9297.h5
52/52 [==============================] - 4s 79ms/step - loss: 0.5410 -
accuracy: 0.8177 - val_loss: 0.9297 - val_accuracy: 0.6914
Epoch 20/30
52/52 [==============================] - ETA: 0s - loss: 0.4849 - accur
acy: 0.8283
Epoch 00020: val_loss did not improve from 0.92973
52/52 [==============================] - 4s 75ms/step - loss: 0.4849 -
accuracy: 0.8283 - val_loss: 0.9587 - val_accuracy: 0.6942
Epoch 21/30
52/52 [==============================] - ETA: 0s - loss: 0.4452 - accur
acy: 0.8469
Epoch 00021: val_loss did not improve from 0.92973
52/52 [==============================] - 4s 75ms/step - loss: 0.4452 -
accuracy: 0.8469 - val_loss: 0.9844 - val_accuracy: 0.7153
Epoch 22/30
52/52 [==============================] - ETA: 0s - loss: 0.4330 - accur
acy: 0.8562
Epoch 00022: val_loss did not improve from 0.92973
52/52 [==============================] - 4s 75ms/step - loss: 0.4330 -
accuracy: 0.8562 - val_loss: 0.9555 - val_accuracy: 0.7069
Epoch 23/30
52/52 [==============================] - ETA: 0s - loss: 0.4126 - accur
acy: 0.8553
Epoch 00023: val_loss did not improve from 0.92973
52/52 [==============================] - 4s 75ms/step - loss: 0.4126 -
accuracy: 0.8553 - val_loss: 0.9983 - val_accuracy: 0.6985
Epoch 24/30
52/52 [==============================] - ETA: 0s - loss: 0.3967 - accur
acy: 0.8598
Epoch 00024: val_loss did not improve from 0.92973
52/52 [==============================] - 4s 75ms/step - loss: 0.3967 -
accuracy: 0.8598 - val_loss: 1.0137 - val_accuracy: 0.7041
Epoch 25/30
52/52 [==============================] - ETA: 0s - loss: 0.3651 - accur
acy: 0.8719
Epoch 00025: val_loss did not improve from 0.92973
52/52 [==============================] - 4s 75ms/step - loss: 0.3651 -
accuracy: 0.8719 - val_loss: 1.0756 - val_accuracy: 0.7041
Epoch 26/30
52/52 [==============================] - ETA: 0s - loss: 0.3430 - accur
acy: 0.8761
Epoch 00026: val_loss improved from 0.92973 to 0.91955, saving model to
cifar_cnn_checkpoint_26_loss0.9196.h5
52/52 [==============================] - 4s 80ms/step - loss: 0.3430 -
```

```
accuracy: 0.8761 - val_loss: 0.9196 - val_accuracy: 0.7195
Epoch 27/30
52/52 [==============================] - ETA: 0s - loss: 0.3160 - accur
acy: 0.8929
Epoch 00027: val_loss did not improve from 0.91955
52/52 [==============================] - 4s 75ms/step - loss: 0.3160 -
accuracy: 0.8929 - val_loss: 0.9841 - val_accuracy: 0.7097
Epoch 28/30
52/52 [==============================] - ETA: 0s - loss: 0.2968 - accur
acy: 0.8962
Epoch 00028: val_loss did not improve from 0.91955
52/52 [==============================] - 4s 75ms/step - loss: 0.2968 -
accuracy: 0.8962 - val_loss: 1.0359 - val_accuracy: 0.7195
Epoch 29/30
52/52 [==============================] - ETA: 0s - loss: 0.2642 - accur
acy: 0.9143
Epoch 00029: val_loss did not improve from 0.91955
52/52 [==============================] - 4s 76ms/step - loss: 0.2642 -
accuracy: 0.9143 - val_loss: 0.9818 - val_accuracy: 0.7237
Epoch 30/30
52/52 [==============================] - ETA: 0s - loss: 0.2835 - accur
acy: 0.9086
Epoch 00030: val_loss did not improve from 0.91955
52/52 [==============================] - 4s 76ms/step - loss: 0.2835 -
accuracy: 0.9086 - val_loss: 1.0143 - val_accuracy: 0.7209
```

Out[28]:

```
<tensorflow.python.keras.callbacks.History at 0x7fdf8a689630>
```

In [28]:

```

```

In [41]:

```
# Evaluate trained model.
scores = model.evaluate(X_test, y_test, verbose=1)
print('Test loss:', scores[0])
print('Test accuracy:', scores[1])
```

```
23/23 [==============================] - 0s 13ms/step - loss: 1.0094 -
accuracy: 0.7247
Test loss: 1.009392499923706
Test accuracy: 0.7247191071510315
```

In [44]:
```
validation_predictions = model.predict_classes(X_test)
report=classification_report(tf.argmax(y_test,axis=1),validation_predict
ions)
print(report)
#Confusion Matrix
```

```
              precision    recall  f1-score   support

           0       0.40      0.05      0.09        41
           1       0.88      0.79      0.83        66
           2       0.90      0.66      0.76        41
           3       0.75      0.92      0.82        84
           4       0.80      0.36      0.50        33
           5       0.70      0.77      0.73        69
           6       0.62      0.91      0.73        97
           7       0.81      0.64      0.71        39
           8       0.64      0.74      0.69        70
           9       0.52      0.43      0.47        28
          10       0.82      0.94      0.88        89
          11       0.73      0.58      0.65        55

    accuracy                           0.72       712
   macro avg       0.71      0.65      0.66       712
weighted avg       0.72      0.72      0.70       712
```

6. Visualize predictions for x_test[2], x_test[3], x_test[33], x_test[36], x_test[59]. (5 Marks)

In [45]:
```
print(validation_predictions[2] , 'Actual class', tf.argmax(y_test[2]))
```

```
10 Actual class tf.Tensor(10, shape=(), dtype=int64)
```

In [46]:
```
##  Text Index 2 Predicted Class correctly : 8 actual  and 8 Predicted (
9 bit , 0 start)
```

In [47]:
```
print(validation_predictions[3] , 'Actual class', tf.argmax(y_test[3]))
```

```
2 Actual class tf.Tensor(2, shape=(), dtype=int64)
```

In [48]:
```
##  Text Index 33 Predicted Class correctly : 6 actual  and 6 predicted
( 7 bit, 0 start)
```

In [49]:
```
print(validation_predictions[33] , 'Actual class', tf.argmax(y_test[33
]))
```

```
2 Actual class tf.Tensor(2, shape=(), dtype=int64)
```

In [50]:
```
##  Text Index 33 Predicted Class INCORRECTLY  : 0 actual  and 6 predict
ed   ( 7 bit, 0 start)
```

In [51]:
```
print(validation_predictions[59] , 'Actual class', tf.argmax(y_test[59
]))
```

```
6 Actual class tf.Tensor(6, shape=(), dtype=int64)
```

In [52]:
```
##  Text Index 59 Predicted Class correctly : 7 actual  and 7 Predicted
 ( 8 bit, 0 start)
```

In [52]:

In [52]:

In [40]:

In [40]:

In [40]: