EXPERIMENT 2

CLASSIFICATION ON CIFAR-10 DATASET (COLOUR IMAGES)

AIM:

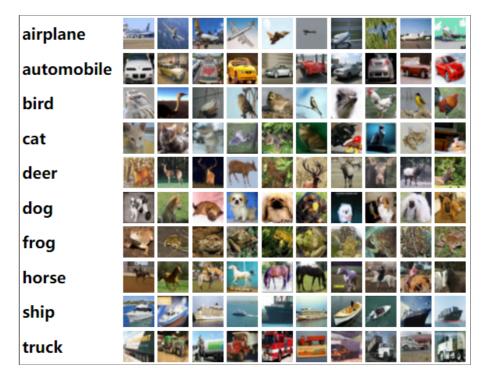
To build and train a Convolutional Neural Network (CNN) for classifying color images from the CIFAR-10 dataset into 10 distinct classes.

PRE-REQUISITES:

- 1. Basics of Machine Learning
- 2. Python Programming
- 3. Knowledge on Numpy, Pandas, Matplotlib, TensorFlow/ Keras
- 4. Jupyter Notebook
- 5. Data Pre-Processing Techniques
- 6. Knowledge on Neural Networks

CIFAR-10 Dataset

- CIFAR-10 contains 60,000 color images of size 32x32 pixels, split into 10 classes.
- The classes include common objects like airplane, car, bird, cat, deer, dog, frog, horse, ship and truck.
- It has 50,000 training images and 10,000 test images, divided among the 10 classes.



1. Importing the Basic Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# It tells Jupyter to display Matplotlib plots directly below the code cell that produced them, inside the notebook
# You don't need to call plt.show()
%matplotlib inline
```

2. Importing the Built-in CIFAR-10 dataset from the Keras

```
In [2]: from tensorflow.keras.datasets import cifar10
```

/Users/srinutupakula/Library/Python/3.9/lib/python/site-packages/urllib3/__init__.py:35: NotOpenSSLWarning: urllib3 v2 only supports OpenSSL 1.1.1+, currently the 'ssl' module is compiled with 'LibreSSL 2.8.3'. See: https://github.com/urllib3/urllib3/issues/3020 warnings.warn(

```
In [3]: # Load the CIFAR-10 dataset as Training and Testing data
    (X_train,y_train),(X_test,y_test) = cifar10.load_data()
```

```
In [4]: X_train.shape, y_train.shape
         # 50,000 Images, each image is 32x32 pixel
 Out[4]: ((50000, 32, 32, 3), (50000, 1))
 In [ ]: # Reading one Image of the CIFAR-10 X_train data
         X_train[12]
 In [6]: # Viewing the Image 12 of X_train
         plt.imshow(X_train[12])
 Out[6]: <matplotlib.image.AxesImage at 0x1645c18b0>
         0
         5
        10
        15
        20
        25
        30
                   5
                          10
                                  15
                                         20
                                                25
                                                        30
 In [7]: # Checking y_train data
         y_train
 Out[7]: array([[6],
                 [9],
                 [9],
                 [9],
                 [1],
                 [1]], dtype=uint8)
         3. Pre-Process the Data as required
 In [8]: # Since, this is classification problem, we need to encode the y_train data
         # If not the model assume the y label is a continuous data
 In [9]: # Import the library
         from tensorflow.keras.utils import to_categorical
In [10]: # Shape of the y_train
         y_train.shape
Out[10]: (50000, 1)
         One-hot Encoding the y
In [11]: # Convert class labels to one-hot encoding
         # num_classes=10 tells the function that your classification task has 10 different classes
         y_train_cat = to_categorical(y_train, num_classes=10)
         y_test_cat = to_categorical(y_test, num_classes=10)
In [12]: # the index of one represents the actual output digit
         # the 8th row belongs to digit 1
         y_train_cat[8]
Out[12]: array([0., 0., 0., 0., 0., 0., 0., 0., 1., 0.])
         Scaling the Data
```

In [13]: # Each pixel value of every image is ranging from 0 to 255 # So, normalize every value in between 0 to 1

```
In [15]: # Shapes of the data
         X_train.shape, y_train.shape, X_test.shape, y_test.shape
Out[15]: ((50000, 32, 32, 3), (50000, 1), (10000, 32, 32, 3), (10000, 1))
          4. Build the Model
In [16]: # import the libraries
          from tensorflow.keras.models import Sequential
          from tensorflow.keras.layers import Dense, Conv2D, MaxPool2D, Flatten
          Create the Model
In [17]: # Model Instance
         model = Sequential()
In [18]: # For more complex data, better to add more number of convolution & pooling layers
          # Convolution Layer
         \verb|model.add(Conv2D(filters=32,kernel\_size=(4,4),input\_shape=(32,32,3),activation='relu')||
          # Pooling Layer
         model.add(MaxPool2D(pool_size=(2,2)))
          # Convolution Layer
         model.add(Conv2D(filters=32,kernel_size=(4,4),input_shape=(32,32,3),activation='relu'))
          # Pooling Layer
         model.add(MaxPool2D(pool_size=(2,2)))
        /Users/srinutupakula/Library/Python/3.9/lib/python/site-packages/keras/src/layers/convolutional/base_conv.py:107: U
        serWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer usin g an `Input(shape)` object as the first layer in the model instead.
          super().__init__(activity_regularizer=activity_regularizer, **kwargs)
In [19]: # Flatten Layer
         model.add(Flatten())
In [20]: # Dense Layers (Fully Connected Layers)
         model.add(Dense(256,activation='relu'))
In [21]: # Output Layer (For multiclass use softmax)
         model.add(Dense(10,activation='softmax'))
          Compile the Model
In [22]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
In [23]: # Model Summary
```

the max value of any pixel is 255, so dividing each value with 255 will normalize the value to maximum 1

model.summary() Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 29, 29, 32)	1,568
max_pooling2d (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_1 (Conv2D)	(None, 11, 11, 32)	16,416
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 32)	0
flatten (Flatten)	(None, 800)	0
dense (Dense)	(None, 256)	205,056
dense_1 (Dense)	(None, 10)	2,570

Total params: 225,610 (881.29 KB)

Trainable params: 225,610 (881.29 KB)

Non-trainable params: 0 (0.00 B)

In [14]: # Normalize the pixel values to range [0, 1]

X_train = X_train / 255.0
X_test = X_test / 255.0

4. Train the Model

```
In [24]: # Train the model with Early Stopping
         from tensorflow.keras.callbacks import EarlyStopping
In [25]: early_stop = EarlyStopping(monitor='val_loss', patience=1)
In [26]: # Train the model
         model.fit(X\_train, y\_train\_cat, epochs=10, validation\_data=(X\_test,y\_test\_cat), callbacks=[early\_stop])
        Epoch 1/10
        1563/1563
                                      – 10s 6ms/step – accuracy: 0.3720 – loss: 1.7000 – val_accuracy: 0.5571 – val_loss: 1.
        2464
        Epoch 2/10
        1563/1563
                                      – 10s 6ms/step – accuracy: 0.5783 – loss: 1.2030 – val_accuracy: 0.6098 – val_loss: 1.
        0996
        Epoch 3/10
        1563/1563
                                      - 11s 7ms/step - accuracy: 0.6524 - loss: 0.9957 - val_accuracy: 0.6529 - val_loss: 0.
        9903
        Epoch 4/10
                                      - 11s 7ms/step - accuracy: 0.6891 - loss: 0.8915 - val_accuracy: 0.6645 - val_loss: 0.
        1563/1563
        9477
        Epoch 5/10
        1563/1563
                                      – 11s 7ms/step – accuracy: 0.7244 – loss: 0.7834 – val_accuracy: 0.6752 – val_loss: 0.
        9502
Out[26]: <keras.src.callbacks.history.History at 0x168423880>
```

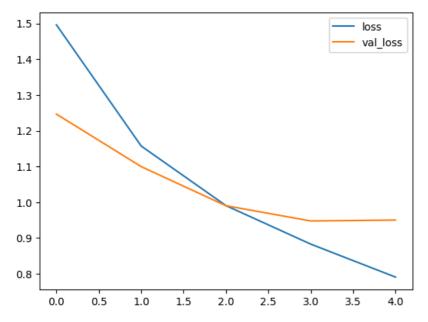
5. Evaluate the Model

In [27]: # Plot the accuracy because we used accuracy metric while compiling the model
metrics = pd.DataFrame(model.history.history)
metrics

Out[27]:		accuracy	loss	val_accuracy	val_loss
	0	0.45680	1.496074	0.5571	1.246428
	1	0.59356	1.157182	0.6098	1.099604
	2	0.65436	0.990567	0.6529	0.990261
	3	0.69186	0.882902	0.6645	0.947666
	4	0.72278	0.790694	0.6752	0.950214

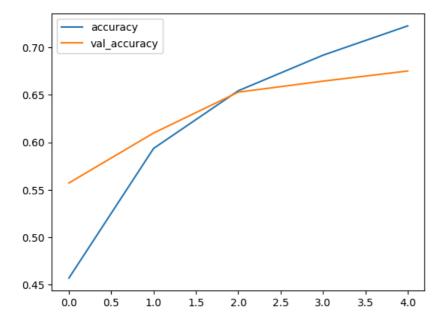
```
In [28]: # Plot loss
metrics[['loss', 'val_loss']].plot()
```

Out[28]: <Axes: >



```
In [29]: # Plot accuracy
metrics[['accuracy', 'val_accuracy']].plot()
```

Out[29]: <Axes: >



Classification report

new_image = new_image.resize((32, 32))

```
In [30]: from sklearn.metrics import classification_report, confusion_matrix
In [31]: # Get the Classifications on test data
         y_pred = model.predict(X_test)
        313/313
                                    - 1s 2ms/step
In [32]: # y_test is one-hot encoded, convert it to class labels too
         y_pred = np.argmax(y_pred, axis=1)
In [33]: # Classification Report
         print(classification_report(y_test,y_pred))
                      precision
                                   recall f1-score
                                                      support
                   0
                           0.71
                                     0.76
                                               0.73
                                                          1000
                                     0.77
                                               0.79
                                                          1000
                   1
                           0.82
                   2
                           0.63
                                     0.52
                                               0.57
                                                          1000
                   3
                           0.48
                                               0.51
                                     0.54
                                                         1000
                   4
                           0.56
                                     0.67
                                               0.61
                                                         1000
                   5
                           0.61
                                     0.52
                                               0.56
                                                         1000
                   6
                           0.80
                                     0.69
                                               0.74
                                                         1000
                   7
                           0.66
                                     0.78
                                               0.71
                                                          1000
                   8
                           0.77
                                     0.78
                                               0.78
                                                         1000
                   9
                           0.78
                                     0.73
                                               0.76
                                                         1000
                                                        10000
            accuracy
                                               0.68
           macro avg
                           0.68
                                     0.68
                                               0.68
                                                        10000
        weighted avg
                           0.68
                                     0.68
                                               0.68
                                                        10000
In [34]: # Confusion Matrix
         print(confusion_matrix(y_test,y_pred))
        [[756 21 32 33 26
                                7
                                    7
                                       22
                                           68 28]
         [ 27 767
                   10
                       15
                            9
                                7
                                    9
                                       10
                                           41 105]
         [ 82
               6 521 76 132 65 46
                                       55
                                            9
                                                8]
                                   52 63
         [
           27
               13 57 540 93 129
                                           18
                                                8]
         [ 19
                3
                   53
                      56 671 41
                                   25 112
                                           18
                                                2]
                6 50 227 74 518 19
         <sup>[</sup> 15
                                      74
                                           12
                                                51
         [ 9
                7
                   47
                      88 92 28 685 25
                                           13
                                                6]
                       49
                                   6 778
         [ 16
                2
                   25
                           64
                              41
                                            5
                                               14]
         [ 97
               23 11
                       20
                           16
                               7
                                    1 10 784
                                               311
         [ 24
               90 15
                       26
                          13
                                    9 36
                                          49 732]]
         Classiying the new image
In [35]: from tensorflow.keras.preprocessing import image
         from PIL import Image
         # RGB Image
         new_image = Image.open('horse.png').convert('RGB')
In [36]: # Resize to 28x28
```

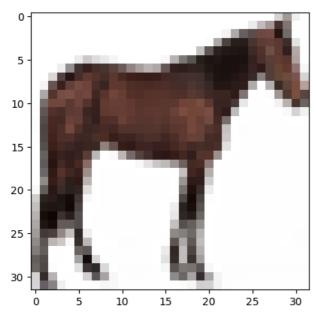
In [37]: new_image

Out[37]:

In [38]: # Convert to NumPy array and normalize
 img_array = np.array(new_image)
 img_array = img_array / 255.0

In [39]: plt.imshow(img_array)

Out[39]: <matplotlib.image.AxesImage at 0x16a930a30>



In [40]: # Reshape to match input shape of model: (1, 32, 32, 3)
img_array = img_array.reshape(1, 32, 32, 3)

In [41]: pred = model.predict(img_array)

1/1 — 0s 11ms/step

In [42]: np.argmax(pred, axis=1)
Index 7 belongs to horse

Out[42]: array([7])

RESULT:

A Convolutional Neural Network (CNN) was successfully implemented to classify the CIFAR-10 dataset. The model demonstrated average performance in recognizing various object classes in color images, achieving an accuracy of 68%.