Classification of Images from the CIFAR-10 Dataset using ANN (MLP) & CNN

OBJECTIVE:

The objective of the "Classification of Images from the CIFAR-10 Dataset using ANN (MLP) & CNN" lab is to equip learners with the knowledge and skills to build and evaluate image classification models using Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). The course begins with fundamental concepts of neural networks and image data representation. It advances to implementing Multilayer Perceptrons (MLP) and CNNs using Python libraries such as TensorFlow and Keras. Learners will gain hands-on experience in preprocessing image data, designing network architectures, and training models to classify images into ten different categories from the CIFAR-10 dataset. By the end of the lab, learners will be proficient in applying ANN and CNN techniques to image classification tasks, enabling them to tackle similar problems in real-world applications.

Classification of Images from the CIFAR-10 Dataset using ANN (MLP) & CNN. The CIFAR-10 dataset consists of color 60,000 images each with 32 x 32 pixel in 10 classes, with 6,000 images per class. There are 50,000 training images and 10,000 test images.

Class labels are:

```
airplane: 0, automobile: 1, bird: 2, cat: 3, deer: 4, dog: 5, frog: 6, horse: 7, ship: 8, truck: 9.
```

Import Tensorflow

```
#!pip install matplotlib
import tensorflow as tf
import matplotlib.pyplot as plt

import matplotlib
matplotlib._version__

3.8.0'

tf._version__

2.17.1'

Check for GPU

physical_devices = tf.config.experimental.list_physical_devices('GPU')
#physical_devices
print('Num GPUs Available: ", len(physical_devices[0], True)

Num GPUs Available: 0

Load Dataset
```

```
from keras.datasets import cifar10
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

```
Downloading data from <a href="https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz">https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz</a>
170498071/170498071 — 3s Ous/step
```

Show some sample images of data set with corresponding labels.

```
cifar10_classes = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
print('Example training images and their labels: ' + str([x[0] for x in y_train[0:10]]))
print('Corresponding classes for the labels: ' + str([cifar10_classes[x[0]] for x in y_train[0:10]]))

fig, axarr = plt.subplots(1, 10)
fig.set_size_inches(20, 6)

for i in range(10):
    image = x_train[i]
    axarr[i].imshow(image)
plt.show()
```

```
Example training images and their labels: [6, 9, 9, 4, 1, 1, 2, 7, 8, 3] Corresponding classes for the labels: ['frog', 'truck', 'truck', 'deer',
                                                                                                                    'automobile', 'automobile', 'bird', 'horse', 'ship', 'cat'
```

```
x_train.shape, y_train.shape, x_test.shape, y_test.shape
→ ((50000, 32, 32, 3), (50000, 1), (10000, 32, 32, 3), (10000, 1))
model.compile(optimizer ='adam',
             loss = 'categorical_crossentropy',
             metrics =['accracy'])
```

Preparing the dataset Normalize the input data

```
X_{train} = x_{train} / 255.0
X_{\text{test}} = x_{\text{test}} / 255.0
# Every Neuron is expected to have value from 0 to 1 to converge quickly(Gradient Descent)
# Import necessary libraries
from tensorflow.keras.utils import to categorical
train_labels = [0, 1, 2, 1, 0] # Example labels
# Convert labels to one-hot encoding
train_labels_one_hot = to_categorical(train_labels)
# Print the one-hot encoded labels
print(train_labels_one_hot)
→ [[1. 0. 0.]
      [0. 1. 0.]
      [0. 0. 1.]
      [0. 1. 0.]
```

MLP Network I/p Layer - Flatten Hidden layer - 2048, AF = 'RELU' O/p Layer - 10, AF-Softmax

```
from tensorflow import keras
from keras.layers import Dense
from keras.layers import Flatten
ann = keras.Sequential()
ann.add(Flatten(input_shape=(32,32,3)))
ann.add(Dense(2048,activation='relu'))
ann.add(Dense(10,activation='softmax'))
/usr/local/lib/python3.10/dist-packages/keras/src/layers/reshaping/flatten.py:37: UserWarning: Do not pass an `input_shape`/`input_c
```

super().__init__(**kwargs)

ann.summary()

4

→ Model: "sequential"

[1. 0. 0.]]

| Layer (type) | Output Shape | Param # |
|-------------------|--------------|-----------|
| flatten (Flatten) | (None, 3072) | 0 |
| dense (Dense) | (None, 2048) | 6,293,504 |
| dense_1 (Dense) | (None, 10) | 20,490 |

Total params: 6,313,994 (24.09 MB) Trainable params: 6,313,994 (24.09 MB) Non-trainable params: 0 (0.00 B)

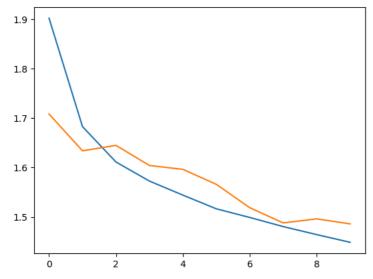
```
ann.compile(loss='sparse_categorical_crossentropy',optimizer='adam',metrics=['accuracy'])
history = ann.fit(X_train ,y_train,epochs=10,validation_data=(X_test,y_test))
```

```
→ Epoch 1/10
    1563/1563
                                  - 142s 90ms/step - accuracy: 0.2903 - loss: 2.2475 - val_accuracy: 0.4005 - val_loss: 1.7081
    Epoch 2/10
    1563/1563
                                  - 141s 90ms/step - accuracy: 0.3911 - loss: 1.6958 - val_accuracy: 0.4150 - val_loss: 1.6338
    Epoch 3/10
    1563/1563
                                   147s 93ms/step - accuracy: 0.4176 - loss: 1.6256 - val_accuracy: 0.4204 - val_loss: 1.6448
    Epoch 4/10
    1563/1563
                                   1975 90ms/step - accuracy: 0.4415 - loss: 1.5707 - val_accuracy: 0.4180 - val_loss: 1.6042
    Epoch 5/10
                                  - 141s 89ms/step - accuracy: 0.4497 - loss: 1.5573 - val_accuracy: 0.4271 - val_loss: 1.5964
    1563/1563
    Epoch 6/10
    1563/1563
                                  - 145s 91ms/step - accuracy: 0.4612 - loss: 1.5165 - val_accuracy: 0.4460 - val_loss: 1.5661
    Epoch 7/10
    1563/1563
                                  - 204s 92ms/step - accuracy: 0.4686 - loss: 1.4955 - val_accuracy: 0.4612 - val_loss: 1.5189
    Epoch 8/10
    1563/1563
                                  - 210s 97ms/step - accuracy: 0.4788 - loss: 1.4603 - val_accuracy: 0.4728 - val_loss: 1.4881
    Epoch 9/10
    1563/1563
                                   192s 91ms/step - accuracy: 0.4808 - loss: 1.4647 - val_accuracy: 0.4737 - val_loss: 1.4963
    Epoch 10/10
    1563/1563
                                  - 207s 94ms/step - accuracy: 0.4892 - loss: 1.4413 - val_accuracy: 0.4732 - val_loss: 1.4862
```

With the below simple function we will be able to plot our training history.

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
```

[<matplotlib.lines.Line2D at 0x7d7034772230>]



CNN Model

cnn.summary()

```
from tensorflow import keras
from keras.layers import Conv2D, Dense, Flatten, MaxPooling2D, Dropout
cnn = keras.Sequential()
cnn.add(Conv2D(32, kernel_size= (3,3), strides=(1,1), padding='same', activation='relu', input_shape = (32,32,3)))
cnn.add(MaxPooling2D((2,2)))
cnn.add(Conv2D(64, kernel_size= (3,3), strides=(1,1), padding='same', activation='relu'))
cnn.add(MaxPooling2D((2,2)))
cnn.add(Conv2D(128, kernel_size= (3,3), strides=(1,1), padding='same', activation='relu'))
cnn.add(MaxPooling2D((2,2)))
cnn.add(Conv2D(256, kernel_size= (3,3), strides=(1,1), padding='same', activation='relu'))
cnn.add(MaxPooling2D((2,2)))
cnn.add(Flatten())
cnn.add(Dense(64,activation='relu'))
cnn.add(Dropout(0.3))
cnn.add(Dense(10,activation='softmax'))
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/
       super().__init__(activity_regularizer=activity_regularizer, **kwargs)
    4
```

```
→ Model: "sequential_1"
```

| Layer (type) | Output Shape | Param # |
|---|--------------------|---------|
| conv2d (Conv2D) | (None, 32, 32, 32) | 896 |
| <pre>max_pooling2d (MaxPooling2D)</pre> | (None, 16, 16, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 16, 16, 64) | 18,496 |
| <pre>max_pooling2d_1 (MaxPooling2D)</pre> | (None, 8, 8, 64) | 0 |
| conv2d_2 (Conv2D) | (None, 8, 8, 128) | 73,856 |
| <pre>max_pooling2d_2 (MaxPooling2D)</pre> | (None, 4, 4, 128) | 0 |
| conv2d_3 (Conv2D) | (None, 4, 4, 256) | 295,168 |
| max_pooling2d_3 (MaxPooling2D) | (None, 2, 2, 256) | 0 |
| flatten_1 (Flatten) | (None, 1024) | 0 |
| dense_2 (Dense) | (None, 64) | 65,600 |
| dropout (Dropout) | (None, 64) | 0 |
| dense_3 (Dense) | (None, 10) | 650 |

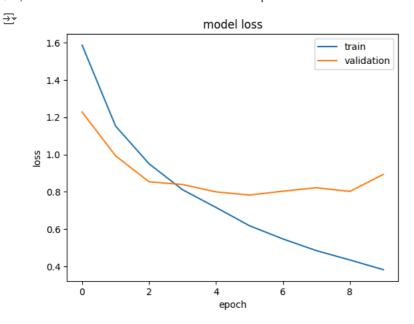
Total params: 454,666 (1.73 MB)
Trainable params: 454,666 (1.73 MB)

```
cnn.compile(loss='sparse_categorical_crossentropy',optimizer='adam',metrics=['accuracy'])
history = cnn.fit(X_train,y_train,epochs=10,validation_data=(X_test,y_test))
```

```
→ Epoch 1/10
    1563/1563
                                  – 187s 118ms/step - accuracy: 0.3167 - loss: 1.8214 - val_accuracy: 0.5587 - val_loss: 1.2280
    Epoch 2/10
    1563/1563
                                  — 185s 118ms/step - accuracy: 0.5706 - loss: 1.2106 - val_accuracy: 0.6520 - val_loss: 0.9928
    Epoch 3/10
    1563/1563
                                  - 219s 130ms/step - accuracy: 0.6603 - loss: 0.9682 - val_accuracy: 0.7083 - val_loss: 0.8535
    Epoch 4/10
    1563/1563
                                  - 246s 119ms/step - accuracy: 0.7151 - loss: 0.8216 - val_accuracy: 0.7161 - val_loss: 0.8389
    Epoch 5/10
    1563/1563 ·
                                  – 219s 130ms/step - accuracy: 0.7556 - loss: 0.7053 - val_accuracy: 0.7320 - val_loss: 0.7995
    Epoch 6/10
    1563/1563
                                  – 250s 123ms/step - accuracy: 0.7906 - loss: 0.6070 - val_accuracy: 0.7352 - val_loss: 0.7822
    Epoch 7/10
    1563/1563 ·
                                  - 192s 116ms/step - accuracy: 0.8193 - loss: 0.5260 - val_accuracy: 0.7431 - val_loss: 0.8031
    Epoch 8/10
    1563/1563
                                  - 202s 117ms/step - accuracy: 0.8389 - loss: 0.4687 - val accuracy: 0.7432 - val loss: 0.8217
    Epoch 9/10
    1563/1563 -
                                  - 183s 117ms/step - accuracy: 0.8573 - loss: 0.4134 - val_accuracy: 0.7554 - val_loss: 0.8017
    Epoch 10/10
    1563/1563
                                  – 183s 117ms/step - accuracy: 0.8731 - loss: 0.3604 - val_accuracy: 0.7501 - val_loss: 0.8933
```

```
def plotLosses(history):
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('model loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.legend(['train', 'validation'], loc='upper right')
    plt.show()
```

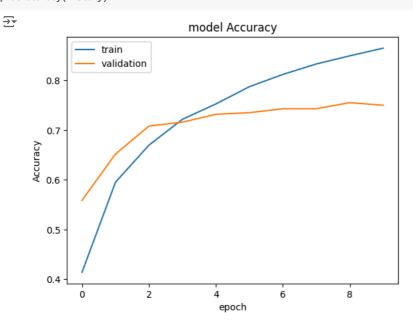
plotLosses(history)



```
def plotAccuracy(history):
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('model Accuracy')
    plt.ylabel('Accuracy')
    plt.xlabel('epoch')

plt.legend(['train', 'validation'], loc='upper left')
    plt.show()
```

plotAccuracy(history)



```
from keras.models import load_model
cnn.save('model111.h5')

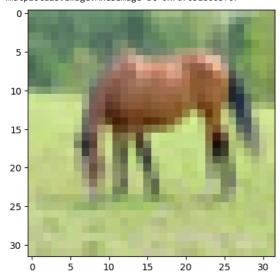
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is or the same of the model model = tf.keras.models.load_model('model111.h5')

WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you will be abstracted to the input the same of the input the same of the input the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you will be abstracted to the input the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you will be input the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you will be import numpy as np # Add a batch dimension to the input the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you will be import numpy as np # Add a batch dimension to the input the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you will be import numpy as np # Add a batch dimension to the input the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you will be import numpy as np # Add a batch dimension to the input the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you will be import numpy as np # Add a batch dimension to the input the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you will be import numpy as np # Add a batch dimension to the input will you will be import numpy as np # Add a batch dimension to the input will you will be import numpy as np # Add a batch dimension to the input will you will be import numpy as np # Add a batch dimension to the input will you will be import numpy as new will be import numpy as np # Add a batch dimension to the input will you will be import numpy as new will be import numpy as new will be import numpy as
```

```
# Now pass it to the model for prediction
model.predict(x_test_sample)
```

plt.imshow(x_test[60])

<matplotlib.image.AxesImage at 0x7d7031866bf0>



```
# Example: if you have class names like this
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck'] # replace with your actual cla
# Get the prediction probabilities
predictions = model.predict(x_test_sample)
# Get the index of the class with the highest probability
predicted_class_index = np.argmax(predictions)
# Get the corresponding class name
predicted_class_name = class_names[predicted_class_index]
print(f"The predicted class is: {predicted_class_name}")
```