

Program 3: CIFAR-10

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Course: MCA B (AI & DS)

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```
In [1]: import tensorflow as tf
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPooling2D
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt
```

```
In [ ]: # Load cifar10 dataset using cifar10 dataset module
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
#saving it as training set and test set( split it as )
```

```
In [ ]: x_train.shape
#50000 images of 32x32 pixels in training set
```

```
Out[ ]: (50000, 32, 32, 3)
```

```
In [4]: x_test.shape
#10000 images of 32x32 pixels in test set)
```

```
Out[4]: (10000, 32, 32, 3)
```

```
In [5]: print(y_test)
```

```
#labels of test set
```

```
[[3]
[8]
[8]
...
[5]
[1]
[7]]
```

```
In [6]: #Displaying Sample Images from the MNIST Dataset
# Select random indices for displaying images
import numpy as np
indices = np.random.randint(0, x_train.shape[0], size=16)
```

```
In [7]: # Create a figure and subplots
fig, axes = plt.subplots(4, 4, figsize=(5, 5))

# Flatten the axes array for easy iteration
axes = axes.flatten()

for i, ax in enumerate(axes):
    image = x_train[indices[i]]
    label = y_train[indices[i]]
```

```

    ax.imshow(image)
    ax.set_title(f"Label: {label}")
    ax.axis('off')

plt.tight_layout()
plt.show()

```

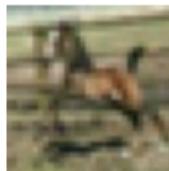
Label: [5]



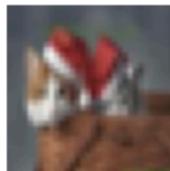
Label: [4]



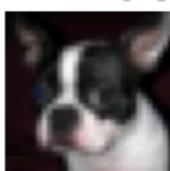
Label: [7]



Label: [3]



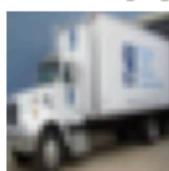
Label: [5]



Label: [1]



Label: [9]



Label: [5]



Label: [4]



Label: [7]



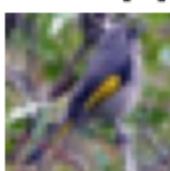
Label: [2]



Label: [8]



Label: [2]



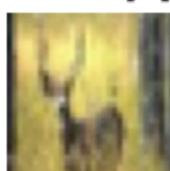
Label: [1]



Label: [9]



Label: [4]



In [8]:

```

# Reshape data for CNN input
#CNNs expect input data to have a specific shape, typically (num_samples, img_rows, img_cols = 32, 32
x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 3) #shape[0] = height
x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 3)

```

In [9]:

```

x_train.shape
#x_test.shape
#1 stands for 1 channel , if color images we will have 3 channels (RGB)

```

Out[9]: (50000, 32, 32, 3)

In [10]:

```

# Normalize pixel values to be between 0 and 1
x_train = x_train / 255.0 # To normalize the pixel values, we divide by 255 (the maximum value of a pixel)
x_test = x_test / 255.0

```

In [11]:

```

# Convert class vectors to binary class matrices

num_classes = 10 # Number of classes in the CIFAR-10 dataset
y_train = to_categorical(y_train, num_classes) #1 hotencoding the labels
y_test = to_categorical(y_test, num_classes)

```

```
In [12]: print(y_test)
```

```
[[0. 0. 0. ... 0. 0. 0.]  
[0. 0. 0. ... 0. 1. 0.]  
[0. 0. 0. ... 0. 1. 0.]  
...  
[0. 0. 0. ... 0. 0. 0.]  
[0. 1. 0. ... 0. 0. 0.]  
[0. 0. 0. ... 1. 0. 0.]]
```

```
In [13]: # Create a CNN model
```

```
model = Sequential()# 32 kernels , general we choose odd dimension for kernal size  
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', strides=(1,1),padding='same'))#32 kernels  
model.add(MaxPooling2D(pool_size=(2, 2)))#2 x 2 blank kernal  
model.add(Flatten()) # only 1 convolution Layer and 1 pooling layer, so we need  
model.add(Dense(128, activation='relu'))#128 neurons or any no of neurons THIS IS  
model.add(Dense(num_classes, activation='softmax'))#according to the no of neurons
```

```
c:\Users\user\Desktop\MCA AI DS 2027\S2\Deep Learning\Lab\tfenv\lib\site-packages  
\keras\src\layers\convolutional\base_conv.py:113: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.  
    super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
In [14]: # Compile the model
```

```
model.compile(loss='categorical_crossentropy', optimizer='adamw', metrics=['accuracy'])  
#this is a classification Problem so we use categorical_crossentropy as the loss  
# 2 class classification , them binary_crossentropy use karte hai  
# advanced optimizers : RMSprop, Adam, Adagrad, Adadelta  
#accuracy to evaluate the model , trained well or not
```

```
In [15]: # Train the model
```

```
#model.fit() standard attributes  
# history variable will store the training history, which includes the Loss and  
# Trying to train model with x_train and y_train , batch size of 128 each , total  
#epoch = can be decided by us ,  
#get trained batch wise , accuracy is the training set accuracy , then the test  
history=model.fit(x_train, y_train, batch_size=128, epochs=10, verbose=1, validation
```

```
Epoch 1/10
391/391 19s 44ms/step - accuracy: 0.4556 - loss: 1.5351 - va
l_accuracy: 0.5266 - val_loss: 1.3118
Epoch 2/10
391/391 16s 42ms/step - accuracy: 0.5694 - loss: 1.2254 - va
l_accuracy: 0.5655 - val_loss: 1.2207
Epoch 3/10
391/391 19s 48ms/step - accuracy: 0.6120 - loss: 1.1096 - va
l_accuracy: 0.5933 - val_loss: 1.1809
Epoch 4/10
391/391 18s 45ms/step - accuracy: 0.6473 - loss: 1.0159 - va
l_accuracy: 0.6184 - val_loss: 1.0904
Epoch 5/10
391/391 18s 45ms/step - accuracy: 0.6699 - loss: 0.9462 - va
l_accuracy: 0.6213 - val_loss: 1.0960
Epoch 6/10
391/391 17s 44ms/step - accuracy: 0.6894 - loss: 0.8982 - va
l_accuracy: 0.6372 - val_loss: 1.0390
Epoch 7/10
391/391 17s 44ms/step - accuracy: 0.7074 - loss: 0.8405 - va
l_accuracy: 0.6388 - val_loss: 1.0398
Epoch 8/10
391/391 17s 43ms/step - accuracy: 0.7209 - loss: 0.8000 - va
l_accuracy: 0.6546 - val_loss: 0.9978
Epoch 9/10
391/391 17s 44ms/step - accuracy: 0.7425 - loss: 0.7447 - va
l_accuracy: 0.6476 - val_loss: 1.0336
Epoch 10/10
391/391 18s 45ms/step - accuracy: 0.7554 - loss: 0.7076 - va
l_accuracy: 0.6532 - val_loss: 1.0057
```

In [16]: `model.summary()`

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 32)	896
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
flatten (Flatten)	(None, 8192)	0
dense (Dense)	(None, 128)	1,048,704
dense_1 (Dense)	(None, 10)	1,290

Total params: 3,152,672 (12.03 MB)
Trainable params: 1,050,890 (4.01 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 2,101,782 (8.02 MB)

In [17]: `# Evaluate the model on the test set
test_loss, test_acc = model.evaluate(x_test, y_test)
print('Test accuracy:', test_acc)`

```
313/313 ━━━━━━━━ 1s 4ms/step - accuracy: 0.6532 - loss: 1.0057
Test accuracy: 0.6531999707221985
```

```
In [18]: plt.figure(figsize=(14, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')

plt.savefig('./foo.png')
plt.show()
```

