DEEP LEARNING PROJECT

IMPLEMENT A DEEP LEARNING MODEL FOR IMAGE CLASSIFICATION OR NATURAL LANGUAGE PROCESSING USING TENSORFLOW OR PYTORCH

IMPORTING LIBRARIES & LOADING DATASET

```
import tensorflow as tf
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt
import numpy as np
```

```
print("Loading CIFAR-10 dataset...")
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
```

```
Loading CIFAR-10 dataset...
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 3s 0us/step
```

NORMALISATION

```
x_train, x_test = x_train / 255.0, x_test / 255.0
```

```
class_names = ['airplane','automobile','bird','cat','deer',
               'dog','frog','horse','ship','truck']
```

Sample images

```
plt.figure(figsize=(10, 5))
for i in range(10):
    plt.subplot(2, 5, i+1)
    plt.imshow(x_train[i])
    plt.title(class_names[y_train[i][0]])
    plt.axis("off")
plt.show()
```

BUILD CNN MODEL

```
model = models.Sequential([
    layers.Conv2D(32, (3,3), activation='relu', input_shape=(32, 32, 3)),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64, (3,3), activation='relu'),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64, (3,3), activation='relu'),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(10)
])
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`inpu
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

SUMMARY

```
model.summary()
```

```
Model: "sequential"
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃       Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━┩
│ conv2d (Conv2D)                 │ (None, 30, 30, 32)     │           896 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ max_pooling2d (MaxPooling2D)    │ (None, 15, 15, 32)     │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_1 (Conv2D)               │ (None, 13, 13, 64)     │        18,496 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ max_pooling2d_1 (MaxPooling2D)  │ (None, 6, 6, 64)       │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_2 (Conv2D)               │ (None, 4, 4, 64)       │        36,928 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ flatten (Flatten)               │ (None, 1024)           │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense (Dense)                   │ (None, 64)             │        65,600 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_1 (Dense)                 │ (None, 10)             │           650 │
└─────────────────────────────────┴────────────────────────┴───────────────┘
 Total params: 122,570 (478.79 KB)
 Trainable params: 122,570 (478.79 KB)
 Non-trainable params: 0 (0.00 B)
```

COMPILE MODEL

```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

TRAIN MODEL

```
history = model.fit(x_train, y_train, epochs=10,
                    validation_data=(x_test, y_test))
```

```
Epoch 1/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 67s 42ms/step - accuracy: 0.3393 - loss: 1.7783 - val_accuracy: 0.5500 - val_loss: 1.2486
Epoch 2/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 79s 40ms/step - accuracy: 0.5750 - loss: 1.1929 - val_accuracy: 0.6182 - val_loss: 1.0668
Epoch 3/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 81s 40ms/step - accuracy: 0.6429 - loss: 1.0176 - val_accuracy: 0.6446 - val_loss: 1.0043
Epoch 4/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 61s 39ms/step - accuracy: 0.6804 - loss: 0.9083 - val_accuracy: 0.6844 - val_loss: 0.9207
Epoch 5/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 83s 40ms/step - accuracy: 0.7149 - loss: 0.8213 - val_accuracy: 0.6953 - val_loss: 0.8870
Epoch 6/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 62s 40ms/step - accuracy: 0.7336 - loss: 0.7623 - val_accuracy: 0.6985 - val_loss: 0.8695
Epoch 7/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 81s 39ms/step - accuracy: 0.7499 - loss: 0.7090 - val_accuracy: 0.7029 - val_loss: 0.8542
Epoch 8/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 82s 39ms/step - accuracy: 0.7649 - loss: 0.6699 - val_accuracy: 0.7041 - val_loss: 0.8660
Epoch 9/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 82s 39ms/step - accuracy: 0.7845 - loss: 0.6170 - val_accuracy: 0.7134 - val_loss: 0.8483
```

```
Epoch 10/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 61s 39ms/step - accuracy: 0.7932 - loss: 0.5867 - val_accuracy: 0.7162 - val_loss: 0.8501
```

EVALUATE MODEL

```
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=2)
print(f'\nTest Accuracy: {test_acc*100:.2f}%')
```

```
313/313 - 3s - 10ms/step - accuracy: 0.7162 - loss: 0.8501

Test Accuracy: 71.62%
```

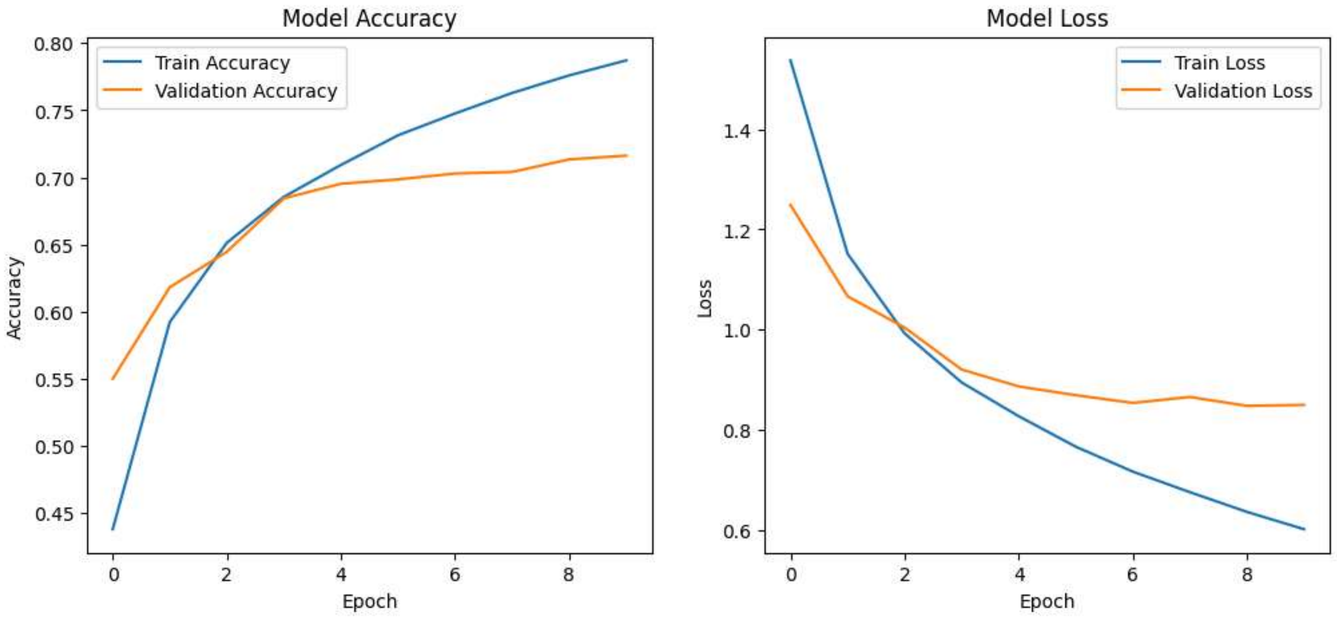
VISUALIZE TRAINING RESULTS

```
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.show()
```


Model Accuracy
Train Accuracy
Validation Accuracy
Accuracy
Epoch
Model Loss
Train Loss
Validation Loss
Loss
Epoch