Experiment No 10

Title : Cifar10 classification with and without normalization CNN as classification model for the Cifar10 dataset CNN as classification model for the Cifar10 dataset

Aim: To compare the performance of a Convolutional Neural Network (CNN) on the CIFAR-10 dataset with and without data normalization. The objective is to observe the impact of normalization on training efficiency, model accuracy, and loss.

Theory: Convolutional Neural Networks (CNNs):

CNNs are a class of deep learning models specifically designed for processing and analyzing grid-like data, such as images. They have been highly successful in image classification tasks due to their ability to automatically learn hierarchical features directly from raw pixel data.

Key Components of CNNs:

Convolutional Layers: These layers apply filters (kernels) to the input data to detect local patterns such as edges and textures. The learned features become more abstract as the network gets deeper.

Pooling Layers: Used to reduce the spatial dimensions (width and height) of the feature maps. Max pooling and average pooling are the most common types.

Activation Functions: ReLU (Rectified Linear Unit) is widely used to introduce non-linearity into the model, which helps the network learn complex patterns.

Fully Connected Layers: These layers are typically added after several convolutional and pooling layers to output class scores (for classification tasks).

Softmax Layer: At the output layer, softmax is commonly used for multi-class classification tasks, such as the CIFAR-10 dataset, which consists of 10 categories.

CIFAR-10 Dataset:

The CIFAR-10 dataset consists of 60,000 32x32 color images in 10 classes (airplanes, cars, birds, cats, deer, dogs, frogs, horses, ships, and trucks), with 6,000 images per class. The dataset is divided into 50,000 training images and 10,000 test images.

Data Normalization:

Normalization is a common preprocessing step in deep learning models. It involves rescaling the pixel values to a standard range (usually between 0 and 1) or transforming the data to have zero mean and unit variance. This step helps in improving the convergence rate during training and stabilizing the learning process.

Without Normalization: The raw pixel values range between 0 and 255, which can result in large gradients during backpropagation, leading to unstable updates of the weights.

With Normalization: Pixel values are rescaled to a range of [0, 1] by dividing each value by 255. This scaling ensures that the network's gradients remain small and consistent, which often results in faster convergence and improved accuracy.

Conclusion:

Comparing the performance of the CNN on CIFAR-10 with and without normalization allows us to understand the importance of data preprocessing in deep learning. Normalization helps in stabilizing training, achieving better accuracy, and faster convergence in comparison to training on raw pixel values.

CNN on CIFAR-10 Dataset

Import necessary libraries

In [12]:
```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt
```

Load and preprocess the CIFAR-10 dataset#

In [2]:
```
# Load the CIFAR-10 dataset
(X_train, Y_train), (X_test, Y_test) = datasets.cifar10.load_data()

# Normalize pixel values to be between 0 and 1
X_train, X_test = X_train / 255.0, X_test / 255.0

# Print the shapes of the dataset
print(f'Training data shape: {X_train.shape}, Training labels shape: {Y_train.shape}')
print(f'Test data shape: {X_test.shape}, Test labels shape: {Y_test.shape}')
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz (https://www.cs.toronto.ed
u/~kriz/cifar-10-python.tar.gz)
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 676s 4us/step
Training data shape: (50000, 32, 32, 3), Training labels shape: (50000, 1)
Test data shape: (10000, 32, 32, 3), Test labels shape: (10000, 1)
```

In [6]:
```
# Build a CNN model
model = models.Sequential([
    # First convolutional layer with 32 filters, 3x3 kernel, and ReLU activation
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)),
    layers.MaxPooling2D((2, 2)),  # Max pooling layer
    # Second convolutional layer
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),  # Max pooling layer
    # Third convolutional layer
    layers.Conv2D(64, (3, 3), activation='relu'),

    # Flatten the feature maps and connect to a dense layer
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(10, activation='softmax')  # Output layer for 10 classes
])
```

In [7]:
```
# Print the model summary
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_2 (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_4 (Conv2D)	(None, 13, 13, 64)	18,496
max_pooling2d_3 (MaxPooling2D)	(None, 6, 6, 64)	0
conv2d_5 (Conv2D)	(None, 4, 4, 64)	36,928
flatten_1 (Flatten)	(None, 1024)	0
dense_2 (Dense)	(None, 64)	65,600
dense_3 (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 the model

In [8]:
```
# Compile the model with an optimizer, loss function, and performance metrics
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Train the model

In [9]:
```
# Train the model on the training data
history = model.fit(X_train, Y_train, epochs=10,
                    validation_data=(X_test, Y_test))
```

```
Epoch 1/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 32s 16ms/step - accuracy: 0.3526 - loss: 1.7425 - val_accuracy: 0.5635 -
val_loss: 1.2154
Epoch 2/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 23s 15ms/step - accuracy: 0.5880 - loss: 1.1658 - val_accuracy: 0.6297 -
val_loss: 1.0609
Epoch 3/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 21s 14ms/step - accuracy: 0.6531 - loss: 0.9846 - val_accuracy: 0.6669 -
val_loss: 0.9618
Epoch 4/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 22s 14ms/step - accuracy: 0.6973 - loss: 0.8634 - val_accuracy: 0.6950 -
val_loss: 0.8949
Epoch 5/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 21s 14ms/step - accuracy: 0.7207 - loss: 0.7974 - val_accuracy: 0.7071 -
val_loss: 0.8498
Epoch 6/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 22s 14ms/step - accuracy: 0.7442 - loss: 0.7277 - val_accuracy: 0.7073 -
val_loss: 0.8507
Epoch 7/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 22s 14ms/step - accuracy: 0.7649 - loss: 0.6692 - val_accuracy: 0.7175 -
val_loss: 0.8253
Epoch 8/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 22s 14ms/step - accuracy: 0.7807 - loss: 0.6251 - val_accuracy: 0.7183 -
val_loss: 0.8316
Epoch 9/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 22s 14ms/step - accuracy: 0.7935 - loss: 0.5827 - val_accuracy: 0.7210 -
val_loss: 0.8423
Epoch 10/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 23s 15ms/step - accuracy: 0.8094 - loss: 0.5402 - val_accuracy: 0.7158 -
val_loss: 0.8467
```

Evaluate the model

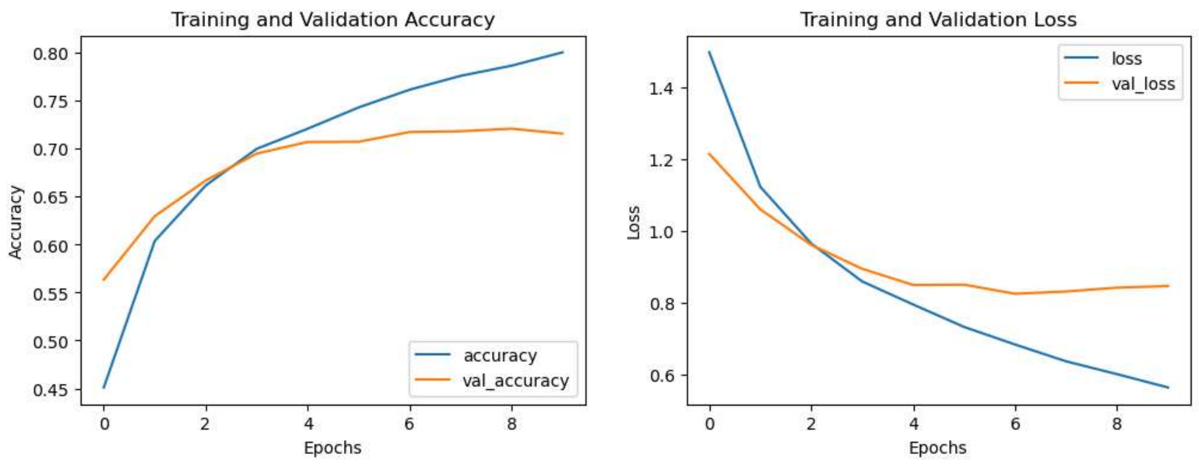
In [39]:
```
# Evaluate the model on the test dataset
test_loss, test_acc = model.evaluate(X_test, Y_test, verbose=2)
print(f'Test accuracy: {test_acc*100}')
```

```
313/313 - 3s - 9ms/step - accuracy: 0.7158 - loss: 0.8467
Test accuracy: 71.57999873161316
```

Visualize training results

In [13]:

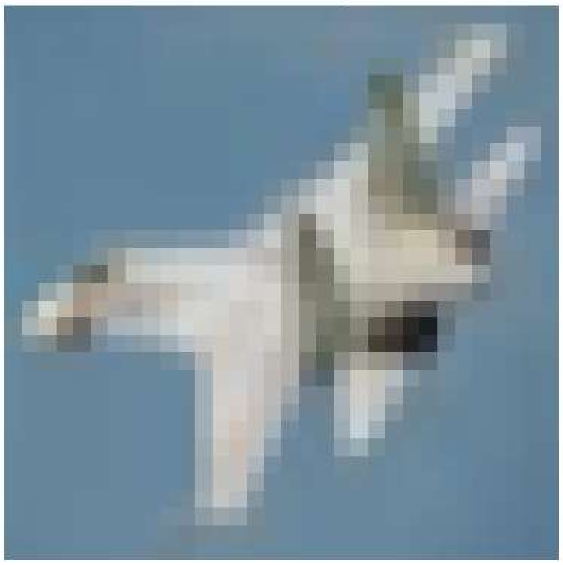
```
# Plot the accuracy and loss curves
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

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

plt.show()
```



Sample Classification

In [32]:
```
import numpy as np
import matplotlib.pyplot as plt

#dictionary to map label indices to class labels
class_names = {0: 'airplane', 1: 'automobile', 2: 'bird', 3: 'cat',
               4: 'deer', 5: 'dog', 6: 'frog', 7: 'horse',
               8: 'ship', 9: 'truck'}

# Select a specific example from the test dataset (e.g., the 10th image)
example_index = 10  # You can change this index to any number between 0 and 9999

# Extract the selected test image and its true label
example_image = X_test[example_index]
true_label_index = Y_test[example_index][0]  # Flatten the label index
true_label_name = class_names[true_label_index]  # Get the class name

# Display the selected image clearly
plt.imshow(example_image)
plt.title(f'True Label: {true_label_name}')
plt.axis('off')  # Turn off the axis to make the image display cleaner
plt.show()
```

True Label: airplane



In [33]:
```
# Reshape the image to match the input shape expected by the model
example_image_reshaped = np.expand_dims(example_image, axis=0)  # Add a batch dimension

# Use the trained model to predict the class
predicted_probs = model.predict(example_image_reshaped)

# Get the predicted class by finding the index with the highest probability
predicted_label_index = np.argmax(predicted_probs)
predicted_label_name = class_names[predicted_label_index]

print(f'Predicted Label: {predicted_label_name}')
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
Predicted Label: airplane
```

In [34]:
```
# Compare the true label with the predicted label
if predicted_label_index == true_label_index:
    print(f"Correct! The model predicted {predicted_label_name} and the true label is {true_label_name}."
else:
    print(f"Incorrect! The model predicted {predicted_label_name} but the true label is {true_label_name}
```

```
Correct! The model predicted airplane and the true label is airplane.
```