```python
import tensorflow as tf
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical

# Load dataset
(x_train_full, y_train_full), (x_test, y_test) = cifar10.load_data()

# Normalize pixel values to [0, 1]
x_train_full, x_test = x_train_full / 255.0, x_test / 255.0

# Split training data into training (60%) and validation (20%)
x_train, x_val = x_train_full[:30000], x_train_full[30000:]
y_train, y_val = y_train_full[:30000], y_train_full[30000:]

# One-hot encode labels
y_train = to_categorical(y_train)
y_val = to_categorical(y_val)
y_test = to_categorical(y_test)
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 4s 0us/step
```

```python
import torch
import torchvision
import torchvision.transforms as transforms

# Define transforms including data augmentation
transform_train = transforms.Compose([
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.RandomResizedCrop(32),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
])

transform_test = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
])

# Load datasets
train_dataset = torchvision.datasets.CIFAR10(root='./data',
train=True, download=True, transform=transform_train)
test_dataset = torchvision.datasets.CIFAR10(root='./data',
train=False, download=True, transform=transform_test)

# Split train dataset into training and validation
train_size = int(0.6 * len(train_dataset))
val_size = len(train_dataset) - train_size
```

```
train_dataset, val_dataset =
torch.utils.data.random_split(train_dataset, [train_size, val_size])

train_loader = torch.utils.data.DataLoader(train_dataset,
batch_size=64, shuffle=True)
val_loader = torch.utils.data.DataLoader(val_dataset, batch_size=64,
shuffle=False)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=64,
shuffle=False)
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to
./data/cifar-10-python.tar.gz

100%|██████████| 170M/170M [00:02<00:00, 66.5MB/s]

Extracting ./data/cifar-10-python.tar.gz to ./data
Files already downloaded and verified
```

```
from tensorflow.keras import layers, models, regularizers

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.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.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`/`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)
```

```
model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])
history = model.fit(x_train, y_train, epochs=20, batch_size=64,
validation_data=(x_val, y_val))
```

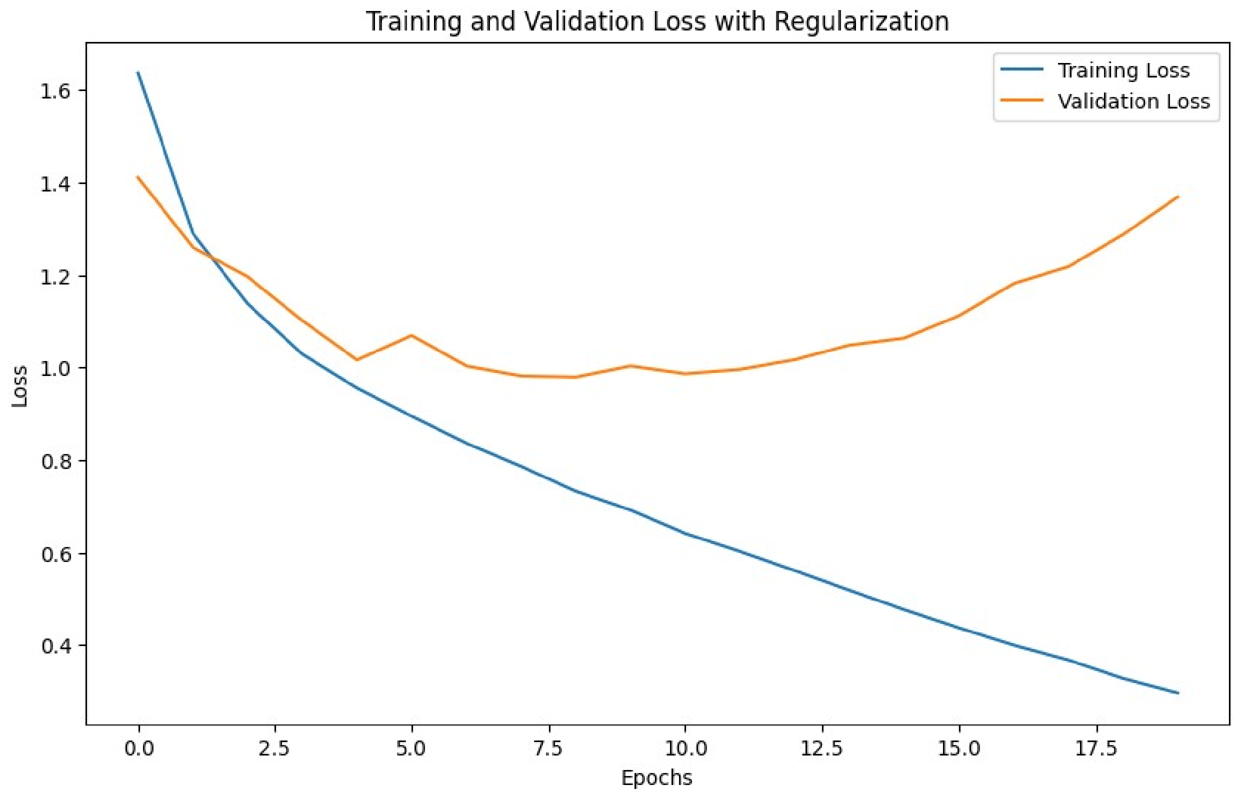
```
Epoch 1/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 52s 107ms/step - accuracy: 0.3168 - loss:
1.8542 - val_accuracy: 0.4968 - val_loss: 1.4103
Epoch 2/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 76s 95ms/step - accuracy: 0.5311 - loss:
1.3122 - val_accuracy: 0.5557 - val_loss: 1.2596
Epoch 3/20
```

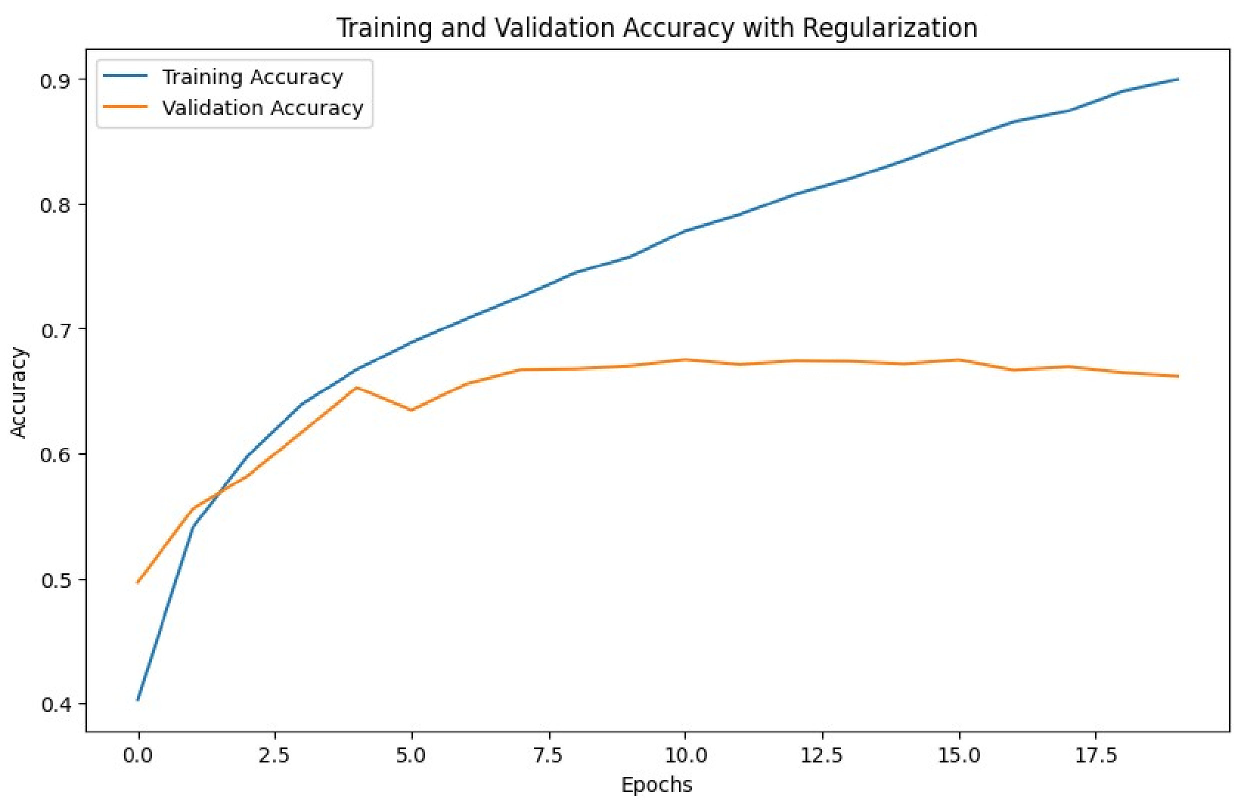
```
469/469 ━━━━━━━━━━━━━━━━━━━━ 44s 95ms/step - accuracy: 0.5896 - loss:
1.1606 - val_accuracy: 0.5820 - val_loss: 1.1960
Epoch 4/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 44s 94ms/step - accuracy: 0.6361 - loss:
1.0358 - val_accuracy: 0.6172 - val_loss: 1.1011
Epoch 5/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 95ms/step - accuracy: 0.6584 - loss:
0.9734 - val_accuracy: 0.6528 - val_loss: 1.0161
Epoch 6/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 45s 97ms/step - accuracy: 0.6921 - loss:
0.8828 - val_accuracy: 0.6348 - val_loss: 1.0690
Epoch 7/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 81s 94ms/step - accuracy: 0.7103 - loss:
0.8352 - val_accuracy: 0.6557 - val_loss: 1.0030
Epoch 8/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 83s 96ms/step - accuracy: 0.7314 - loss:
0.7777 - val_accuracy: 0.6672 - val_loss: 0.9815
Epoch 9/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 95ms/step - accuracy: 0.7483 - loss:
0.7261 - val_accuracy: 0.6678 - val_loss: 0.9792
Epoch 10/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 48s 101ms/step - accuracy: 0.7577 - loss:
0.6834 - val_accuracy: 0.6701 - val_loss: 1.0029
Epoch 11/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 80s 98ms/step - accuracy: 0.7835 - loss:
0.6279 - val_accuracy: 0.6752 - val_loss: 0.9863
Epoch 12/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 44s 95ms/step - accuracy: 0.8002 - loss:
0.5887 - val_accuracy: 0.6712 - val_loss: 0.9956
Epoch 13/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 95ms/step - accuracy: 0.8156 - loss:
0.5387 - val_accuracy: 0.6742 - val_loss: 1.0167
Epoch 14/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 95ms/step - accuracy: 0.8263 - loss:
0.5022 - val_accuracy: 0.6738 - val_loss: 1.0480
Epoch 15/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 96ms/step - accuracy: 0.8400 - loss:
0.4599 - val_accuracy: 0.6716 - val_loss: 1.0632
Epoch 16/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 46s 99ms/step - accuracy: 0.8615 - loss:
0.4141 - val_accuracy: 0.6751 - val_loss: 1.1114
Epoch 17/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 80s 96ms/step - accuracy: 0.8716 - loss:
0.3811 - val_accuracy: 0.6668 - val_loss: 1.1811
Epoch 18/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 81s 94ms/step - accuracy: 0.8846 - loss:
0.3468 - val_accuracy: 0.6695 - val_loss: 1.2176
Epoch 19/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 95ms/step - accuracy: 0.8958 - loss:
```

```
0.3159 - val_accuracy: 0.6648 - val_loss: 1.2871
Epoch 20/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 95ms/step - accuracy: 0.9111 - loss:
0.2708 - val_accuracy: 0.6619 - val_loss: 1.3683
```

without regularization

```
import tensorflow as tf
from tensorflow.keras import layers, models, regularizers
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss with Regularization')
plt.show()

# Plot training and validation accuracy
plt.figure(figsize=(10, 6))
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Training and Validation Accuracy with Regularization')
plt.show()
```





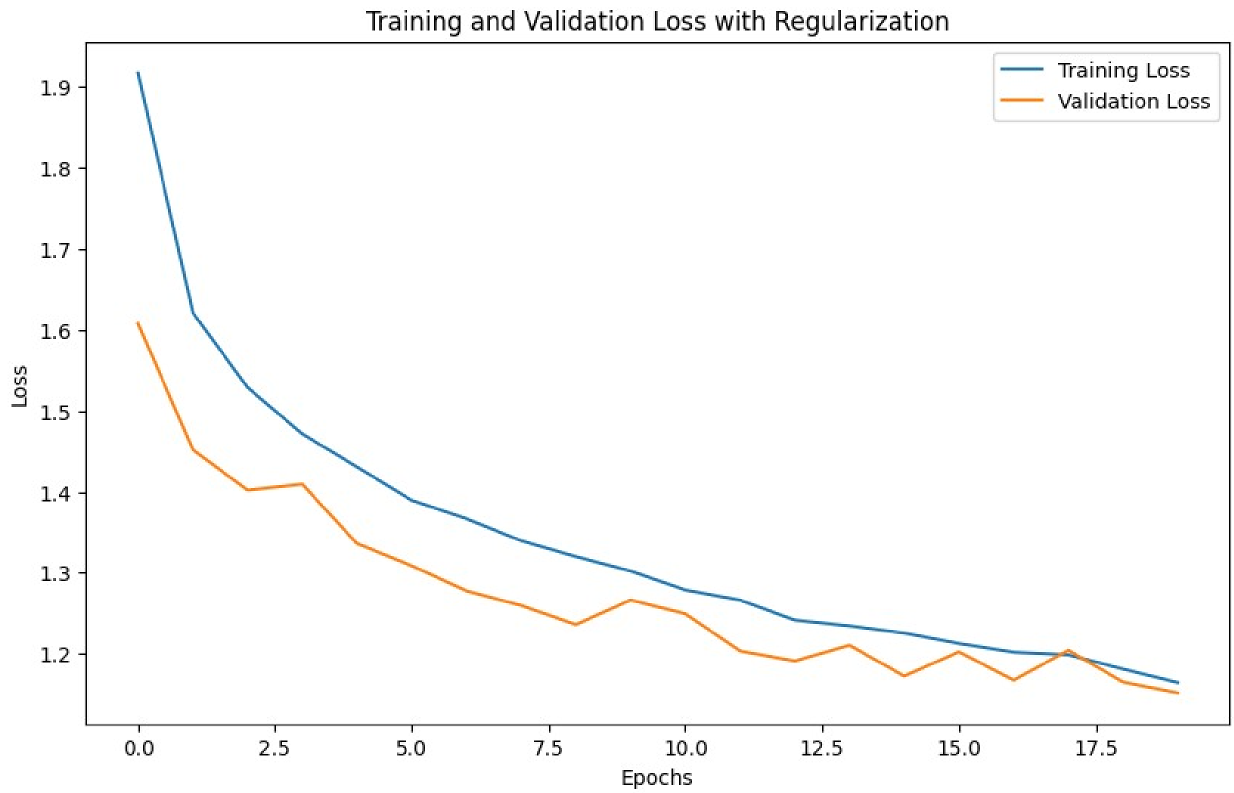
Step 4: Implement Regularization

```python
# Define CNN model with L2 Regularization and Dropout
def build_model():
    model = models.Sequential()

    # Convolutional Layer 1
    model.add(layers.Conv2D(32, (3, 3), activation='relu',
                            kernel_regularizer=regularizers.l2(0.001),
                            input_shape=(32, 32, 3)))
    model.add(layers.MaxPooling2D((2, 2)))

    # Convolutional Layer 2
    model.add(layers.Conv2D(64, (3, 3), activation='relu',

kernel_regularizer=regularizers.l2(0.001)))
    model.add(layers.MaxPooling2D((2, 2)))

    # Flatten Layer
    model.add(layers.Flatten())

    # Fully Connected Layer
    model.add(layers.Dense(128, activation='relu',
                           kernel_regularizer=regularizers.l2(0.001)))

    # Dropout Layer
    model.add(layers.Dropout(0.5))

    # Output Layer
    model.add(layers.Dense(10, activation='softmax'))

    return model


# Compile the model
model = build_model()
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
history = model.fit(x_train, y_train, epochs=20, batch_size=64,
                    validation_data=(x_val, y_val))
```

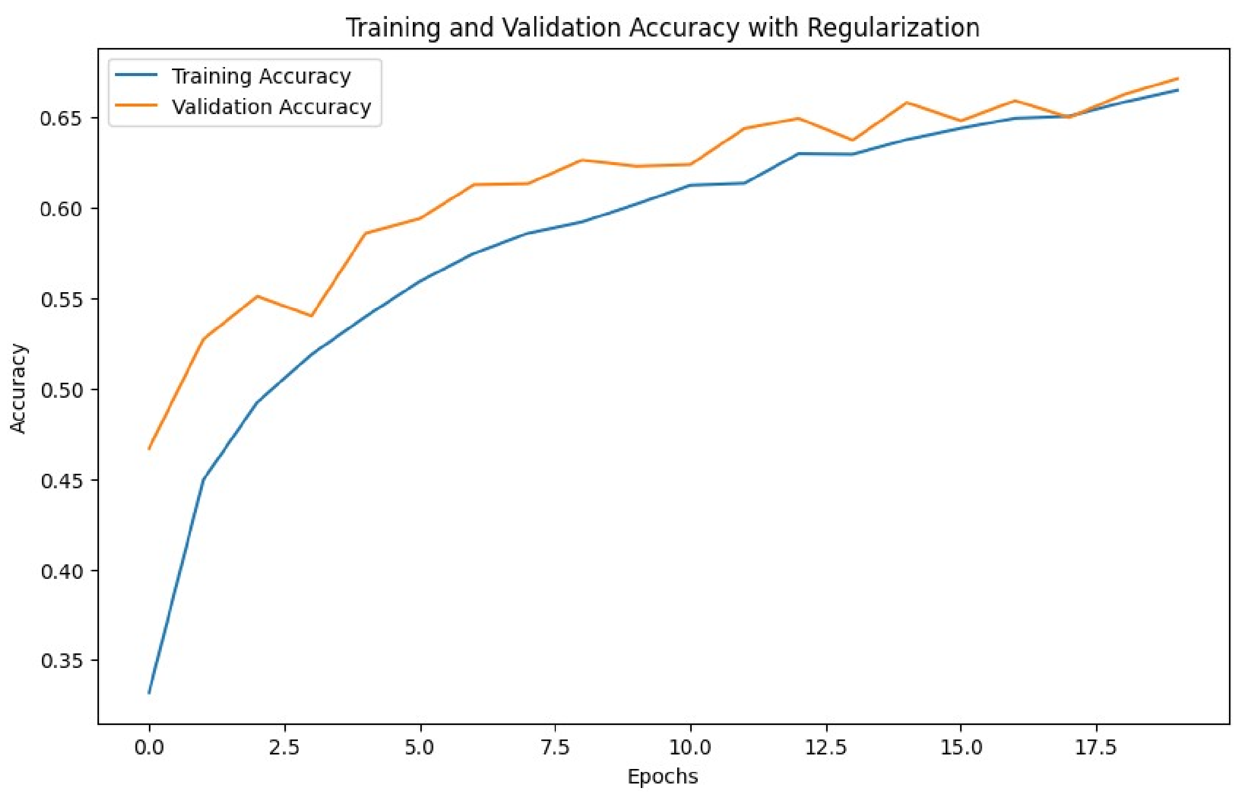
```
Epoch 1/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 49s 100ms/step - accuracy: 0.2612 - loss:
2.1188 - val_accuracy: 0.4669 - val_loss: 1.6078
Epoch 2/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 48s 102ms/step - accuracy: 0.4343 - loss:
1.6488 - val_accuracy: 0.5273 - val_loss: 1.4520
```

```
Epoch 3/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 80s 98ms/step - accuracy: 0.4887 - loss:
1.5423 - val_accuracy: 0.5511 - val_loss: 1.4020
Epoch 4/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 48s 102ms/step - accuracy: 0.5175 - loss:
1.4774 - val_accuracy: 0.5402 - val_loss: 1.4093
Epoch 5/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 80s 98ms/step - accuracy: 0.5335 - loss:
1.4364 - val_accuracy: 0.5860 - val_loss: 1.3361
Epoch 6/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 84s 102ms/step - accuracy: 0.5582 - loss:
1.3836 - val_accuracy: 0.5940 - val_loss: 1.3086
Epoch 7/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 46s 97ms/step - accuracy: 0.5701 - loss:
1.3727 - val_accuracy: 0.6128 - val_loss: 1.2776
Epoch 8/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 46s 97ms/step - accuracy: 0.5885 - loss:
1.3303 - val_accuracy: 0.6133 - val_loss: 1.2595
Epoch 9/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 98ms/step - accuracy: 0.5916 - loss:
1.3094 - val_accuracy: 0.6265 - val_loss: 1.2360
Epoch 10/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 99ms/step - accuracy: 0.6064 - loss:
1.2883 - val_accuracy: 0.6230 - val_loss: 1.2662
Epoch 11/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 81s 97ms/step - accuracy: 0.6117 - loss:
1.2739 - val_accuracy: 0.6240 - val_loss: 1.2493
Epoch 12/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 45s 96ms/step - accuracy: 0.6152 - loss:
1.2593 - val_accuracy: 0.6439 - val_loss: 1.2033
Epoch 13/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 83s 98ms/step - accuracy: 0.6337 - loss:
1.2204 - val_accuracy: 0.6495 - val_loss: 1.1909
Epoch 14/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 83s 100ms/step - accuracy: 0.6288 - loss:
1.2269 - val_accuracy: 0.6375 - val_loss: 1.2104
Epoch 15/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 80s 97ms/step - accuracy: 0.6428 - loss:
1.2114 - val_accuracy: 0.6582 - val_loss: 1.1724
Epoch 16/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 83s 100ms/step - accuracy: 0.6449 - loss:
1.2037 - val_accuracy: 0.6482 - val_loss: 1.2023
Epoch 17/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 46s 97ms/step - accuracy: 0.6538 - loss:
1.1890 - val_accuracy: 0.6593 - val_loss: 1.1673
Epoch 18/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 86s 106ms/step - accuracy: 0.6611 - loss:
1.1788 - val_accuracy: 0.6500 - val_loss: 1.2042
Epoch 19/20
```

```
469/469 ━━━━━━━━━━━━━━━━━━━━ 79s 100ms/step - accuracy: 0.6668 - loss:
1.1574 - val_accuracy: 0.6626 - val_loss: 1.1650
Epoch 20/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 101ms/step - accuracy: 0.6690 - loss:
1.1532 - val_accuracy: 0.6715 - val_loss: 1.1516

# Evaluate the model
test_loss, test_accuracy = model.evaluate(x_test, y_test)
print(f"Test Loss: {test_loss}, Test Accuracy: {test_accuracy}")

# Plot training and validation loss
plt.figure(figsize=(10, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss with Regularization')
plt.show()

# Plot training and validation accuracy
plt.figure(figsize=(10, 6))
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Training and Validation Accuracy with Regularization')
plt.show()

313/313 ━━━━━━━━━━━━━━━━━━━━ 5s 16ms/step - accuracy: 0.6765 - loss:
1.1458
Test Loss: 1.1531802415847778, Test Accuracy: 0.67330002784729
```



Training and Validation Loss with Regularization
Training Loss
Validation Loss
Loss
Epochs
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5



Training and Validation Accuracy with Regularization
Training Accuracy
Validation Accuracy
Accuracy
Epochs
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

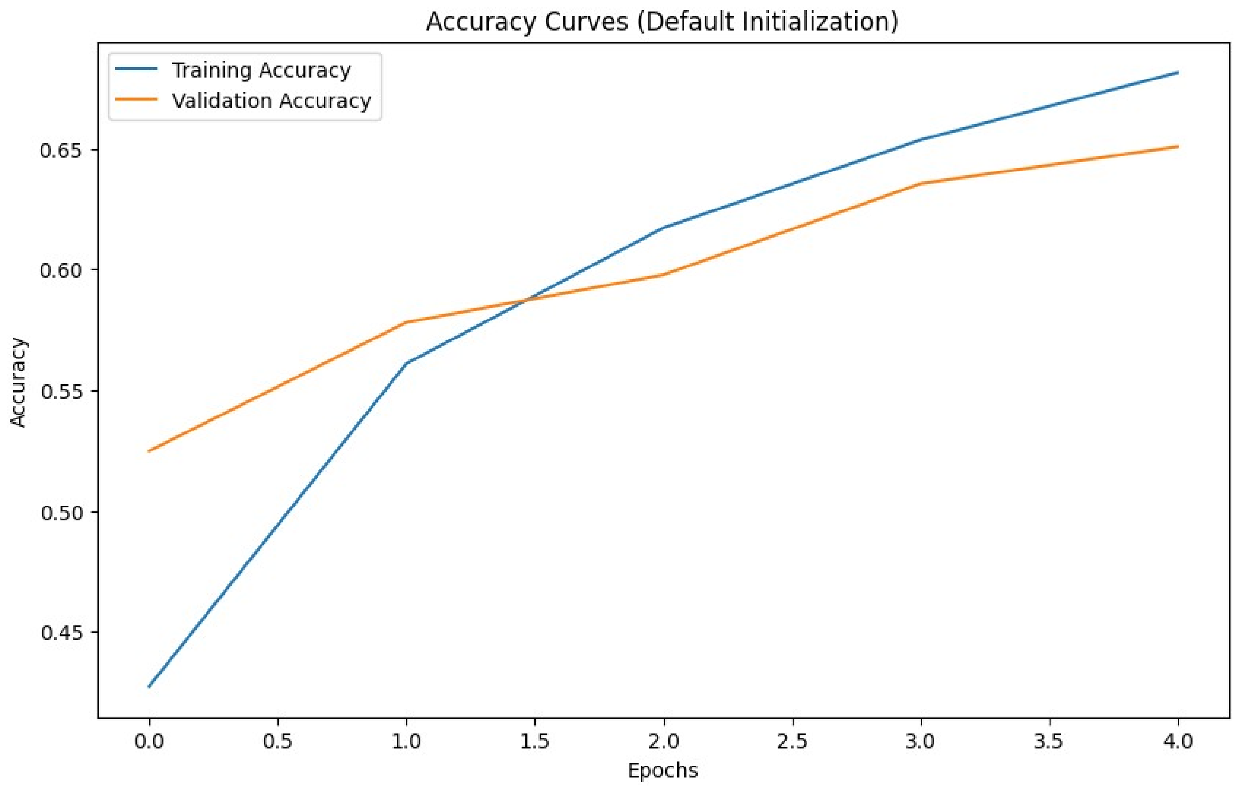
1. Weight Initialization: o Experiment with different weight initialization methods: Default initialization Xavier (Glorot) Initialization He Initialization

```
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt

# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Normalize the data
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

# One-hot encode the labels
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)

# Split dataset into training, validation, and test sets
x_train, x_val = x_train[:30000], x_train[30000:]
y_train, y_val = y_train[:30000], y_train[30000:]

# Build the CNN Model with Variable Weight Initialization
def build_model(initializer):
    model = models.Sequential()

    # Convolutional Layer 1
    model.add(layers.Conv2D(32, (3, 3), activation='relu',
                            kernel_initializer=initializer,
                            input_shape=(32, 32, 3)))
    model.add(layers.MaxPooling2D((2, 2)))

    # Convolutional Layer 2
    model.add(layers.Conv2D(64, (3, 3), activation='relu',
                            kernel_initializer=initializer))
    model.add(layers.MaxPooling2D((2, 2)))

    # Flatten Layer
    model.add(layers.Flatten())

    # Fully Connected Layer
    model.add(layers.Dense(128, activation='relu',
                           kernel_initializer=initializer))

    # Output Layer
    model.add(layers.Dense(10, activation='softmax'))

    return model
```

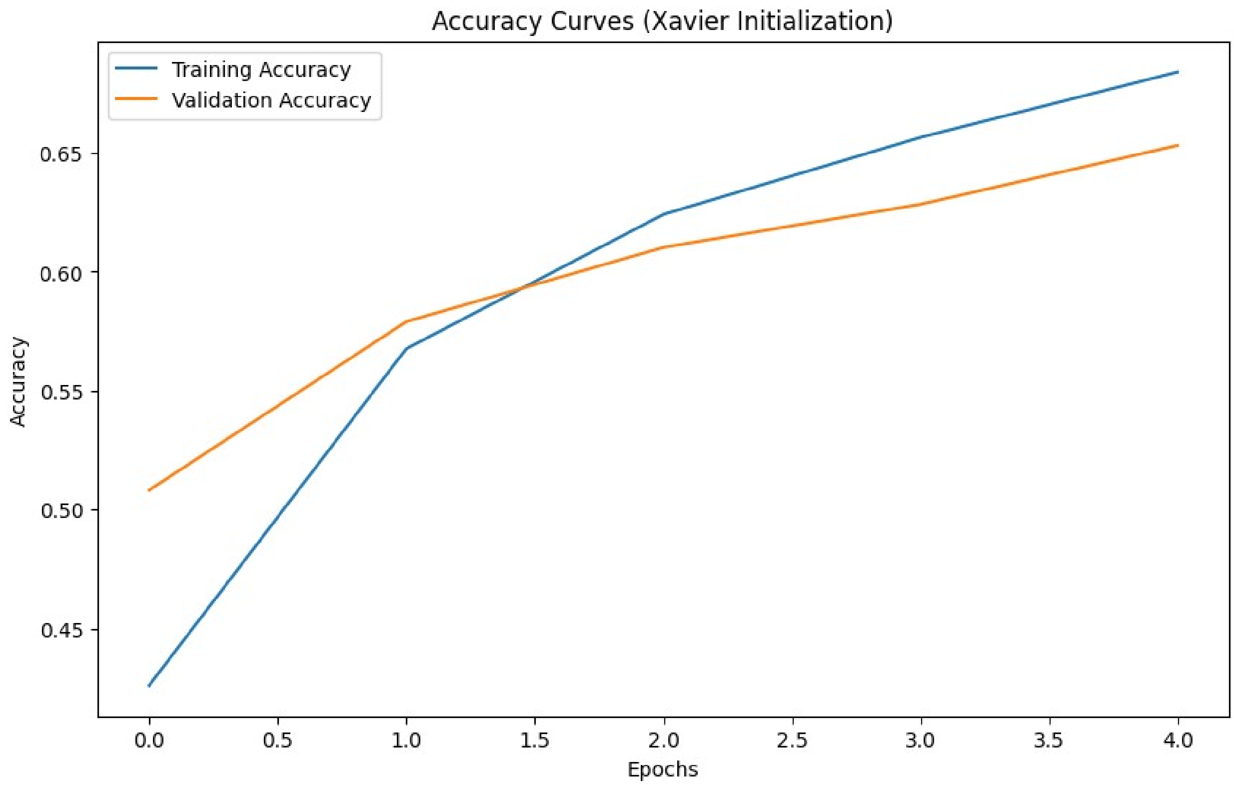
```python
# Experiment with different initializers
initializers = {
    'Default': 'glorot_uniform',  # Default initializer in Keras
    'Xavier': tf.keras.initializers.GlorotUniform(),
    'He': tf.keras.initializers.HeNormal()
}

results = {}

for name, initializer in initializers.items():
    print(f"\nTraining model with {name} initialization...")
    model = build_model(initializer)
    model.compile(optimizer='adam',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    history = model.fit(x_train, y_train, epochs=5, batch_size=64,
                        validation_data=(x_val, y_val), verbose=1)
    test_loss, test_accuracy = model.evaluate(x_test, y_test)
    results[name] = {'loss': test_loss, 'accuracy': test_accuracy}

    # Plot training and validation accuracy for each initializer
    plt.figure(figsize=(10, 6))
    plt.plot(history.history['accuracy'], label='Training Accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation
Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.title(f'Accuracy Curves ({name} Initialization)')
    plt.legend()
    plt.show()

# Compare results
for name, metrics in results.items():
    print(f"\n{name} Initialization -> Test Loss:
{metrics['loss']:.4f}, Test Accuracy: {metrics['accuracy']:.4f}")
```

```
Training model with Default initialization...
Epoch 1/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 48s 99ms/step - accuracy: 0.3372 - loss:
1.8161 - val_accuracy: 0.5247 - val_loss: 1.3374
Epoch 2/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 45s 96ms/step - accuracy: 0.5492 - loss:
1.2619 - val_accuracy: 0.5780 - val_loss: 1.2028
Epoch 3/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 86s 105ms/step - accuracy: 0.6154 - loss:
1.0975 - val_accuracy: 0.5977 - val_loss: 1.1627
Epoch 4/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 79s 99ms/step - accuracy: 0.6524 - loss:
0.9963 - val_accuracy: 0.6355 - val_loss: 1.0523
```

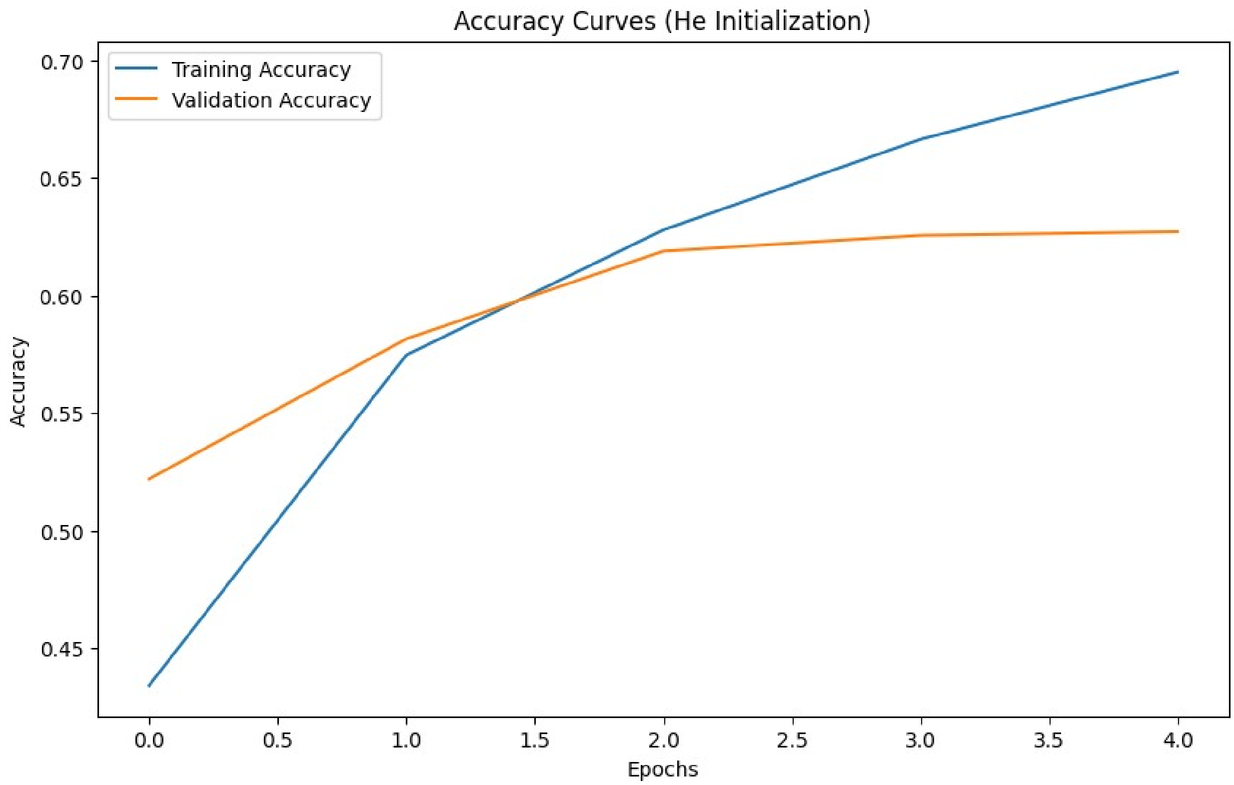
```
Epoch 5/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 81s 96ms/step - accuracy: 0.6845 - loss:
0.9086 - val_accuracy: 0.6508 - val_loss: 1.0149
313/313 ━━━━━━━━━━━━━━━━━━━━ 4s 12ms/step - accuracy: 0.6469 - loss:
1.0053
```




```
Training model with Xavier initialization...
Epoch 1/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 49s 100ms/step - accuracy: 0.3326 - loss:
1.8258 - val_accuracy: 0.5082 - val_loss: 1.3674
Epoch 2/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 81s 98ms/step - accuracy: 0.5467 - loss:
1.2674 - val_accuracy: 0.5790 - val_loss: 1.2090
Epoch 3/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 81s 96ms/step - accuracy: 0.6173 - loss:
1.0929 - val_accuracy: 0.6102 - val_loss: 1.1403
Epoch 4/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 84s 101ms/step - accuracy: 0.6543 - loss:
0.9896 - val_accuracy: 0.6283 - val_loss: 1.0789
Epoch 5/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 80s 96ms/step - accuracy: 0.6838 - loss:
0.9078 - val_accuracy: 0.6531 - val_loss: 1.0082
313/313 ━━━━━━━━━━━━━━━━━━━━ 4s 13ms/step - accuracy: 0.6601 - loss:
0.9852
```




```
Training model with He initialization...
Epoch 1/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 51s 104ms/step - accuracy: 0.3448 - loss:
1.8173 - val_accuracy: 0.5220 - val_loss: 1.3641
Epoch 2/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 45s 97ms/step - accuracy: 0.5615 - loss:
1.2444 - val_accuracy: 0.5816 - val_loss: 1.1965
Epoch 3/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 84s 101ms/step - accuracy: 0.6268 - loss:
1.0748 - val_accuracy: 0.6189 - val_loss: 1.1007
Epoch 4/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 102ms/step - accuracy: 0.6667 - loss:
0.9640 - val_accuracy: 0.6256 - val_loss: 1.0776
Epoch 5/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 81s 101ms/step - accuracy: 0.7011 - loss:
0.8653 - val_accuracy: 0.6272 - val_loss: 1.1057
313/313 ━━━━━━━━━━━━━━━━━━━━ 4s 13ms/step - accuracy: 0.6356 - loss:
1.0861
```




```
Default Initialization -> Test Loss: 1.0089, Test Accuracy: 0.6484

Xavier Initialization -> Test Loss: 0.9932, Test Accuracy: 0.6525

He Initialization -> Test Loss: 1.0925, Test Accuracy: 0.6324
```

Grid Search Implementation

```
from sklearn.model_selection import ParameterGrid
import tensorflow as tf

# Define hyperparameter grid
param_grid = {
    'learning_rate': [0.001, 0.01],
    'batch_size': [32, 64],
    'epochs': [10, 20],
    'optimizer': ['adam', 'sgd']
}

# Create a grid of parameters
grid = list(ParameterGrid(param_grid))

# Record results
```

```
results = []

# Loop through each parameter combination
for params in grid:
    print(f"Training with params: {params}")

    # Build model
    model = tf.keras.Sequential([
        tf.keras.layers.Conv2D(32, (3, 3), activation='relu',
input_shape=(32, 32, 3)),
        tf.keras.layers.MaxPooling2D((2, 2)),
        tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
        tf.keras.layers.MaxPooling2D((2, 2)),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dropout(0.5),
        tf.keras.layers.Dense(10, activation='softmax')
    ])

    # Compile model
    optimizer = params['optimizer']
    if optimizer == 'adam':
        optimizer =
tf.keras.optimizers.Adam(learning_rate=params['learning_rate'])
    elif optimizer == 'sgd':
        optimizer =
tf.keras.optimizers.SGD(learning_rate=params['learning_rate'])

    model.compile(optimizer=optimizer,
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

    # Train model
    history = model.fit(
        x_train, y_train,
        batch_size=params['batch_size'],
        epochs=params['epochs'],
        validation_data=(x_val, y_val),
        verbose=0
    )

    # Evaluate on validation set
    val_loss, val_accuracy = model.evaluate(x_val, y_val, verbose=0)
    results.append({'params': params, 'val_accuracy': val_accuracy})

# Find the best hyperparameter combination
best_result = max(results, key=lambda x: x['val_accuracy'])
print(f"\nBest Params: {best_result['params']}, Validation Accuracy:
{best_result['val_accuracy']:.4f}")
```

```
Training with params: {'batch_size': 32, 'epochs': 10,
'learning_rate': 0.001, 'optimizer': 'adam'}

/usr/local/lib/python3.10/dist-packages/keras/src/layers/
convolutional/base_conv.py:107: 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)

Training with params: {'batch_size': 32, 'epochs': 10,
'learning_rate': 0.001, 'optimizer': 'sgd'}
Training with params: {'batch_size': 32, 'epochs': 10,
'learning_rate': 0.01, 'optimizer': 'adam'}
Training with params: {'batch_size': 32, 'epochs': 10,
'learning_rate': 0.01, 'optimizer': 'sgd'}
Training with params: {'batch_size': 32, 'epochs': 20,
'learning_rate': 0.001, 'optimizer': 'adam'}
Training with params: {'batch_size': 32, 'epochs': 20,
'learning_rate': 0.001, 'optimizer': 'sgd'}
```

Random Search Implementation

```
import random

# Define hyperparameter space
param_space = {
    'learning_rate': [0.001, 0.01, 0.1, 0.0001],
    'batch_size': [32, 64, 128],
    'epochs': [10, 20, 30],
    'optimizer': ['adam', 'sgd', 'rmsprop']
}

# Randomly sample combinations
n_samples = 5  # Number of random combinations to test
random_combinations = [
    {k: random.choice(v) for k, v in param_space.items()} for _ in
range(n_samples)
]

results = []

for params in random_combinations:
    print(f"Training with params: {params}")

    # Model creation, compilation, and training steps remain the same
as Grid Search.
```

```
    model = tf.keras.Sequential([
        tf.keras.layers.Conv2D(32, (3, 3), activation='relu',
input_shape=(32, 32, 3)),
        tf.keras.layers.MaxPooling2D((2, 2)),
        tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
        tf.keras.layers.MaxPooling2D((2, 2)),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dropout(0.5),
        tf.keras.layers.Dense(10, activation='softmax')
    ])

    optimizer = params['optimizer']
    if optimizer == 'adam':
        optimizer =
tf.keras.optimizers.Adam(learning_rate=params['learning_rate'])
    elif optimizer == 'sgd':
        optimizer =
tf.keras.optimizers.SGD(learning_rate=params['learning_rate'])
    elif optimizer == 'rmsprop':
        optimizer =
tf.keras.optimizers.RMSprop(learning_rate=params['learning_rate'])

    model.compile(optimizer=optimizer,
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

    history = model.fit(
        x_train, y_train,
        batch_size=params['batch_size'],
        epochs=params['epochs'],
        validation_data=(x_val, y_val),
        verbose=0
    )

    val_loss, val_accuracy = model.evaluate(x_val, y_val, verbose=0)
    results.append({'params': params, 'val_accuracy': val_accuracy})

# Find best hyperparameter combination
best_result = max(results, key=lambda x: x['val_accuracy'])
print(f"\nBest Params: {best_result['params']}, Validation Accuracy:
{best_result['val_accuracy']:.4f}")
```

```
Training with params: {'learning_rate': 0.01, 'batch_size': 64,
'epochs': 30, 'optimizer': 'adam'}
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/
convolutional/base_conv.py:107: 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)

Training with params: {'learning_rate': 0.001, 'batch_size': 128,
'epochs': 20, 'optimizer': 'rmsprop'}
Training with params: {'learning_rate': 0.0001, 'batch_size': 128,
'epochs': 20, 'optimizer': 'adam'}
Training with params: {'learning_rate': 0.001, 'batch_size': 64,
'epochs': 30, 'optimizer': 'sgd'}
Training with params: {'learning_rate': 0.01, 'batch_size': 32,
'epochs': 10, 'optimizer': 'sgd'}

Best Params: {'learning_rate': 0.001, 'batch_size': 128, 'epochs': 20,
'optimizer': 'rmsprop'}, Validation Accuracy: 0.6619
```

1. Observe Gradient Norms and Gradient Clipping

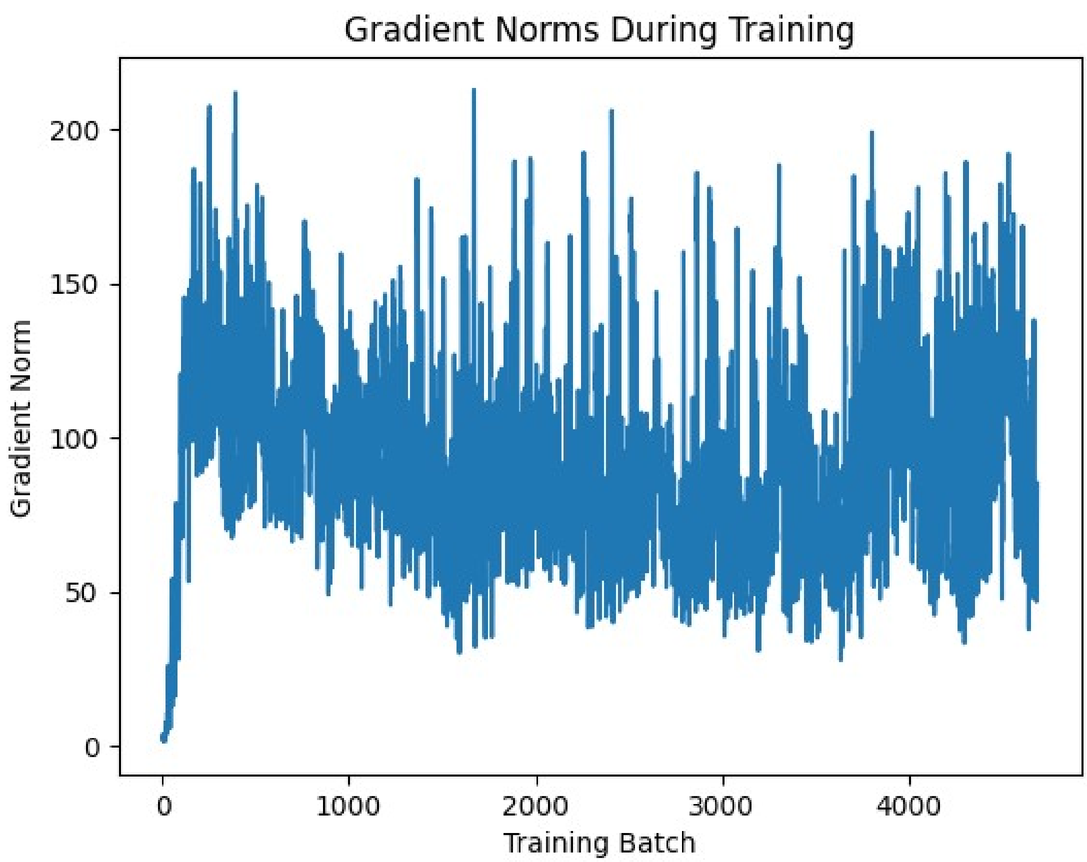
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical

# Load CIFAR-10 dataset
(x_train_full, y_train_full), (x_test, y_test) = cifar10.load_data()

# Normalize pixel values to [0, 1]
x_train_full, x_test = x_train_full / 255.0, x_test / 255.0

# Split training data into training (60%) and validation (20%)
x_train, x_val = x_train_full[:30000], x_train_full[30000:]
y_train, y_val = y_train_full[:30000], y_train_full[30000:]

# One-hot encode labels
y_train = to_categorical(y_train)
y_val = to_categorical(y_val)
y_test = to_categorical(y_test)

# Define the model
model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu',
input_shape=(32, 32, 3)),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D((2, 2)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation='relu'),
```

```
    tf.keras.layers.Dense(10, activation='softmax')
])

# Compile the model
model.compile(optimizer=tf.keras.optimizers.Adam(),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Build the model (necessary for gradient monitoring)
model.build(input_shape=(None, 32, 32, 3))

# Gradient Monitoring Callback
class GradientMonitor(tf.keras.callbacks.Callback):
    def __init__(self):
        self.gradient_norms = []

    def on_train_batch_end(self, batch, logs=None):
        with tf.GradientTape() as tape:
            # Forward pass using dummy data to avoid undefined input
error
            dummy_input = tf.random.uniform((32, 32, 32, 3))  # Batch
size of 32
            logits = self.model(dummy_input, training=True)
            dummy_target = tf.one_hot(tf.random.uniform((32,),
maxval=10, dtype=tf.int32), 10)
            loss = self.model.compiled_loss(dummy_target, logits,
regularization_losses=self.model.losses)

        # Compute gradients
        gradients = tape.gradient(loss,
self.model.trainable_variables)
        # Calculate norm for each layer
        norms = [tf.norm(g).numpy() if g is not None else 0 for g in
gradients]
        self.gradient_norms.append(sum(norms))

# Apply Gradient Clipping
optimizer = tf.keras.optimizers.Adam(clipnorm=1.0)  # Clip gradients
by norm
model.compile(optimizer=optimizer, loss='categorical_crossentropy',
metrics=['accuracy'])

# Gradient monitor instance
gradient_monitor = GradientMonitor()

# Train the model
history = model.fit(
    x_train, y_train,
    epochs=5,
    batch_size=32,
```

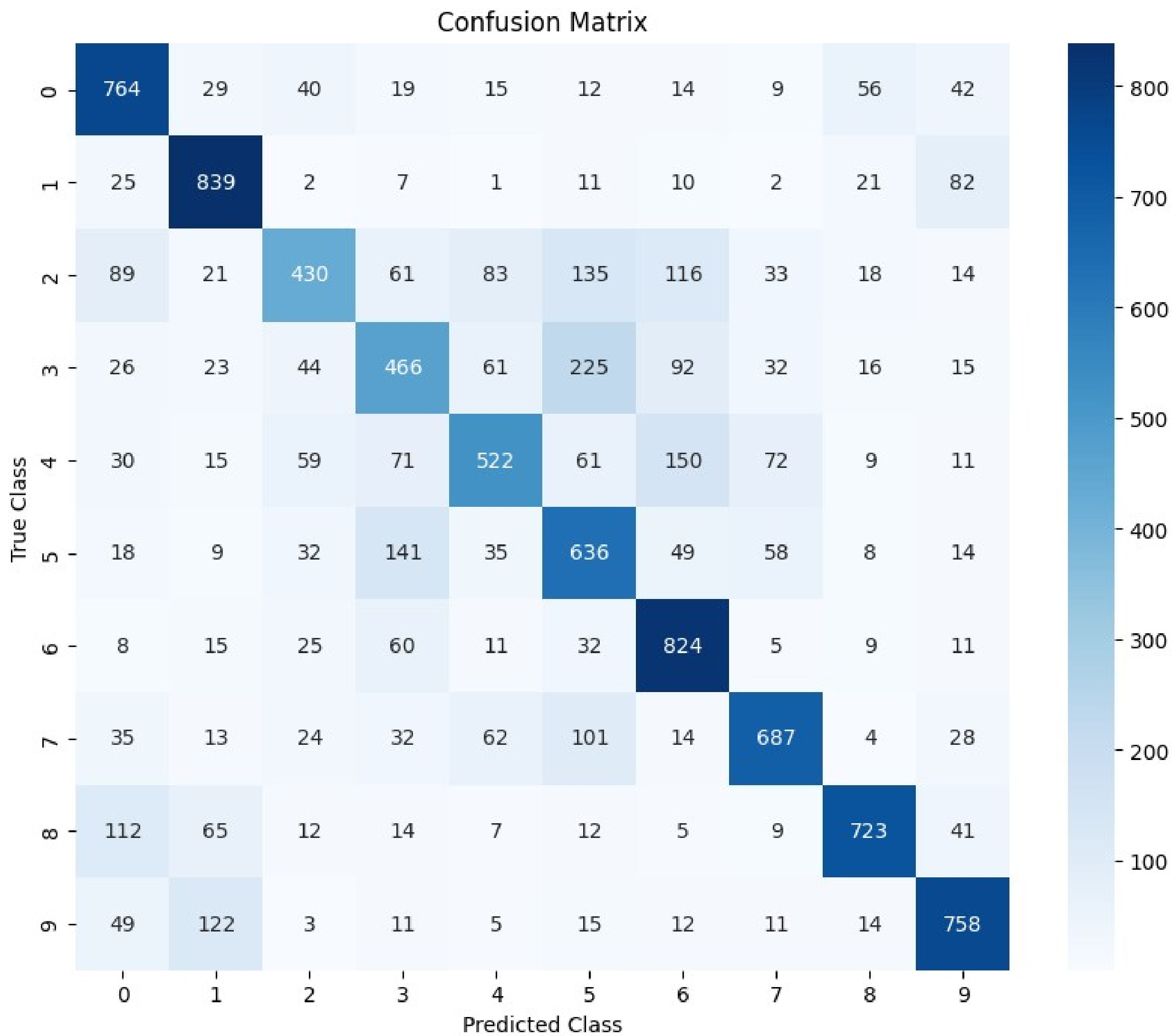
```python
    validation_data=(x_val, y_val),
    callbacks=[gradient_monitor]
)

# Plot gradient norms
plt.plot(gradient_monitor.gradient_norms)
plt.title("Gradient Norms During Training")
plt.xlabel("Training Batch")
plt.ylabel("Gradient Norm")
plt.show()

# Evaluate the model
test_loss, test_accuracy = model.evaluate(x_test, y_test, verbose=0)
print(f"Test Loss: {test_loss:.4f}, Test Accuracy:
{test_accuracy:.4f}")

# Generate Confusion Matrix and Classification Report
y_pred = model.predict(x_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true_classes = np.argmax(y_test, axis=1)

conf_matrix = confusion_matrix(y_true_classes, y_pred_classes)
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=list(range(10)), yticklabels=list(range(10)))
plt.xlabel('Predicted Class')
plt.ylabel('True Class')
plt.title('Confusion Matrix')
plt.show()

# Classification Report
class_report = classification_report(y_true_classes, y_pred_classes,
target_names=[str(i) for i in range(10)])
print("Classification Report:\n", class_report)
```

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

/usr/local/lib/python3.10/dist-packages/keras/src/layers/
convolutional/base_conv.py:107: 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)

Epoch 1/5

/usr/local/lib/python3.10/dist-packages/keras/src/backend/tensorflow/
trainer.py:617: UserWarning: `model.compiled_loss()` is deprecated.
```

```
Instead, use `model.compute_loss(x, y, y_pred, sample_weight,
training)`.
  warnings.warn(

938/938 ━━━━━━━━━━━━━━━━━━━━ 137s 141ms/step - accuracy: 0.3709 -
loss: 1.7299 - val_accuracy: 0.4926 - val_loss: 1.3959
Epoch 2/5
938/938 ━━━━━━━━━━━━━━━━━━━━ 124s 132ms/step - accuracy: 0.5794 -
loss: 1.1774 - val_accuracy: 0.6053 - val_loss: 1.1303
Epoch 3/5
938/938 ━━━━━━━━━━━━━━━━━━━━ 140s 130ms/step - accuracy: 0.6469 -
loss: 1.0121 - val_accuracy: 0.6345 - val_loss: 1.0451
Epoch 4/5
938/938 ━━━━━━━━━━━━━━━━━━━━ 147s 136ms/step - accuracy: 0.6826 -
loss: 0.9048 - val_accuracy: 0.6492 - val_loss: 1.0210
Epoch 5/5
938/938 ━━━━━━━━━━━━━━━━━━━━ 136s 130ms/step - accuracy: 0.7251 -
loss: 0.7895 - val_accuracy: 0.6683 - val_loss: 0.9717
```




```
Test Loss: 0.9714, Test Accuracy: 0.6649
313/313 ━━━━━━━━━━━━━━━━━━━━ 6s 18ms/step
```




```
Classification Report:
              precision    recall  f1-score   support

           0       0.66      0.76      0.71      1000
           1       0.73      0.84      0.78      1000
           2       0.64      0.43      0.51      1000
           3       0.53      0.47      0.50      1000
           4       0.65      0.52      0.58      1000
           5       0.51      0.64      0.57      1000
           6       0.64      0.82      0.72      1000
           7       0.75      0.69      0.72      1000
           8       0.82      0.72      0.77      1000
           9       0.75      0.76      0.75      1000

    accuracy                           0.66     10000
   macro avg       0.67      0.66      0.66     10000
```

```
weighted avg       0.67      0.66      0.66     10000
```