

Convolutional Neural Network

Group No :151

Group Member Names:

Peyala Samarasimha Reddy - 2023AA05072 100% Contribution

Monisha G - 2023AA05536 100% Contribution

Akshay Mohan - 2023AA05315 100% Contribution

Sreelakshmi Ajith - 2023AA05316 100% Contribution

```
In [14]: !pip uninstall tensorflow  
!pip install tensorflow
```

Found existing installation: tensorflow 2.17.0

Uninstalling tensorflow-2.17.0:

Would remove:

```
/usr/local/bin/import_pb_to_tensorboard
/usr/local/bin/saved_model_cli
/usr/local/bin/tensorboard
/usr/local/bin/tf_upgrade_v2
/usr/local/bin/tflite_convert
/usr/local/bin/toco
/usr/local/bin/toco_from_protos
/usr/local/lib/python3.10/dist-packages/tensorflow-2.17.0.dist-info/*
/usr/local/lib/python3.10/dist-packages/tensorflow/*
```

Proceed (Y/n)? y

Y

Successfully uninstalled tensorflow-2.17.0

Collecting tensorflow

Using cached tensorflow-2.17.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (4.2 kB)

Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.4.0)

Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.6.3)

Requirement already satisfied: flatbuffers>=24.3.25 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (24.3.25)

Requirement already satisfied: gast!=0.5.0,!0.5.1,!0.5.2,>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.6.0)

Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.2.0)

Requirement already satisfied: h5py>=3.10.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.11.0)

Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (18.1.1)

Requirement already satisfied: ml-dtypes<0.5.0,>=0.3.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.4.1)

Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.3.0)

Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from tensorflow) (24.1)

Requirement already satisfied: protobuf!=4.21.0,!4.21.1,!4.21.2,!4.21.3,!4.21.4,!4.21.5,<5.0.0dev,>=3.20.3 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.20.3)

Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.32.3)

Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from tensorflow) (71.0.4)

Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.16.0)

Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.4.0)

Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (4.12.2)

Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.16.0)

Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.64.1)

Requirement already satisfied: tensorboard<2.18,>=2.17 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.17.0)

Requirement already satisfied: keras>=3.2.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.4.1)

Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.37.1)

Requirement already satisfied: numpy<2.0.0,>=1.23.5 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.26.4)

Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from astunparse>=1.6.0->tensorflow) (0.44.0)

Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-packages (from k

eras>=3.2.0->tensorflow) (13.8.1)
 Requirement already satisfied: namex in /usr/local/lib/python3.10/dist-packages (from keras>=3.2.0->tensorflow) (0.0.8)
 Requirement already satisfied: optree in /usr/local/lib/python3.10/dist-packages (from keras>=3.2.0->tensorflow) (0.12.1)
 Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorflow) (3.3.2)
 Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorflow) (3.10)
 Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorflow) (2.0.7)
 Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorflow) (2024.8.30)
 Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.18,>=2.17->tensorflow) (3.7)
 Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.18,>=2.17->tensorflow) (0.7.2)
 Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.18,>=2.17->tensorflow) (3.0.4)
 Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.10/dist-packages (from werkzeug>=1.0.1->tensorflow) (2.1.5)
 Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.10/dist-packages (from rich->keras>=3.2.0->tensorflow) (3.0.0)
 Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.10/dist-packages (from rich->keras>=3.2.0->tensorflow) (2.18.0)
 Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-packages (from markdown-it-py>=2.2.0->rich->keras>=3.2.0->tensorflow) (0.1.2)
 Using cached tensorflow-2.17.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (601.3 MB)
 Installing collected packages: tensorflow
 Successfully installed tensorflow-2.17.0

```
In [1]: import tensorflow as tf
        print(tf.__version__)
```

2.17.0

```
In [2]: # Import Libraries
        # - Tensorflow
        # - Keras
        # - numpy and random

        import tensorflow as tf
        from tensorflow.keras import models
        from tensorflow.keras import layers

        import random
        import numpy as np

        import matplotlib.pyplot as plt
        %matplotlib inline
```

```
In [4]: random.seed(42)           # Initialize the random number generator.
        np.random.seed(42)        # With the seed reset, the same set of numbers will appear ev
        tf.random.set_seed(42)    # sets the graph-level random seed
```

Dataset - MNIST

```
In [5]: # Use the MNIST dataset of Keras.

        mnist = tf.keras.datasets.mnist

        (Xtrain, Ytrain), (Xtest, Ytest) = mnist.load_data()
```

```

# Display size of dataset
Xtrain = Xtrain.reshape((60000,28,28,1))
Xtrain = Xtrain.astype('float32')/255

Xtest = Xtest.reshape((10000,28,28,1))
Xtest = Xtest.astype('float32')/255

Ytrain = tf.keras.utils.to_categorical(Ytrain)
Ytest = tf.keras.utils.to_categorical(Ytest)

print(Xtrain.shape, Xtest.shape)
print(Ytrain.shape, Ytest.shape)

```

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz>

```

11490434/11490434 ————— 1s 0us/step
(60000, 28, 28, 1) (10000, 28, 28, 1)
(60000, 10) (10000, 10)

```

Create a CNN Model

```

In [6]: # Create a Sequential model object
cnnModel = models.Sequential()

# Add layers Conv2D for CNN and specify MaxPooling

# Layer 1 = input layer
cnnModel.add(layers.Conv2D(32, (3,3), activation="relu", input_shape=(28,28,1) ))

cnnModel.add(layers.MaxPooling2D((2,2)))

# Layer 2
cnnModel.add(layers.Conv2D(64, (3,3), activation="relu"))

cnnModel.add(layers.MaxPooling2D((2,2)))

# Layer 3
cnnModel.add(layers.Conv2D(64, (3,3), activation="relu" ))

cnnModel.add(layers.Flatten())

# Add Dense layers or fully connected layers
# Layer 4
cnnModel.add(layers.Dense(64, activation="relu" ))

# Layer 5
cnnModel.add(layers.Dense(32, activation="relu" ))

# Layer 6
cnnModel.add(layers.Dense(10, activation="softmax" ))

cnnModel.summary()

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:10
7: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When usi
ng Sequential models, prefer using an `Input(shape)` object as the first layer in the
model instead.

```

```

super().__init__(activity_regularizer=activity_regularizer, **kwargs)

```

Model: "sequential"

Layer (type)	Output Shape	
conv2d (Conv2D)	(None, 26, 26, 32)	
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	
conv2d_1 (Conv2D)	(None, 11, 11, 64)	
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	
conv2d_2 (Conv2D)	(None, 3, 3, 64)	
flatten (Flatten)	(None, 576)	
dense (Dense)	(None, 64)	
dense_1 (Dense)	(None, 32)	
dense_2 (Dense)	(None, 10)	

Total params: 95,082 (371.41 KB)

Trainable params: 95,082 (371.41 KB)























Non-trainable params: 0 (0.00 B)

```
In [7]: # Configure the model for training, by using appropriate optimizers and regularizati
# Available optimizer: adam, rmsprop, adagrad, sgd
# loss: objective that the model will try to minimize.
# Available loss: categorical_crossentropy, binary_crossentropy, mean_squared_error
# metrics: List of metrics to be evaluated by the model during training and testing.
```

```
cnnModel.compile(optimizer = "adam", loss = "categorical_crossentropy", metrics = ["a
```

```
In [8]: # train the model

history = cnnModel.fit(Xtrain, Ytrain, epochs = 25, batch_size = 64, validation_split
```

Epoch 1/25
844/844  **53s** 61ms/step - accuracy: 0.8367 - loss: 0.5159 - val_acc
uracy: 0.9810 - val_loss: 0.0624
Epoch 2/25
844/844  **83s** 62ms/step - accuracy: 0.9802 - loss: 0.0636 - val_acc
uracy: 0.9862 - val_loss: 0.0500
Epoch 3/25
844/844  **80s** 60ms/step - accuracy: 0.9874 - loss: 0.0409 - val_acc
uracy: 0.9862 - val_loss: 0.0525
Epoch 4/25
844/844  **82s** 60ms/step - accuracy: 0.9900 - loss: 0.0320 - val_acc
uracy: 0.9887 - val_loss: 0.0441
Epoch 5/25
844/844  **53s** 62ms/step - accuracy: 0.9919 - loss: 0.0246 - val_acc
uracy: 0.9875 - val_loss: 0.0483
Epoch 6/25
844/844  **79s** 59ms/step - accuracy: 0.9934 - loss: 0.0216 - val_acc
uracy: 0.9888 - val_loss: 0.0490
Epoch 7/25
844/844  **83s** 60ms/step - accuracy: 0.9946 - loss: 0.0170 - val_acc
uracy: 0.9893 - val_loss: 0.0443
Epoch 8/25
844/844  **81s** 60ms/step - accuracy: 0.9945 - loss: 0.0159 - val_acc
uracy: 0.9903 - val_loss: 0.0410
Epoch 9/25
844/844  **83s** 60ms/step - accuracy: 0.9952 - loss: 0.0140 - val_acc
uracy: 0.9893 - val_loss: 0.0444
Epoch 10/25
844/844  **50s** 59ms/step - accuracy: 0.9969 - loss: 0.0093 - val_acc
uracy: 0.9895 - val_loss: 0.0444
Epoch 11/25
844/844  **82s** 59ms/step - accuracy: 0.9969 - loss: 0.0090 - val_acc
uracy: 0.9883 - val_loss: 0.0563
Epoch 12/25
844/844  **49s** 58ms/step - accuracy: 0.9965 - loss: 0.0107 - val_acc
uracy: 0.9915 - val_loss: 0.0412
Epoch 13/25
844/844  **86s** 63ms/step - accuracy: 0.9977 - loss: 0.0067 - val_acc
uracy: 0.9902 - val_loss: 0.0516
Epoch 14/25
844/844  **79s** 60ms/step - accuracy: 0.9969 - loss: 0.0087 - val_acc
uracy: 0.9890 - val_loss: 0.0614
Epoch 15/25
844/844  **81s** 59ms/step - accuracy: 0.9981 - loss: 0.0050 - val_acc
uracy: 0.9898 - val_loss: 0.0563
Epoch 16/25
844/844  **82s** 59ms/step - accuracy: 0.9970 - loss: 0.0100 - val_acc
uracy: 0.9915 - val_loss: 0.0488
Epoch 17/25
844/844  **50s** 59ms/step - accuracy: 0.9982 - loss: 0.0056 - val_acc
uracy: 0.9927 - val_loss: 0.0449
Epoch 18/25
844/844  **51s** 61ms/step - accuracy: 0.9982 - loss: 0.0056 - val_acc
uracy: 0.9913 - val_loss: 0.0558
Epoch 19/25
844/844  **82s** 60ms/step - accuracy: 0.9981 - loss: 0.0060 - val_acc
uracy: 0.9908 - val_loss: 0.0499
Epoch 20/25
844/844  **81s** 59ms/step - accuracy: 0.9986 - loss: 0.0041 - val_acc
uracy: 0.9897 - val_loss: 0.0595
Epoch 21/25
844/844  **87s** 65ms/step - accuracy: 0.9986 - loss: 0.0043 - val_acc
uracy: 0.9905 - val_loss: 0.0573
Epoch 22/25
844/844  **78s** 60ms/step - accuracy: 0.9985 - loss: 0.0039 - val_acc
uracy: 0.9905 - val_loss: 0.0575

Epoch 23/25
844/844 ————— **81s** 60ms/step - accuracy: 0.9987 - loss: 0.0043 - val_acc
 uracy: 0.9898 - val_loss: 0.0573
 Epoch 24/25
844/844 ————— **81s** 59ms/step - accuracy: 0.9983 - loss: 0.0059 - val_acc
 uracy: 0.9900 - val_loss: 0.0716
 Epoch 25/25
844/844 ————— **82s** 59ms/step - accuracy: 0.9973 - loss: 0.0083 - val_acc
 uracy: 0.9925 - val_loss: 0.0496

```
In [10]: print('Final training loss \t', history.history['loss'][-1])
         print('Final training accuracy ', history.history['accuracy'][-1])
```

Final training loss 0.005073322914540768
 Final training accuracy 0.9984074234962463

Results and Outputs

```
In [11]: # testing the model

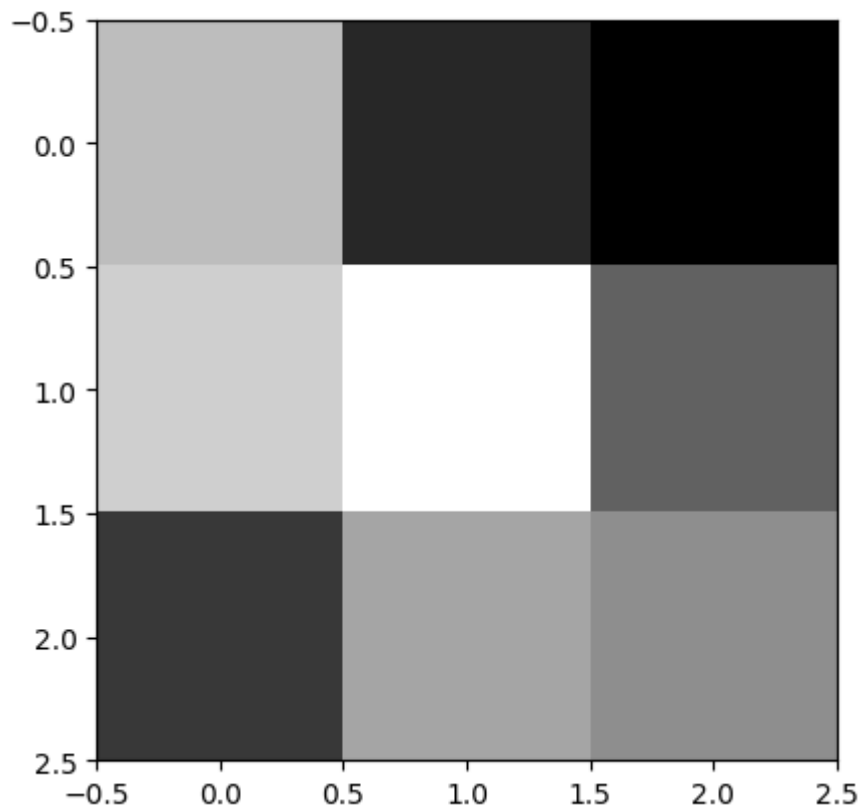
         testLoss, testAccuracy = cnnModel.evaluate( Xtest, Ytest)
```

313/313 ————— **3s** 10ms/step - accuracy: 0.9885 - loss: 0.0761

```
In [12]: print('Testing loss \t', testLoss)
         print('Testing accuracy ', testAccuracy)
```

Testing loss 0.05195753276348114
 Testing accuracy 0.9919999837875366

```
In [13]: # shows the weights in layer 0 conv2d as gray map
         top_layer = cnnModel.layers[0]
         plt.imshow(top_layer.get_weights()[0][:, :, :, 0].squeeze(), cmap='gray')
         plt.show()
```



```
In [16]: # plotting training and validation loss
```

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)
```

```

plt.plot(epochs, loss, color='red', label='Training loss')
plt.plot(epochs, val_loss, color='green', label='Validation loss')
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

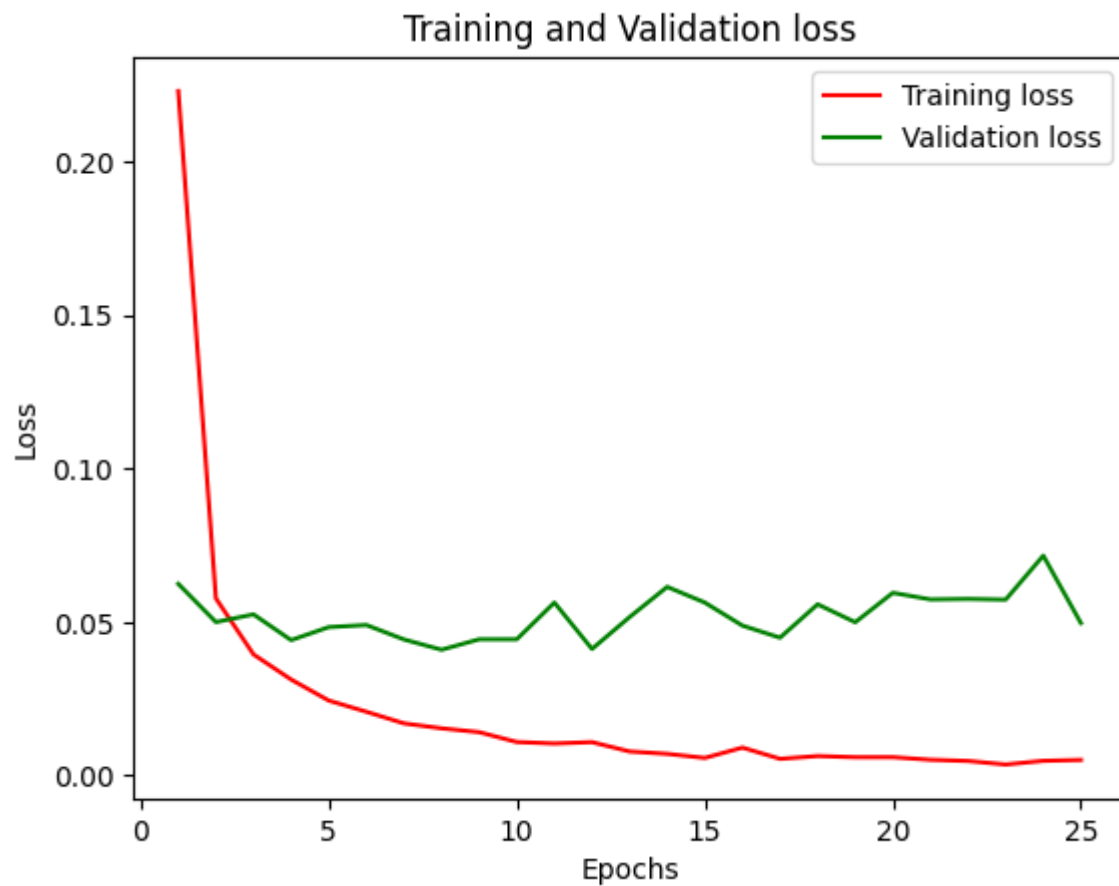
```

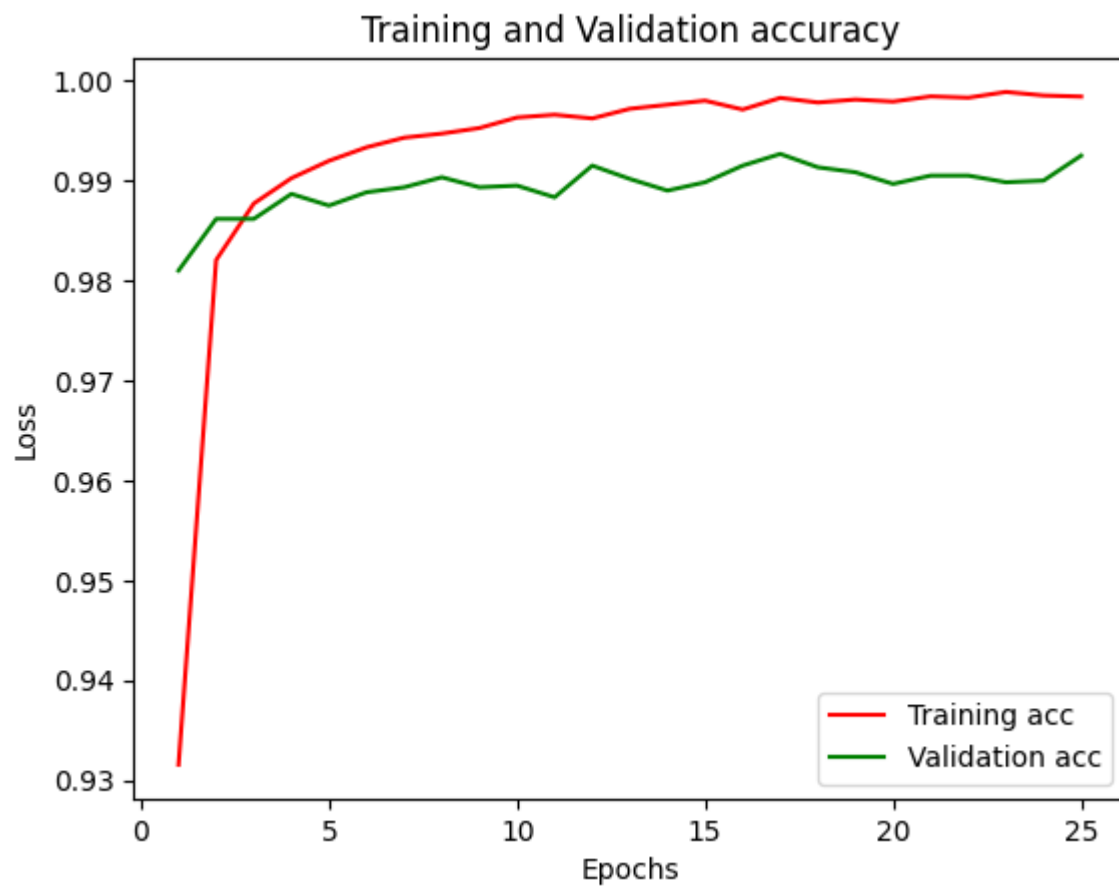
plotting training and validation accuracy

```

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
plt.plot(epochs, acc, color='red', label='Training acc')
plt.plot(epochs, val_acc, color='green', label='Validation acc')
plt.title('Training and Validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

```





Confusion Matrix generation

Prediction for a specific testing data generate confusion matrix

```
In [17]: Y_prediction = cnnModel.predict(Xtest)

# Convert predictions classes to one hot vectors
Y_pred_classes = np.argmax(Y_prediction, axis = 1)

# Convert validation observations to one hot vectors
Y_true = np.argmax(Ytest,axis = 1)
```

313/313 ————— 3s 10ms/step

```
In [18]: # Classification Report

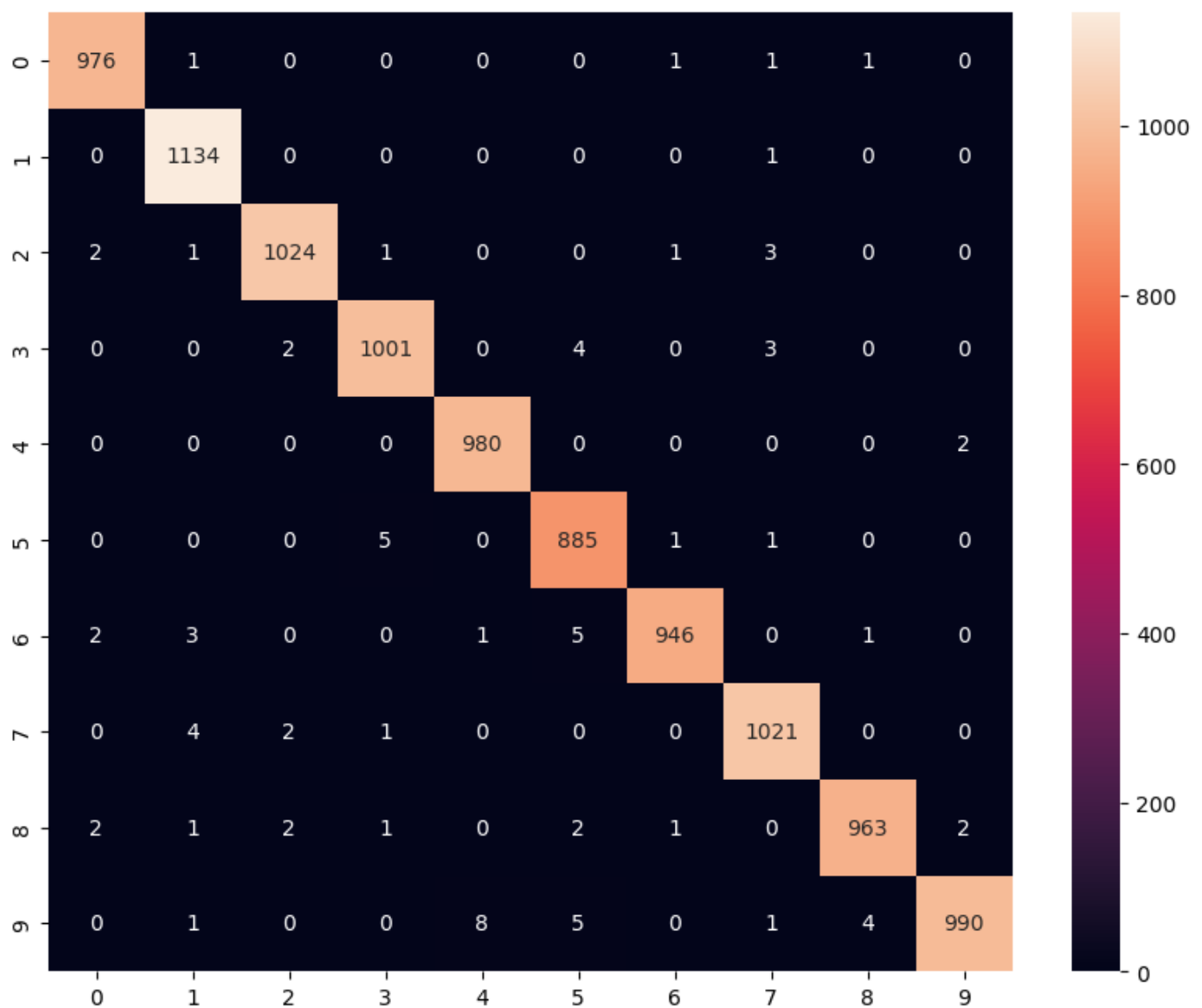
from sklearn.metrics import classification_report
print(classification_report(Y_true, Y_pred_classes))
```

	precision	recall	f1-score	support
0	0.99	1.00	0.99	980
1	0.99	1.00	0.99	1135
2	0.99	0.99	0.99	1032
3	0.99	0.99	0.99	1010
4	0.99	1.00	0.99	982
5	0.98	0.99	0.99	892
6	1.00	0.99	0.99	958
7	0.99	0.99	0.99	1028
8	0.99	0.99	0.99	974
9	1.00	0.98	0.99	1009
accuracy			0.99	10000
macro avg	0.99	0.99	0.99	10000
weighted avg	0.99	0.99	0.99	10000

```
In [19]: # confusion matrix
from sklearn.metrics import confusion_matrix
import seaborn as sns

# compute the confusion matrix
confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)

plt.figure(figsize=(10,8))
sns.heatmap(confusion_mtx, annot=True, fmt="d");
```



Modify the code to get a better testing

accuracy.

- Change the number of hidden units
- Increase the number of hidden layers
- Use a different optimizer
- Train for more epochs for better graphs
- Try using CIFAR dataset

CIFAR-10 Image Classification using a 3-Layer CNN with 256 and 128 Hidden Units and RMSprop Optimizer

```
In [20]: # Importing required libraries
import numpy as np
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt

# Load 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

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

# Model building
model = models.Sequential()

# Add first convolutional layer
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model.add(layers.MaxPooling2D((2, 2)))

# Add second convolutional layer
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# Add third convolutional layer
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# Flattening the results
model.add(layers.Flatten())

# Add first dense layer (hidden units increased to 256)
model.add(layers.Dense(256, activation='relu'))

# Add second dense layer to increase hidden layers
model.add(layers.Dense(128, activation='relu'))

# Add output layer
model.add(layers.Dense(10, activation='softmax'))

cnnModel.summary()
```

```
# Compile the model using RMSprop optimizer instead of Adam
model.compile(optimizer='RMSprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Train the model (increase epochs to 50)
history = model.fit(x_train, y_train, epochs=50, validation_data=(x_test, y_test))























# Plotting training and validation accuracy over epochs
```























Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>

170498071/170498071  **11s** 0us/step

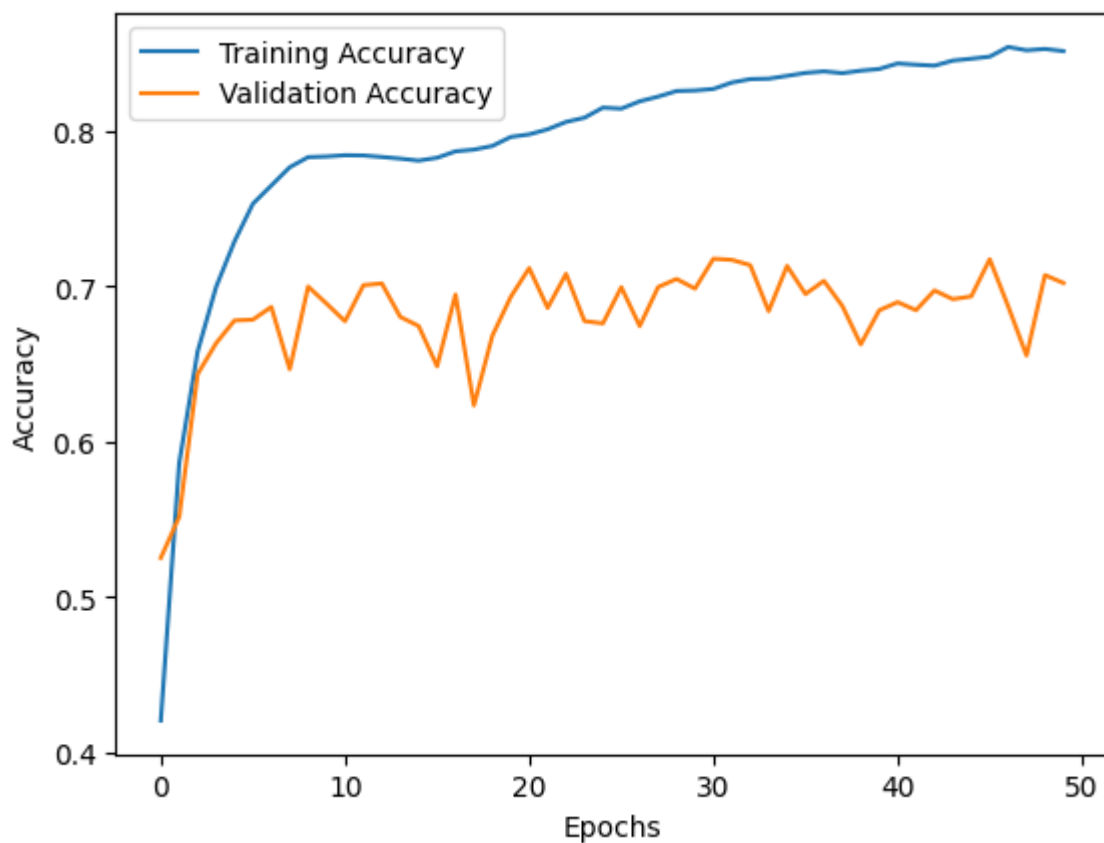
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

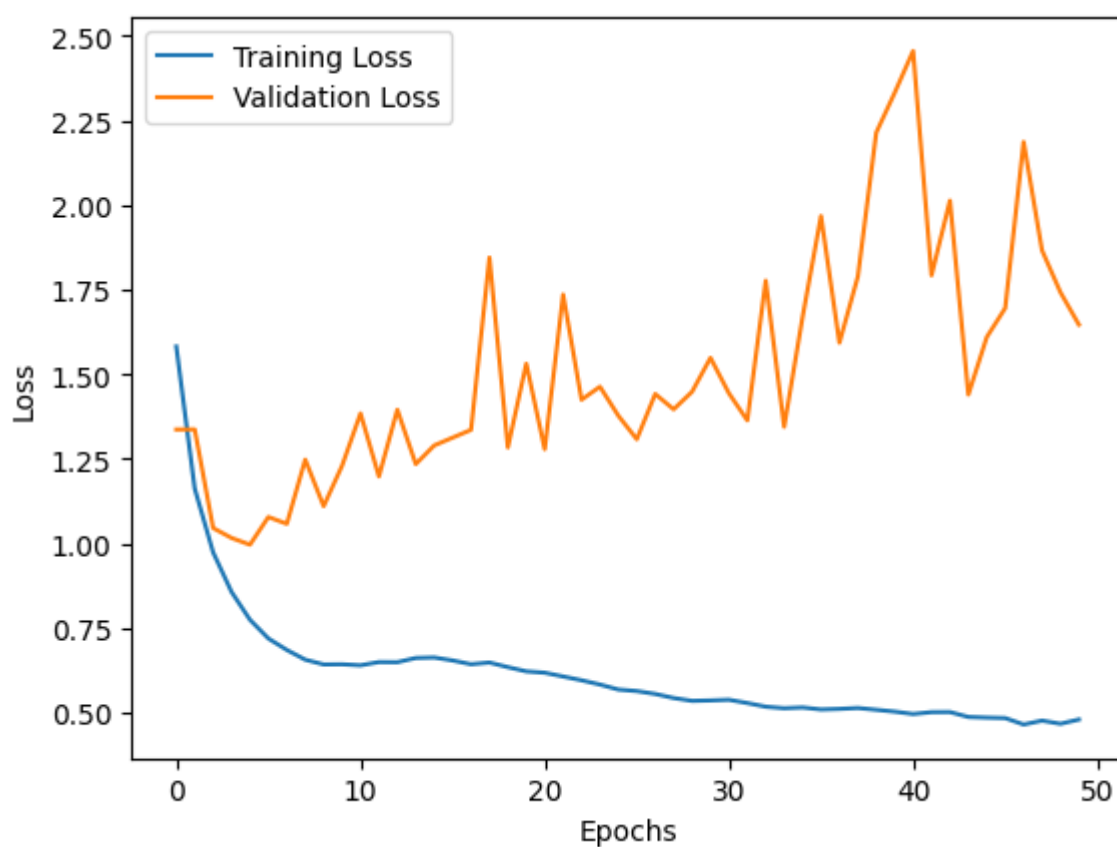
```
    super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Epoch 1/50
1563/1563  **77s** 48ms/step - accuracy: 0.3224 - loss: 1.8183 - val_accuracy: 0.5253 - val_loss: 1.3370
Epoch 2/50
1563/1563  **77s** 49ms/step - accuracy: 0.5640 - loss: 1.2252 - val_accuracy: 0.5517 - val_loss: 1.3373
Epoch 3/50
1563/1563  **80s** 48ms/step - accuracy: 0.6434 - loss: 1.0145 - val_accuracy: 0.6436 - val_loss: 1.0460
Epoch 4/50
1563/1563  **76s** 49ms/step - accuracy: 0.6898 - loss: 0.8838 - val_accuracy: 0.6634 - val_loss: 1.0166
Epoch 5/50
1563/1563  **75s** 48ms/step - accuracy: 0.7209 - loss: 0.7969 - val_accuracy: 0.6781 - val_loss: 0.9968
Epoch 6/50
1563/1563  **78s** 50ms/step - accuracy: 0.7474 - loss: 0.7358 - val_accuracy: 0.6786 - val_loss: 1.0786
Epoch 7/50
1563/1563  **78s** 48ms/step - accuracy: 0.7614 - loss: 0.6970 - val_accuracy: 0.6868 - val_loss: 1.0583
Epoch 8/50
1563/1563  **82s** 48ms/step - accuracy: 0.7743 - loss: 0.6642 - val_accuracy: 0.6467 - val_loss: 1.2481
Epoch 9/50
1563/1563  **81s** 48ms/step - accuracy: 0.7799 - loss: 0.6495 - val_accuracy: 0.6999 - val_loss: 1.1105
Epoch 10/50
1563/1563  **76s** 49ms/step - accuracy: 0.7825 - loss: 0.6505 - val_accuracy: 0.6889 - val_loss: 1.2301
Epoch 11/50
1563/1563  **81s** 48ms/step - accuracy: 0.7821 - loss: 0.6439 - val_accuracy: 0.6776 - val_loss: 1.3845
Epoch 12/50
1563/1563  **82s** 48ms/step - accuracy: 0.7828 - loss: 0.6551 - val_accuracy: 0.7008 - val_loss: 1.1982
Epoch 13/50
1563/1563  **82s** 48ms/step - accuracy: 0.7825 - loss: 0.6468 - val_accuracy: 0.7019 - val_loss: 1.3955
Epoch 14/50
1563/1563  **83s** 49ms/step - accuracy: 0.7814 - loss: 0.6576 - val_accuracy: 0.6804 - val_loss: 1.2349
Epoch 15/50
1563/1563  **77s** 49ms/step - accuracy: 0.7803 - loss: 0.6661 - val_accuracy: 0.6745 - val_loss: 1.2898
Epoch 16/50
1563/1563  **81s** 49ms/step - accuracy: 0.7804 - loss: 0.6608 - val_accuracy: 0.6486 - val_loss: 1.3129
Epoch 17/50
1563/1563  **81s** 48ms/step - accuracy: 0.7857 - loss: 0.6500 - val_accuracy: 0.6948 - val_loss: 1.3359
Epoch 18/50
1563/1563  **77s** 49ms/step - accuracy: 0.7876 - loss: 0.6496 - val_accuracy: 0.6234 - val_loss: 1.8449
Epoch 19/50
1563/1563  **81s** 48ms/step - accuracy: 0.7895 - loss: 0.6391 - val_accuracy: 0.6683 - val_loss: 1.2840
Epoch 20/50
1563/1563  **82s** 48ms/step - accuracy: 0.7935 - loss: 0.6277 - val_accuracy: 0.6933 - val_loss: 1.5315
Epoch 21/50
1563/1563  **76s** 49ms/step - accuracy: 0.7960 - loss: 0.6315 - val_accuracy: 0.7118 - val_loss: 1.2789
Epoch 22/50
1563/1563  **75s** 48ms/step - accuracy: 0.7992 - loss: 0.6154 - val_accuracy: 0.6862 - val_loss: 1.7356

Epoch 23/50
1563/1563  **77s** 49ms/step - accuracy: 0.8045 - loss: 0.6002 - val_accuracy: 0.7081 - val_loss: 1.4250
Epoch 24/50
1563/1563  **75s** 48ms/step - accuracy: 0.8102 - loss: 0.5829 - val_accuracy: 0.6777 - val_loss: 1.4634
Epoch 25/50
1563/1563  **82s** 48ms/step - accuracy: 0.8147 - loss: 0.5692 - val_accuracy: 0.6762 - val_loss: 1.3776
Epoch 26/50
1563/1563  **77s** 49ms/step - accuracy: 0.8139 - loss: 0.5631 - val_accuracy: 0.6995 - val_loss: 1.3082
Epoch 27/50
1563/1563  **81s** 48ms/step - accuracy: 0.8203 - loss: 0.5524 - val_accuracy: 0.6745 - val_loss: 1.4419
Epoch 28/50
1563/1563  **82s** 48ms/step - accuracy: 0.8205 - loss: 0.5485 - val_accuracy: 0.6996 - val_loss: 1.3966
Epoch 29/50
1563/1563  **82s** 48ms/step - accuracy: 0.8255 - loss: 0.5387 - val_accuracy: 0.7048 - val_loss: 1.4485
Epoch 30/50
1563/1563  **82s** 48ms/step - accuracy: 0.8264 - loss: 0.5332 - val_accuracy: 0.6986 - val_loss: 1.5488
Epoch 31/50
1563/1563  **77s** 49ms/step - accuracy: 0.8279 - loss: 0.5404 - val_accuracy: 0.7178 - val_loss: 1.4441
Epoch 32/50
1563/1563  **82s** 49ms/step - accuracy: 0.8312 - loss: 0.5283 - val_accuracy: 0.7171 - val_loss: 1.3639
Epoch 33/50
1563/1563  **81s** 49ms/step - accuracy: 0.8321 - loss: 0.5244 - val_accuracy: 0.7137 - val_loss: 1.7766
Epoch 34/50
1563/1563  **78s** 50ms/step - accuracy: 0.8329 - loss: 0.5138 - val_accuracy: 0.6841 - val_loss: 1.3450
Epoch 35/50
1563/1563  **76s** 48ms/step - accuracy: 0.8354 - loss: 0.5096 - val_accuracy: 0.7132 - val_loss: 1.6694
Epoch 36/50
1563/1563  **78s** 50ms/step - accuracy: 0.8382 - loss: 0.5081 - val_accuracy: 0.6951 - val_loss: 1.9676
Epoch 37/50
1563/1563  **82s** 50ms/step - accuracy: 0.8396 - loss: 0.5070 - val_accuracy: 0.7036 - val_loss: 1.5931
Epoch 38/50
1563/1563  **80s** 48ms/step - accuracy: 0.8350 - loss: 0.5211 - val_accuracy: 0.6874 - val_loss: 1.7886
Epoch 39/50
1563/1563  **80s** 47ms/step - accuracy: 0.8377 - loss: 0.5174 - val_accuracy: 0.6627 - val_loss: 2.2141
Epoch 40/50
1563/1563  **82s** 47ms/step - accuracy: 0.8416 - loss: 0.4940 - val_accuracy: 0.6846 - val_loss: 2.3317
Epoch 41/50
1563/1563  **80s** 51ms/step - accuracy: 0.8431 - loss: 0.4989 - val_accuracy: 0.6899 - val_loss: 2.4552
Epoch 42/50
1563/1563  **76s** 47ms/step - accuracy: 0.8413 - loss: 0.5060 - val_accuracy: 0.6847 - val_loss: 1.7924
Epoch 43/50
1563/1563  **74s** 47ms/step - accuracy: 0.8407 - loss: 0.5057 - val_accuracy: 0.6974 - val_loss: 2.0131
Epoch 44/50
1563/1563  **83s** 48ms/step - accuracy: 0.8435 - loss: 0.4985 - val_accuracy: 0.6918 - val_loss: 1.4399

Epoch 45/50
1563/1563 ————— **82s** 48ms/step - accuracy: 0.8493 - loss: 0.4717 - val_accuracy: 0.6936 - val_loss: 1.6100
Epoch 46/50
1563/1563 ————— **81s** 47ms/step - accuracy: 0.8493 - loss: 0.4778 - val_accuracy: 0.7175 - val_loss: 1.6955
Epoch 47/50
1563/1563 ————— **81s** 47ms/step - accuracy: 0.8561 - loss: 0.4688 - val_accuracy: 0.6873 - val_loss: 2.1864
Epoch 48/50
1563/1563 ————— **82s** 47ms/step - accuracy: 0.8533 - loss: 0.4695 - val_accuracy: 0.6555 - val_loss: 1.8660
Epoch 49/50
1563/1563 ————— **75s** 48ms/step - accuracy: 0.8546 - loss: 0.4620 - val_accuracy: 0.7073 - val_loss: 1.7421
Epoch 50/50
1563/1563 ————— **82s** 48ms/step - accuracy: 0.8512 - loss: 0.4787 - val_accuracy: 0.7022 - val_loss: 1.6467





313/313 - 4s - 12ms/step - accuracy: 0.7022 - loss: 1.6467

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

Test accuracy: 0.7021999955177307

```
In [22]: model = models.Sequential()

# Add first convolutional layer
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model.add(layers.MaxPooling2D((2, 2)))

# Add second convolutional layer
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# Add third convolutional layer
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# Flattening the results
model.add(layers.Flatten())

# Add first dense layer (hidden units increased to 256)
model.add(layers.Dense(256, activation='relu'))

# Add second dense layer to increase hidden layers
model.add(layers.Dense(128, activation='relu'))

# Add output layer
model.add(layers.Dense(10, activation='softmax'))

cnnModel.summary()
```

Model: "sequential"

Layer (type)	Output Shape	
conv2d (Conv2D)	(None, 26, 26, 32)	
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	
conv2d_1 (Conv2D)	(None, 11, 11, 64)	
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	
conv2d_2 (Conv2D)	(None, 3, 3, 64)	
flatten (Flatten)	(None, 576)	
dense (Dense)	(None, 64)	
dense_1 (Dense)	(None, 32)	
dense_2 (Dense)	(None, 10)	

Total params: 285,248 (1.09 MB)

Trainable params: 95,082 (371.41 KB)

Non-trainable params: 0 (0.00 B)

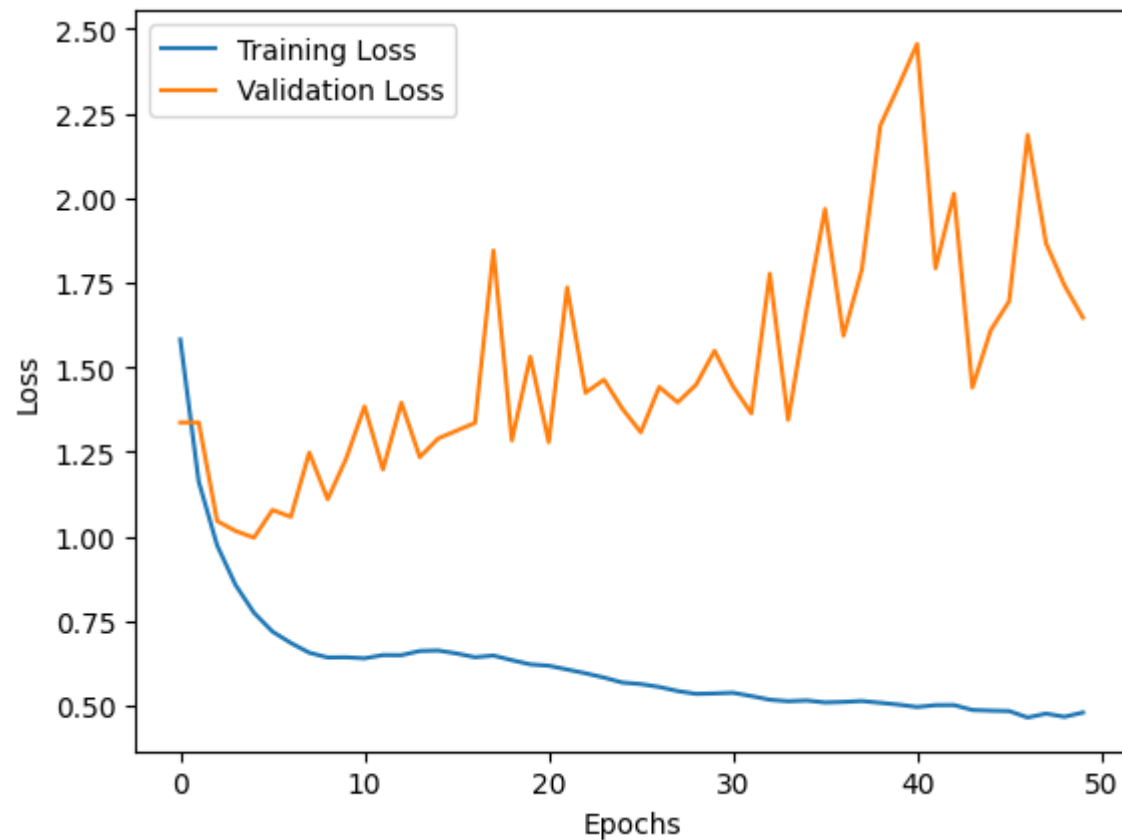
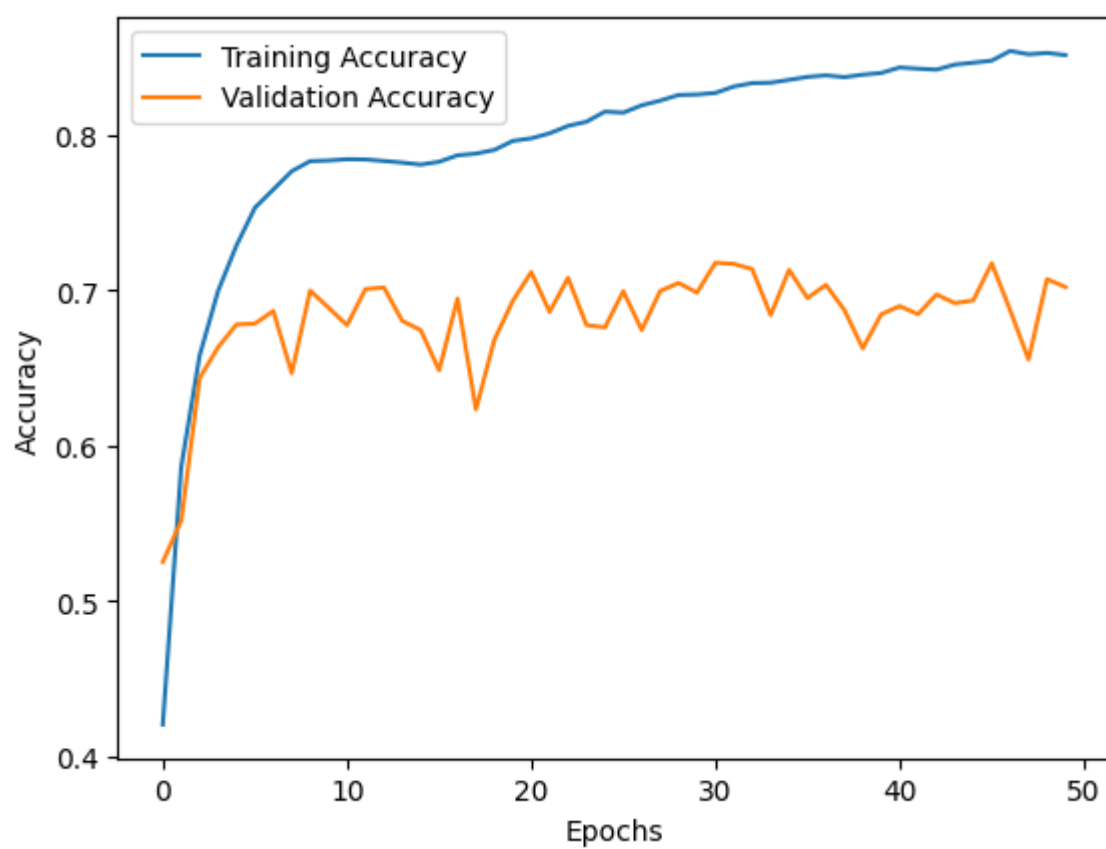
Optimizer params: 190,166 (742.84 KB)

```
In [21]: 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.show()

# Plotting training and validation loss over epochs
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.show()

# 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}")

# Save the model if needed
model.save('cnn_cifar10_model.h5')
```



313/313 - 5s - 18ms/step - accuracy: 0.7022 - loss: 1.6467

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

Test accuracy: 0.7021999955177307