

```
In [ ]: # Drive Mount
from google.colab import drive
drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
In [ ]: # Core libraries
import numpy as np
import matplotlib.pyplot as plt

# TensorFlow and Keras for building the neural network
import tensorflow as tf
from tensorflow import keras
```

```
In [ ]: from tensorflow.keras import layers
```

Objective 1: Convolutional Neural Network. Optimized for image data

```
In [ ]: # Load the MNIST dataset directly from Keras
# It automatically splits into training (60,000 images) and test (10,000 images)
(x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()

# Print the shapes to understand the data structure
print("Training images:", x_train.shape)
print("Training labels:", y_train.shape)
print("Test images:", x_test.shape)
print("Test labels:", y_test.shape)

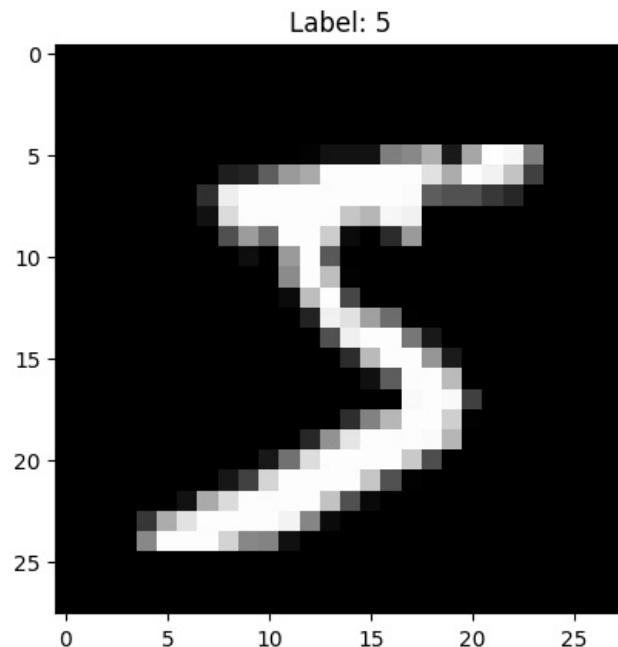
# Display the first example image
plt.imshow(x_train[0], cmap="gray") # grayscale visualization
plt.title(f"Label: {y_train[0]}")
plt.show()
```

Training images: (60000, 28, 28)

Training labels: (60000,)

Test images: (10000, 28, 28)

Test labels: (10000,)



```
In [ ]: # Convert pixel values from integers (0-255) to floats (0-1)
# This normalization helps the model train more effectively
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0

# CNNs expect 4D input: (samples, height, width, channels)
# Our data is (60000, 28, 28) - we add a channel dimension of 1 (grayscale)
x_train = np.expand_dims(x_train, -1) # becomes (60000, 28, 28, 1)
x_test = np.expand_dims(x_test, -1) # becomes (10000, 28, 28, 1)

# One-hot encode the labels
# Instead of numbers 0-9, we convert them to vectors like [0,0,0,1,0,0,0,0,0,0]
y_train = keras.utils.to_categorical(y_train, 10)
y_test = keras.utils.to_categorical(y_test, 10)
```

```
In [ ]: # Define a Sequential model - a linear stack of layers
model = keras.Sequential([
```

```

# Convolution layer: 32 filters, each 3x3 pixels
# This layer learns simple patterns like edges
layers.Conv2D(32, (3,3), activation='relu', input_shape=(28, 28, 1)),

# Pooling layer: reduces size (28x28 → 14x14) while keeping important info
layers.MaxPooling2D((2,2)),

# Another convolution: deeper features (e.g., curves, loops)
layers.Conv2D(64, (3,3), activation='relu'),

# Another pooling: further reduce size (14x14 → 7x7)
layers.MaxPooling2D((2,2)),

# Flatten: turn 2D feature maps into a 1D vector for the dense layers
layers.Flatten(),

# Dense layer: learns complex combinations of features
layers.Dense(64, activation='relu'),

# Output layer: 10 neurons for 10 digit classes (0–9)
# 'softmax' turns outputs into probabilities that sum to 1
layers.Dense(10, activation='softmax')
])

# Print a summary of the architecture
model.summary()

```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_10 (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_11 (Conv2D)	(None, 11, 11, 64)	18,496
max_pooling2d_11 (MaxPooling2D)	(None, 5, 5, 64)	0
flatten_5 (Flatten)	(None, 1600)	0
dense_10 (Dense)	(None, 64)	102,464
dense_11 (Dense)	(None, 10)	650

Total params: 121,930 (476.29 KB)

Trainable params: 121,930 (476.29 KB)

Non-trainable params: 0 (0.00 B)

```
In [ ]: model.compile(
    optimizer=keras.optimizers.Adam(learning_rate=0.001),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)
```

```
In [ ]: # Train the CNN using the training data
# validation_split=0.2 uses 20% of training data to validate performance each epoch
history = model.fit(
    x_train, y_train,
    epochs=5,           # You can increase this to 10 or more for better accuracy
    batch_size=64,      # How many images per gradient update
    validation_split=0.2
)
```

```

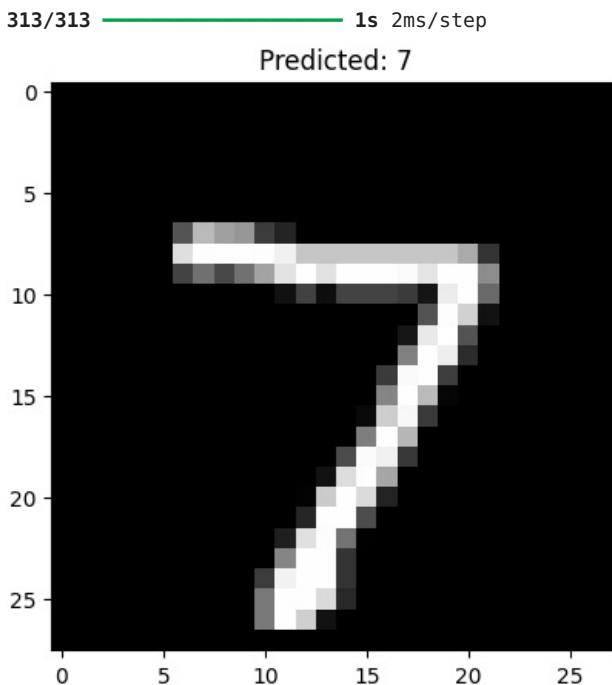
Epoch 1/5
750/750 8s 6ms/step - accuracy: 0.8497 - loss: 0.4910 - val_accuracy: 0.9807 - val_loss: 0.0662
Epoch 2/5
750/750 3s 3ms/step - accuracy: 0.9792 - loss: 0.0675 - val_accuracy: 0.9860 - val_loss: 0.0483
Epoch 3/5
750/750 3s 3ms/step - accuracy: 0.9860 - loss: 0.0448 - val_accuracy: 0.9869 - val_loss: 0.0449
Epoch 4/5
750/750 3s 3ms/step - accuracy: 0.9900 - loss: 0.0295 - val_accuracy: 0.9870 - val_loss: 0.0432
Epoch 5/5
750/750 3s 5ms/step - accuracy: 0.9915 - loss: 0.0254 - val_accuracy: 0.9876 - val_loss: 0.0435

```

```
In [ ]: # Test the trained model on new data it has never seen
test_loss, test_acc = model.evaluate(x_test, y_test)
```

```
print(f"Test accuracy: {test_acc * 100:.2f}%")  
313/313 ━━━━━━ 1s 3ms/step - accuracy: 0.9860 - loss: 0.0426  
Test accuracy: 98.85%
```

```
In [ ]: # Predict on one image  
predictions = model.predict(x_test)  
  
# Get the index of the highest probability → the predicted digit  
predicted_label = np.argmax(predictions[0])  
  
# Show the image with the prediction  
plt.imshow(x_test[0].reshape(28, 28), cmap='gray')  
plt.title(f"Predicted: {predicted_label}")  
plt.show()
```

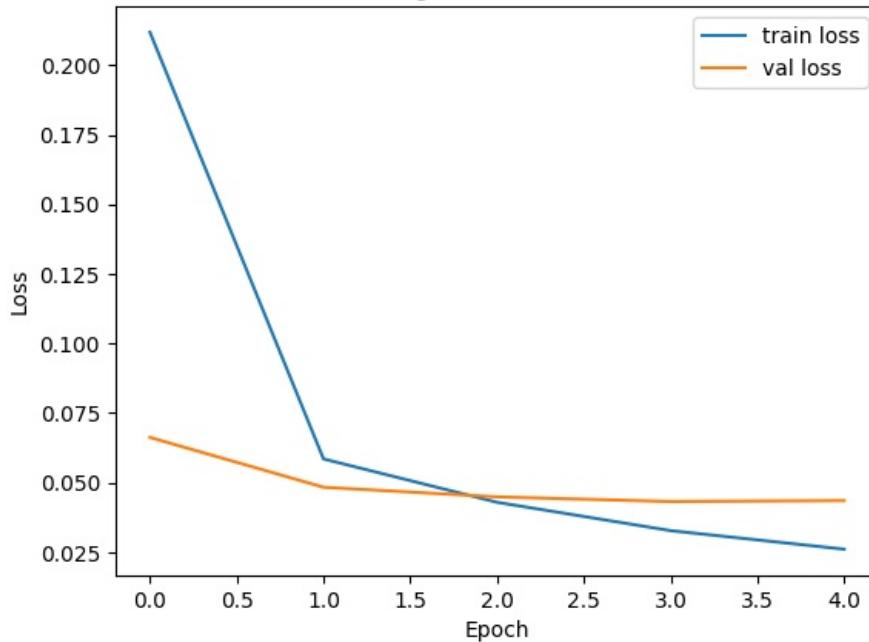


```
In [ ]: # Save  
model.save("/content/digit_cnn.h5")  
  
# Load later  
loaded_model = keras.models.load_model("/content/digit_cnn.h5")
```

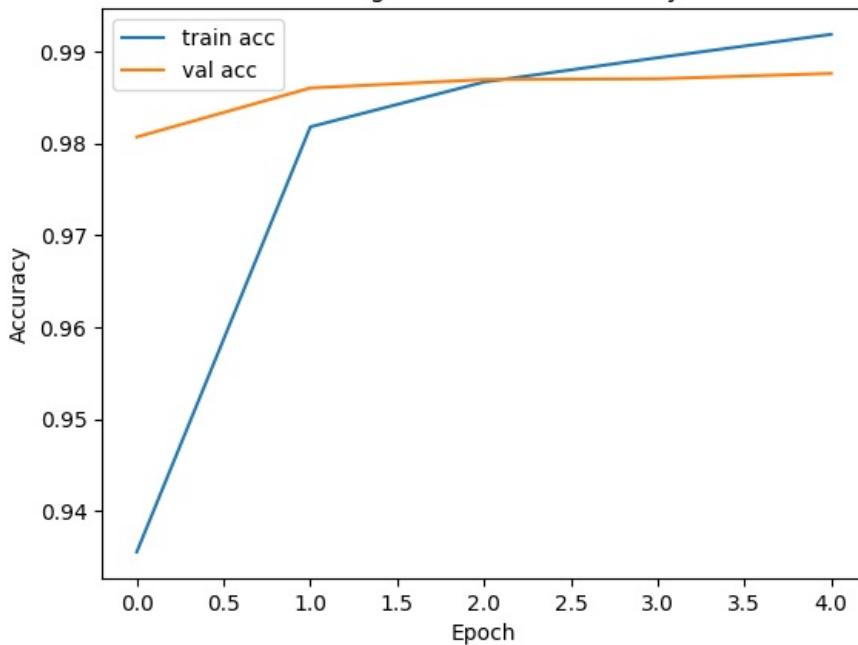
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.

```
In [ ]: plt.plot(history.history['loss'], label='train loss')  
plt.plot(history.history['val_loss'], label='val loss')  
plt.legend()  
plt.xlabel('Epoch')  
plt.ylabel('Loss')  
plt.title('Training vs Validation Loss')  
plt.show()  
  
plt.plot(history.history['accuracy'], label='train acc')  
plt.plot(history.history['val_accuracy'], label='val acc')  
plt.legend()  
plt.xlabel('Epoch')  
plt.ylabel('Accuracy')  
plt.title('Training vs Validation Accuracy')  
plt.show()
```

Training vs Validation Loss



Training vs Validation Accuracy



```
In [ ]: from google.colab import drive
drive.mount('/content/drive')
!jupyter nbconvert --to html '/content/drive/MyDrive/HNR499/HNR499_Model1'
```