```
from google.colab import drive
drive.mount('/content/drive')
Fr Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force remount=True).
Task 1: Data Preparation
import os
import numpy as np
from tensorflow.keras.utils import to_categorical
from PIL import Image
# Define dataset paths
train_dir = "/content/drive/MyDrive/Final-Year AI/week4/DevanagariHandwrittenDigitDataset/Train"
test_dir = "/content/drive/MyDrive/Final-Year AI/week4/DevanagariHandwrittenDigitDataset/Test"
# Define image size
img_height, img_width = 28, 28
# Function to load images and labels using PIL
def load_images_from_folder(folder):
    images = []
    labels = []
    # Get sorted class names (e.g., digit_0, digit_1, ..., digit_9)
    class_names = sorted(os.listdir(folder))
    class_map = {name: i for i, name in enumerate(class_names)} # Map class names to labels
    for class_name in class_names:
        class_path = os.path.join(folder, class_name)
        label = class_map[class_name]
        for filename in os.listdir(class_path):
            img_path = os.path.join(class_path, filename)
            # Load image using PIL
            img = Image.open(img_path).convert("L") # Convert to grayscale
            img = img.resize((img_width, img_height)) # Resize to (28, 28)
            img = np.array(img) / 255.0 # Normalize pixel values to [0, 1]
            images.append(img)
            labels.append(label)
    return np.array(images), np.array(labels)
# Load training and testing datasets
x_train, y_train = load_images_from_folder(train_dir)
x_test, y_test = load_images_from_folder(test_dir)
# Flatten images for Keras input
x_train = x_train.reshape(-1, img_height * img_width) # Shape: (num_samples, 784)
x_test = x_test.reshape(-1, img_height * img_width)
# One-hot encode labels
y_train = to_categorical(y_train, num_classes=10)
y_test = to_categorical(y_test, num_classes=10)
```

Print dataset shapes for verification

Visualize some images
import matplotlib.pyplot as plt

plt.axis("off")

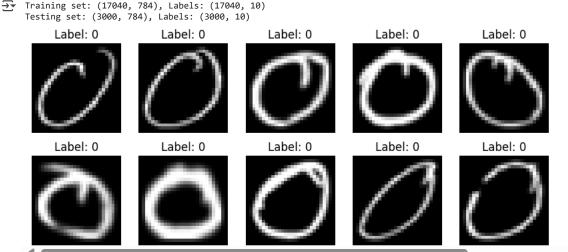
plt.show()

plt.figure(figsize=(10, 4))
for i in range(10):

plt.subplot(2, 5, i + 1)

print(f"Training set: {x_train.shape}, Labels: {y_train.shape}")
print(f"Testing set: {x_test.shape}, Labels: {y_test.shape}")

plt.imshow(x_train[i].reshape(28, 28), cmap='gray')
plt.title(f"Label: {np.argmax(y_train[i])}")



Task 2: Build the FCN Model

```
from tensorflow.keras import models, layers

# Create a Sequential model
model = models.Sequential([
    layers.Input(shape=(img_height * img_width,)),  # Input layer (flattened image)
    layers.Dense(64, activation="sigmoid"),  # 1st hidden layer
    layers.Dense(128, activation="sigmoid"),  # 2nd hidden layer
    layers.Dense(256, activation="sigmoid"),  # 3rd hidden layer
    layers.Dense(10, activation="softmax")  # Output layer (10 classes)
])

# Print model summary
model.summary()
```

→ Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 64)	50,240
dense_1 (Dense)	(None, 128)	8,320
dense_2 (Dense)	(None, 256)	33,024
dense_3 (Dense)	(None, 10)	2,570

Total params: 94,154 (367.79 KB)
Trainable nanams: 04 154 (367.70 KB)

Task 3: Compile the Model

```
# Compile the model
model.compile(
    optimizer="adam", # Optimizer
    loss = "categorical\_crossentropy", \quad \# \ Loss \ function \ for \ multi-class \ classification
    metrics=["accuracy"] # Evaluation metric
)
Task 4: Train the Model
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
# Define callbacks
callbacks = [
    ModelCheckpoint(filepath="my_model.keras", save_best_only=True),
    EarlyStopping(monitor="val_loss", patience=4)
]
# Train the model
history = model.fit(
    x_train, y_train,
```

```
batch_size=128,
    epochs=500,
    validation_split=0.2,
    callbacks=callbacks
)
→ Epoch 1/500
     107/107 -
                                - 1s 8ms/step - accuracy: 0.9857 - loss: 0.0518 - val_accuracy: 0.0023 - val_loss: 16.1936
     Epoch 2/500
     107/107
                                 – 1s 7ms/step - accuracy: 0.9926 - loss: 0.0346 - val_accuracy: 0.0023 - val_loss: 16.4000
     Epoch 3/500
     107/107
                                — 1s 7ms/step - accuracy: 0.9925 - loss: 0.0341 - val_accuracy: 0.0023 - val_loss: 16.7773
     Epoch 4/500
     107/107 -
                                 - 1s 7ms/step - accuracy: 0.9944 - loss: 0.0248 - val_accuracy: 0.0023 - val_loss: 17.0040
     Epoch 5/500
                                - 1s 7ms/step - accuracy: 0.9950 - loss: 0.0218 - val accuracy: 0.0023 - val loss: 17.1836
     107/107 -
Task 5: Evaluate the Model
# Evaluate the model on the test set
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=2)
print(f"Test accuracy: {test_acc:.4f}")
→ 94/94 - 0s - 2ms/step - accuracy: 0.7803 - loss: 3.4954
     Test accuracy: 0.7803
Task 6: Save and Load the Model
# Import TensorFlow
import tensorflow as tf
# Save the trained model in the native Keras format (.keras)
model.save("devnagari_fcn_model.keras")
# Load the saved model
loaded_model = tf.keras.models.load_model("devnagari_fcn_model.keras")
# Re-evaluate the loaded model on the test set
loaded_test_loss, loaded_test_acc = loaded_model.evaluate(x_test, y_test, verbose=2)
print(f"Loaded model test accuracy: {loaded_test_acc:.4f}")
→ 94/94 - 1s - 6ms/step - accuracy: 0.7803 - loss: 3.4954
     Loaded model test accuracy: 0.7803
Task 7: Predictions
# Make predictions on test data
predictions = loaded_model.predict(x_test)
# Convert predictions from probabilities to digit labels
predicted_labels = np.argmax(predictions, axis=1)
true_labels = np.argmax(y_test, axis=1)
# Display the first prediction
print(f"Predicted label for first image: {predicted_labels[0]}")
print(f"True label for first image: {true_labels[0]}")
<del>→</del> 94/94 -
                               - 0s 2ms/step
     Predicted label for first image: 0
     True label for first image: 0
Visualization
# Plot training and validation loss
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='orange')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
```

```
# Plot training and validation accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='orange')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy')
plt.legend()
plt.tight_layout()
plt.show()
₹
                                Training and Validation Loss
                                                                                                     Training and Validation Accuracy
         17.5
                                                                                 1.0
         15.0
                                                                                 0.8
         12.5
                                                                                 0.6
         10.0
                                                                               Accuracy
                                                               Training Loss
                                                                                                                                   Training Accuracy
       Loss
                                                                                                                                   Validation Accuracy
                                                               Validation Loss
          7.5
                                                                                 0.4
          5.0
```

2.5

0.0

0.0

0.5

1.0

1.5

2.0

Epochs

2.5

3.0

3.5

4.0

0.2

0.0

0.0

0.5

1.0

1.5

2.0

Epochs

2.5

3.0

3.5

4.0