```
[ ] !pip install gdown

    !gdown 1xsjOC7I9AsIaKUl4eiF8A7aCBsiFaS8T

    !unzip "devnagari.zip"
```

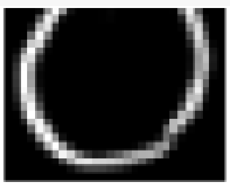
Show hidden output

```
import tensorflow as tf
print(tf.keras.__version__)
from PIL import Image
import glob
import numpy as np
import matplotlib.pyplot as plt
import os
from tensorflow.keras.utils import to_categorical
from tensorflow.keras import layers, models
```

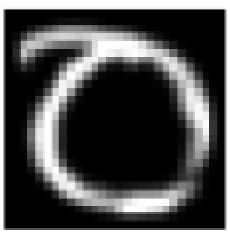
```
3.8.0
```

```
train_path = "DevanagariHandwrittenDigitDataset/Train/"
test_path = "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 = []
  class_names = sorted(os.listdir(folder)) # Sorted class names (digit_0, digit_1, ...)
  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_path)
x_test, y_test = load_images_from_folder(test_path)
```

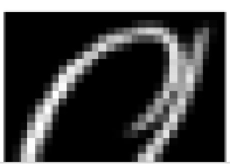
```
[ ] num_classes = 10

    # Reshape images for Keras input
    x_train = x_train.reshape(-1, img_height, img_width, 1) # Shape (num_samples, 28, 28, 1)
    x_test = x_test.reshape(-1, img_height, img_width, 1)
    # One-hot encode labels
    y_train = to_categorical(y_train, num_classes=num_classes)
    y_test = to_categorical(y_test, num_classes=num_classes)
    # Print dataset shape
    print(f"Training set: {x_train.shape}, Labels: {y_train.shape}")
    print(f"Testing set: {x_test.shape}, Labels: {y_test.shape}")
    # Visualize some images

    for i in range(10):
      plt.figure(figsize=(10, 4))
      plt.subplot(2, 5, i + 1)
      plt.imshow(x_train[i].reshape(28, 28), cmap="gray")
      plt.title(f"Label: {np.argmax(y_train[i])}")
      plt.axis("off")
      plt.show()
```



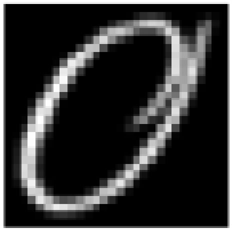
Label: 0



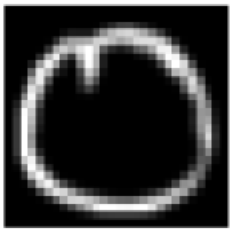
Label: 0



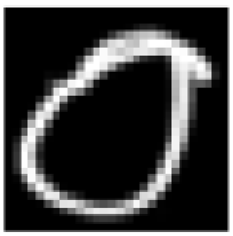
Label: 0



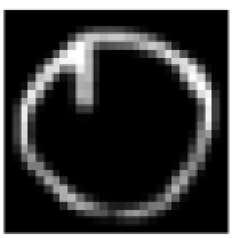
Label: 0



Label: 0



Label: 0



Task 2: Build the FCN Model

Task 2: Build the FCN Model

Model Architecture

- Create a Sequential model using Keras.
- Add 3 hidden layers with the following number of neurons:

– 1st hidden layer: 64 neurons

– 2nd hidden layer: 128 neurons

– 3rd hidden layer: 256 neurons

- Use sigmoid activation functions for all hidden layers.
- Add an output layer with 10 units with softmax (since Devnagari digits have 10 classes) and a softmax activation function.

```
[ ] input_shape = (28, 28, 1)
    model = keras.Sequential([
        keras.layers.Input(shape = input_shape),
        keras.layers.Flatten(),
        keras.layers.Dense(16, activation='sigmoid'),
        keras.layers.Dense(32, activation='sigmoid'),
        keras.layers.Dense(32, activation='sigmoid'),
        keras.layers.Dense(num_classes, activation='softmax'),
    ])
```

```
model.summary()
```

```
[ ] model.summary()
```

Model: "sequential_10"

Layer (type)	Output Shape	Param #
flatten_10 (Flatten)	(None, 784)	0
dense_40 (Dense)	(None, 16)	12,560
dense_41 (Dense)	(None, 32)	544
dense_42 (Dense)	(None, 32)	1,056
dense_43 (Dense)	(None, 10)	330

Total params: 14,490 (56.60 KB)
Trainable params: 14,490 (56.60 KB)
Non-trainable params: 0 (0.00 B)

Task 3: Compile the Model

Model Compilation

- Choose an appropriate optimizer (e.g., Adam), loss function (e.g., sparse categorical crossentropy), and evaluation metric (e.g., accuracy).

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

Task 3: Compile the Model

Model Compilation

• Choose an appropriate optimizer (e.g., Adam), loss function (e.g., sparse categorical crossentropy), and evaluation metric (e.g., accuracy).

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

Task 4: Train the Model

Model Training

• Use the model.fit() function to train the model. Set the batch size to 128 and the number of epochs to 20.

• Use validation split (validation split=0.2) to monitor the model's performance on validation data.

• Optionally, use callbacks such as ModelCheckpoint and EarlyStopping for saving the best model and avoiding overfitting.

```
batch_size = 128
epochs = 20

callbacks = [
    keras.callbacks.EarlyStopping(monitor="val_loss", patience = 4)
]

model.fit(
    x = x_train,
    y = y_train,
    batch_size = batch_size,
    epochs = epochs,
    validation_split = 0.2,
    callbacks = callbacks
)
```

```
Epoch 1/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.2046 - loss: 2.3074 - val_accuracy: 0.0000e+00 - val_loss: 3.9464
Epoch 2/20
```

```
Epoch 1/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.2046 - loss: 2.3074 - val_accuracy: 0.0000e+00 - val_loss: 3.9464
Epoch 2/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.4878 - loss: 1.9105 - val_accuracy: 0.0000e+00 - val_loss: 4.6360
Epoch 3/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6297 - loss: 1.4534 - val_accuracy: 0.0000e+00 - val_loss: 5.1182
Epoch 4/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7542 - loss: 1.0365 - val_accuracy: 0.0000e+00 - val_loss: 5.5507
Epoch 5/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.8376 - loss: 0.7891 - val_accuracy: 0.0000e+00 - val_loss: 5.9151
<keras.src.callbacks.history.History at 0x7ce37d4da1d0>
```

Task 5: Evaluate the Model

Model Evaluation

• After training, evaluate the model using model.evaluate() on the test set to check the test accuracy and loss.

```
test_loss, test_acc = model.evaluate(
    x=x_test,
    y=y_test,
    batch_size=batch_size,
    verbose=2,
    sample_weight=None,
    steps=None,
    callbacks=callbacks
)

print(f"Testing accuracy: {test_acc:.4f} The accuracy value computed based on the test dataset. It shows the proportion of correct predictions made by the model.")
print(f"Testing loss: {test_loss:.4f} The loss value computed based on the test dataset. This gives an indication of how well the model is performing on unseen data.")
```

```
24/24 - 0s - 4ms/step - accuracy: 0.6920 - loss: 1.7144
Testing accuracy: 0.6920 The accuracy value computed based on the test dataset. It shows the proportion of correct predictions made by the model.
Testing loss: 1.7144 The loss value computed based on the test dataset. This gives an indication of how well the model is performing on unseen data.
```

Task 6: Save and Load the Model

Model Saving and Loading

• Save the trained model to an .h5 file using model.save().

• Load the saved model and re-evaluate its performance on the test set.

```
model.save("devanagari_digit_model.keras")
```

```
loaded_model = tf.keras.models.load_model("devanagari_digit_model.keras")

loaded_model.compile(
    optimizer="adam",
    loss="categorical_crossentropy",
    metrics=["accuracy"]
)

test_loss, test_acc = loaded_model.evaluate(
    x=x_test,
    y=y_test,
    batch_size=batch_size,
    verbose=2
)

print(f"Testing accuracy: {test_acc:.4f}")
print(f"Testing loss: {test_loss:.4f}")
```

```
24/24 - 0s - 16ms/step - accuracy: 0.6920 - loss: 1.7144
Testing accuracy: 0.6920
Testing loss: 1.7144
```

```
predictions = model.predict(x_test)

prediction_labels = np.argmax(predictions, axis=1)
actual_labels = np.argmax(y_test, axis=1)

print(f"Predicted labels: {prediction_labels[:10]}")
print(f"Actual labels: {actual_labels[:10]}")
```

```
94/94 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
Predicted labels: [0 0 0 0 0 0 0 0 0 0]
Actual labels: [0 0 0 0 0 0 0 0 0 0]
```

```
history = model.fit(
    x=x_train,
    y=y_train,
    batch_size=batch_size,
    epochs=epochs,
    validation_split=0.2,
    callbacks=callbacks
)
```

```
Epoch 1/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.8805 - loss: 0.6245 - val_accuracy: 0.0000e+00 - val_loss: 6.2283
Epoch 2/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9001 - loss: 0.5043 - val_accuracy: 0.0000e+00 - val_loss: 6.5030
Epoch 3/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9274 - loss: 0.4099 - val_accuracy: 0.0000e+00 - val_loss: 6.7833
Epoch 4/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9333 - loss: 0.3465 - val_accuracy: 0.0000e+00 - val_loss: 7.0317
Epoch 5/20
107/107 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9443 - loss: 0.2902 - val_accuracy: 0.0000e+00 - val_loss: 7.3033
```

```python
plt.figure(figsize=(12, 7))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'])

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'])

plt.show()
```