```
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_remoun
```

Importing Required Libraries

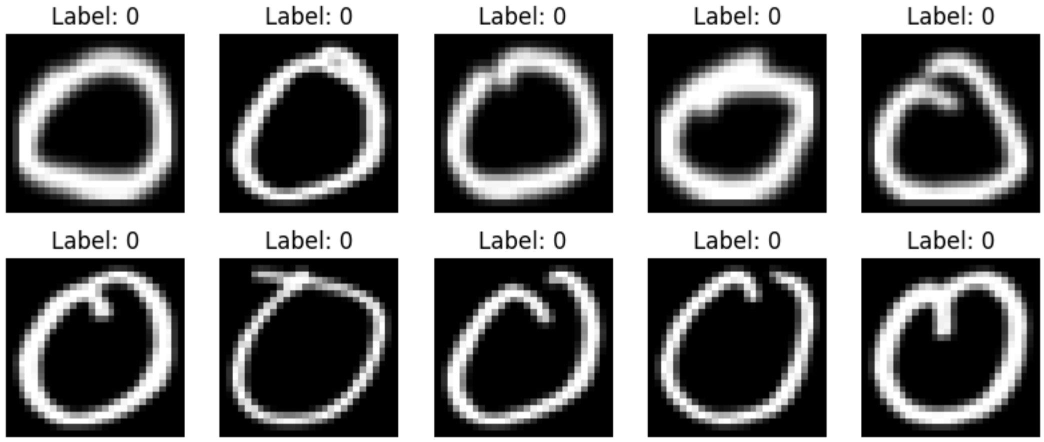
```
import os
import numpy as np
import tensorflow as tf
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from sklearn.utils import shuffle
import matplotlib.pyplot as plt
from PIL import Image

from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, BatchNormalization, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping

import matplotlib.pyplot as plt
```

Sgd Optimizer Model

```
# Define dataset paths
train_dir = "/content/drive/MyDrive/AI and ML/Week4/DevanagariHandwrittenDigitDataset/Train/"
test_dir = "/content/drive/MyDrive/AI and ML/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 = []
    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_dir)
x_test, y_test = load_images_from_folder(test_dir)

# 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=10)
y_test = to_categorical(y_test, num_classes=10)

# 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
plt.figure(figsize=(10, 4))
for i in range(10):
    plt.subplot(2, 5, i + 1)
```

```
    plt.subplot(2, 5, i + 1)
    plt.imshow(x_train[i].reshape(28, 28), cmap='gray')  # Fixed incorrect quotes
    plt.title(f"Label: {np.argmax(y_train[i])}")
    plt.axis("off")
plt.show()
```

```
Training set: (17000, 28, 28, 1), Labels: (17000, 10)
Testing set: (3010, 28, 28, 1), Labels: (3010, 10)
```




```
num_classes = 10
input_shape = (28*28, 1)
model = keras.Sequential(
[
keras.layers.Input(shape=input_shape),
keras.layers.Flatten(),
keras.layers.Dense(64, activation="sigmoid"),
keras.layers.Dense(128, activation="sigmoid"),
keras.layers.Dense(256, activation="sigmoid"),
keras.layers.Dense(num_classes, activation="softmax"),
]
)
```

```
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
flatten_1 (Flatten)	(None, 784)	0
dense_4 (Dense)	(None, 64)	50,240
dense_5 (Dense)	(None, 128)	8,320
dense_6 (Dense)	(None, 256)	33,024
dense_7 (Dense)	(None, 10)	2,570

Total params: 94,154 (367.79 KB)
Trainable params: 94,154 (367.79 KB)
Non-trainable params: 0 (0.00 B)

```
model.compile(
optimizer="sgd",
loss="categorical_crossentropy",
metrics=["accuracy"]
)
```

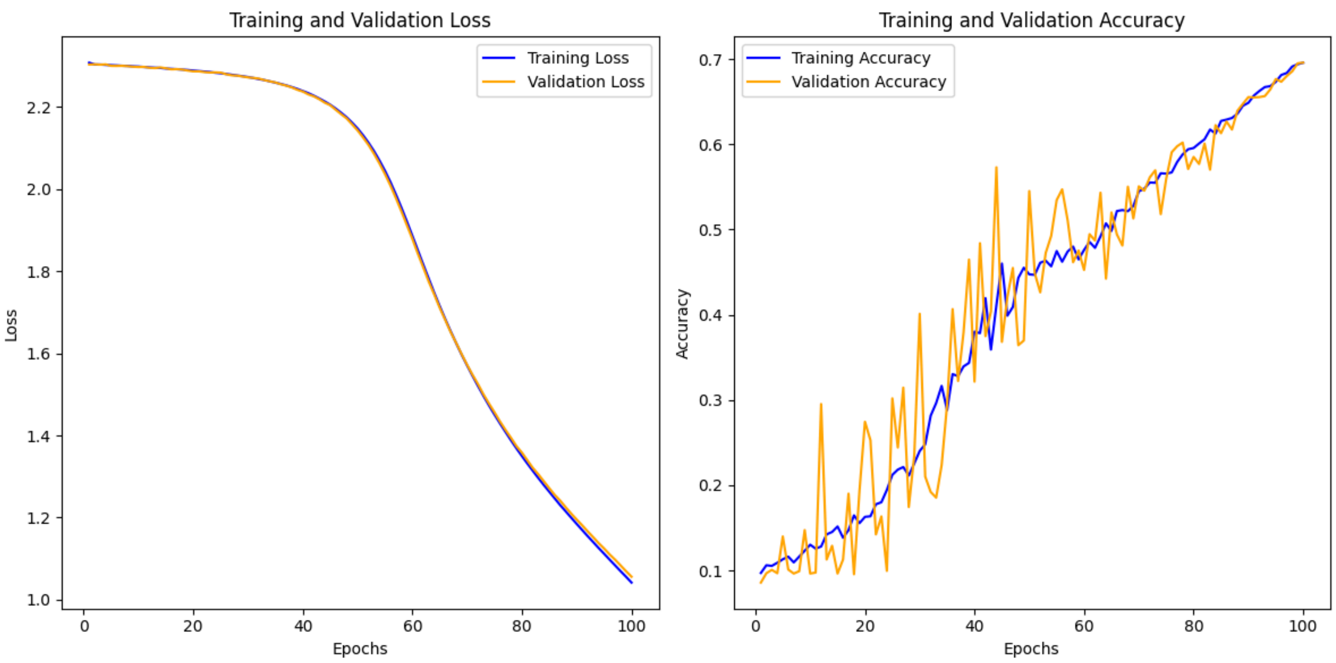
```
x_train, y_train = shuffle(x_train, y_train, random_state=42)

batch_size = 128
epochs = 100

callbacks = [
    keras.callbacks.ModelCheckpoint(filepath="model_at_epoch_{epoch}.keras"),
    keras.callbacks.EarlyStopping(monitor="val_loss", patience = 4,),
]

history = model.fit(
    x_train,
    y_train,
    batch_size=batch_size,
    epochs=epochs,
    validation_split = 0.15,
```

```
    callbacks=callbacks,
)
```

```
Epoch 1/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - accuracy: 0.0974 - loss: 2.3146 - val_accuracy: 0.0859 - val_loss: 2.3023
Epoch 2/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1069 - loss: 2.3022 - val_accuracy: 0.0969 - val_loss: 2.3029
Epoch 3/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.1035 - loss: 2.3025 - val_accuracy: 0.1008 - val_loss: 2.3020
Epoch 4/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.1082 - loss: 2.3017 - val_accuracy: 0.0969 - val_loss: 2.3027
Epoch 5/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.1067 - loss: 2.3011 - val_accuracy: 0.1400 - val_loss: 2.2991
Epoch 6/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1221 - loss: 2.3000 - val_accuracy: 0.1012 - val_loss: 2.2989
Epoch 7/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1121 - loss: 2.2991 - val_accuracy: 0.0965 - val_loss: 2.2992
Epoch 8/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1160 - loss: 2.2989 - val_accuracy: 0.0992 - val_loss: 2.2984
Epoch 9/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1237 - loss: 2.2980 - val_accuracy: 0.1475 - val_loss: 2.2970
Epoch 10/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.1364 - loss: 2.2977 - val_accuracy: 0.0965 - val_loss: 2.2963
Epoch 11/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.1222 - loss: 2.2966 - val_accuracy: 0.0976 - val_loss: 2.2966
Epoch 12/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.1231 - loss: 2.2953 - val_accuracy: 0.2953 - val_loss: 2.2944
Epoch 13/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.1545 - loss: 2.2949 - val_accuracy: 0.1129 - val_loss: 2.2936
Epoch 14/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.1331 - loss: 2.2939 - val_accuracy: 0.1290 - val_loss: 2.2953
Epoch 15/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.1419 - loss: 2.2927 - val_accuracy: 0.0965 - val_loss: 2.2933
Epoch 16/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.1324 - loss: 2.2918 - val_accuracy: 0.1129 - val_loss: 2.2907
Epoch 17/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.1330 - loss: 2.2911 - val_accuracy: 0.1902 - val_loss: 2.2912
Epoch 18/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1821 - loss: 2.2902 - val_accuracy: 0.0957 - val_loss: 2.2900
Epoch 19/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1443 - loss: 2.2893 - val_accuracy: 0.1933 - val_loss: 2.2876
Epoch 20/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.1665 - loss: 2.2880 - val_accuracy: 0.2745 - val_loss: 2.2858
Epoch 21/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.1581 - loss: 2.2865 - val_accuracy: 0.2529 - val_loss: 2.2857
Epoch 22/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1815 - loss: 2.2853 - val_accuracy: 0.1424 - val_loss: 2.2841
Epoch 23/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.1730 - loss: 2.2848 - val_accuracy: 0.1635 - val_loss: 2.2829
Epoch 24/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.2059 - loss: 2.2826 - val_accuracy: 0.0996 - val_loss: 2.2833
Epoch 25/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.2044 - loss: 2.2820 - val_accuracy: 0.3020 - val_loss: 2.2826
Epoch 26/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.2293 - loss: 2.2803 - val_accuracy: 0.2443 - val_loss: 2.2787
Epoch 27/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.2270 - loss: 2.2773 - val_accuracy: 0.3145 - val_loss: 2.2761
Epoch 28/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.1986 - loss: 2.2759 - val_accuracy: 0.1745 - val_loss: 2.2753
Epoch 29/100
113/113 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.2110 - loss: 2.2745 - val_accuracy: 0.2345 - val_loss: 2.2732
```

```
import matplotlib.pyplot as plt

# Assuming 'history' is the object returned by model.fit()
# Extracting training and validation loss
train_loss = history.history['loss']
val_loss = history.history['val_loss']

# Extracting training and validation accuracy (if metrics were specified)
train_acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

# Plotting training and validation loss
plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
plt.plot(range(1, len(train_loss) + 1), train_loss, label='Training Loss', color='blue')
plt.plot(range(1, len(val_loss) + 1), val_loss, label='Validation Loss', color='orange')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()

# Plotting training and validation accuracy
plt.subplot(1, 2, 2)
```

```
plt.plot(range(1, len(train_acc) + 1), train_acc, label='Training Accuracy', color='blue')
plt.plot(range(1, len(val_acc) + 1), val_acc, label='Validation Accuracy', color='orange')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```




```
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=2)
print(f"Test Accuracy: {test_acc:.4f}")
```

```
95/95 - 0s - 2ms/step - accuracy: 0.7000 - loss: 1.0323
Test Accuracy: 0.7000
```

```
model.save("devnagari_digit_classifier.h5")

loaded_model = tf.keras.models.load_model("devnagari_digit_classifier.h5")

test_loss, test_acc = loaded_model.evaluate(x_test, y_test, verbose=2)
print(f"Loaded Model Test Accuracy: {test_acc:.4f}")
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be e
95/95 - 1s - 6ms/step - accuracy: 0.7000 - loss: 1.0323
Loaded Model Test Accuracy: 0.7000
```

```
predictions = model.predict(x_test)

predicted_labels = np.argmax(predictions, axis=1)

print(f"Predicted label for first image: {predicted_labels[0]}")
print(f"True label for first image: {np.argmax(y_test[0])}")
```

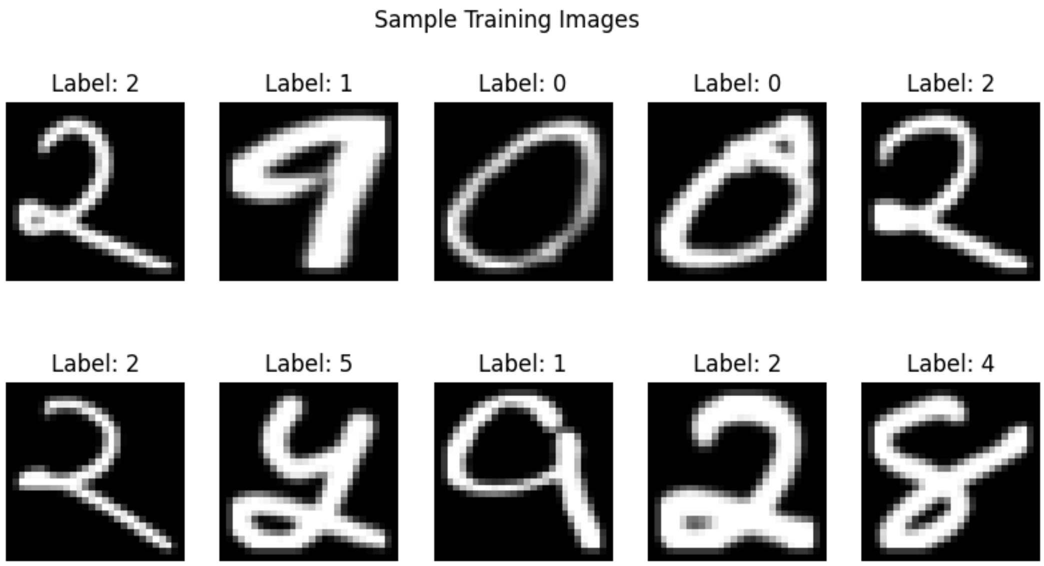
```
95/95 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
Predicted label for first image: 0
True label for first image: 0
```

Adam Optimizer Model

Task 1 - Data Preparation

```
train_dir = "/content/drive/MyDrive/AI and ML/Week4/DevanagariHandwrittenDigitDataset/Train/"
test_dir = "/content/drive/MyDrive/AI and ML/Week4/DevanagariHandwrittenDigitDataset/Test"

def load_images_from_folder(folder):
    images, labels = [], []
    classes = sorted(os.listdir(folder))
    class_map = {class_name: i for i, class_name in enumerate(classes)}

    for class_name in classes:
        class_folder = os.path.join(folder, class_name)
        if not os.path.isdir(class_folder):
            continue

        for image_name in os.listdir(class_folder):
            image_path = os.path.join(class_folder, image_name)
            try:
                img = Image.open(image_path).convert('L')
                img = img.resize((28, 28))
                img = np.array(img) / 255.0
                images.append(img)
                labels.append(class_map[class_name])
            except Exception as e:
                print(f"Error loading image {image_path}: {e}")

    return np.array(images), np.array(labels)

x_train, y_train = load_images_from_folder(train_dir)
x_test, y_test = load_images_from_folder(test_dir)

x_train = x_train.reshape(x_train.shape[0], 28*28)
x_test = x_test.reshape(x_test.shape[0], 28*28)

y_train = to_categorical(y_train, num_classes=10)
y_test = to_categorical(y_test, num_classes=10)

x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test_size=0.2, random_state=42)

print(f"Training Data Shape: {x_train.shape}, Validation Shape: {x_val.shape}, Test Shape: {x_test.shape}")
print(f"One-hot Encoded Labels Shape: {y_train.shape}")

fig, axes = plt.subplots(2, 5, figsize=(10, 5))
for i, ax in enumerate(axes.flat):
    ax.imshow(x_train[i].reshape(28, 28), cmap="gray")
    ax.set_title(f"Label: {np.argmax(y_train[i])}")
    ax.axis("off")

plt.suptitle("Sample Training Images")
plt.show()
```

```
Training Data Shape: (13600, 784), Validation Shape: (3400, 784), Test Shape: (3010, 784)
One-hot Encoded Labels Shape: (13600, 10)
```



Task 2 - Building Fully Connected Neural Network Model

```
model = Sequential([
    Dense(64, activation='sigmoid', input_shape=(28*28,)),
    Dense(128, activation='sigmoid'),
    Dense(256, activation='sigmoid'),
```

```
    Dense(10, activation='softmax')
])

model.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`in
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
dense_8 (Dense)	(None, 64)	50,240
dense_9 (Dense)	(None, 128)	8,320
dense_10 (Dense)	(None, 256)	33,024
dense_11 (Dense)	(None, 10)	2,570

Total params: 94,154 (367.79 KB)
Trainable params: 94,154 (367.79 KB)
Non-trainable params: 0 (0.00 B)

Task 3 - Compiling the Model

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

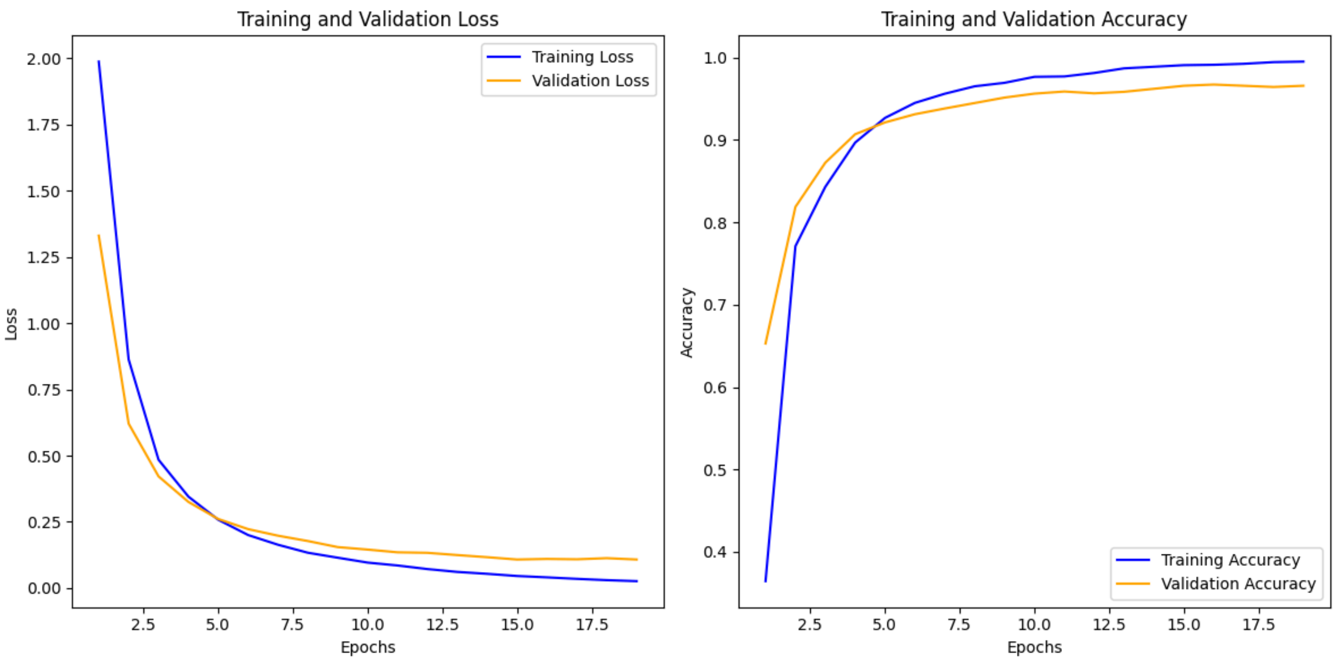
Task 4 - Train the Model

```
callbacks = [
    keras.callbacks.ModelCheckpoint(filepath="model_at_epoch_{epoch}.keras", save_best_only=True, monitor="val_loss"),
    keras.callbacks.EarlyStopping(monitor="val_loss", patience = 4, restore_best_weights=True)
]

# Train the model
history = model.fit(
    x_train, y_train,
    batch_size=128,
    epochs=20,
    validation_split=0.2,
    callbacks=callbacks
)
```

```
Epoch 1/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step - accuracy: 0.2190 - loss: 2.2195 - val_accuracy: 0.6529 - val_loss: 1.3307
Epoch 2/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.7347 - loss: 1.0614 - val_accuracy: 0.8188 - val_loss: 0.6207
Epoch 3/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8370 - loss: 0.5261 - val_accuracy: 0.8724 - val_loss: 0.4217
Epoch 4/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.8895 - loss: 0.3684 - val_accuracy: 0.9070 - val_loss: 0.3252
Epoch 5/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9223 - loss: 0.2664 - val_accuracy: 0.9213 - val_loss: 0.2606
Epoch 6/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9415 - loss: 0.2112 - val_accuracy: 0.9312 - val_loss: 0.2224
Epoch 7/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9543 - loss: 0.1659 - val_accuracy: 0.9382 - val_loss: 0.1976
Epoch 8/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step - accuracy: 0.9644 - loss: 0.1373 - val_accuracy: 0.9449 - val_loss: 0.1774
Epoch 9/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.9726 - loss: 0.1131 - val_accuracy: 0.9515 - val_loss: 0.1545
Epoch 10/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9770 - loss: 0.0955 - val_accuracy: 0.9563 - val_loss: 0.1451
Epoch 11/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9780 - loss: 0.0841 - val_accuracy: 0.9588 - val_loss: 0.1348
Epoch 12/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9820 - loss: 0.0706 - val_accuracy: 0.9566 - val_loss: 0.1329
Epoch 13/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9901 - loss: 0.0567 - val_accuracy: 0.9585 - val_loss: 0.1244
Epoch 14/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9896 - loss: 0.0526 - val_accuracy: 0.9621 - val_loss: 0.1164
Epoch 15/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9880 - loss: 0.0491 - val_accuracy: 0.9658 - val_loss: 0.1076
Epoch 16/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9933 - loss: 0.0358 - val_accuracy: 0.9673 - val_loss: 0.1098
Epoch 17/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9926 - loss: 0.0331 - val_accuracy: 0.9658 - val_loss: 0.1084
Epoch 18/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9935 - loss: 0.0299 - val_accuracy: 0.9643 - val_loss: 0.1127
```

```
Epoch 19/20
85/85 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9947 - loss: 0.0272 - val_accuracy: 0.9658 - val_loss: 0.1076
```

```
# Assuming 'history' is the object returned by model.fit()
# Extracting training and validation loss
train_loss = history.history['loss']
val_loss = history.history['val_loss']

# Extracting training and validation accuracy (if metrics were specified)
train_acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

# Plotting training and validation loss
plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
plt.plot(range(1, len(train_loss) + 1), train_loss, label='Training Loss', color='blue')
plt.plot(range(1, len(val_loss) + 1), val_loss, label='Validation Loss', color='orange')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()

# Plotting training and validation accuracy
plt.subplot(1, 2, 2)
plt.plot(range(1, len(train_acc) + 1), train_acc, label='Training Accuracy', color='blue')
plt.plot(range(1, len(val_acc) + 1), val_acc, label='Validation Accuracy', color='orange')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



Task 5 - Evaluate the Model

```
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=2)
print(f"Test Accuracy: {test_acc:.4f}")
print(f"Test Loss: {test_loss:.4f}")
```

```
95/95 - 0s - 2ms/step - accuracy: 0.9708 - loss: 0.1037
Test Accuracy: 0.9708
Test Loss: 0.1037
```

Task 6 - Saving and Loading the Model

```
model.save("devnagari_digit_classifier.h5")
print("Model saved successfully as 'devnagari_digit_classifier.h5'!")

loaded_model = tf.keras.models.load_model("devnagari_digit_classifier.h5")
print("Model loaded successfully!")

test_loss, test_acc = loaded_model.evaluate(x_test, y_test, verbose=2)
print(f"Loaded Model Test Accuracy: {test_acc:.4f}")
print(f"Loaded Model Test Loss: {test_loss:.4f}")
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be e
Model saved successfully as 'devnagari_digit_classifier.h5'!
Model loaded successfully!
95/95 - 1s - 9ms/step - accuracy: 0.9708 - loss: 0.1037
Loaded Model Test Accuracy: 0.9708
Loaded Model Test Loss: 0.1037
```

Task 7 - Making Predictions

```
num_samples = 5
random_indices = np.random.choice(len(x_test), num_samples, replace=False)
sample_images = x_test[random_indices]
sample_labels = y_test[random_indices]

predictions = loaded_model.predict(sample_images)

predicted_labels = np.argmax(predictions, axis=1)
true_labels = np.argmax(sample_labels, axis=1)

plt.figure(figsize=(10, 5))
for i in range(num_samples):
    plt.subplot(1, num_samples, i + 1)
    plt.imshow(sample_images[i].reshape(28, 28), cmap="gray")
    plt.title(f"Pred: {predicted_labels[i]}\nTrue: {true_labels[i]}")
    plt.axis("off")

plt.suptitle("Model Predictions on Test Images")
plt.show()
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
```