

Handwritten_character_model

March 4, 2025

Import Necessary Libraries

```
[2]: import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from tqdm.notebook import tqdm
```

Load Data

Dataset Comprises of two files. One is “img”, which includes all the images of Numbers and Alphabets. Other is “label.csv”, which includes the label for each image.

```
[3]: # Load the CSV file
df = pd.read_csv("/content/drive/MyDrive/label.csv")

# Display first few rows
print(df.head())
```

	image	label
0	Img/img001-001.png	0
1	Img/img001-002.png	0
2	Img/img001-003.png	0
3	Img/img001-004.png	0
4	Img/img001-005.png	0

```
[10]: from PIL import Image # Use PIL for image processing
# Path to the image folder
image_folder = "/content/drive/MyDrive"
```

```
[11]: # Define image dimensions (resize for uniformity)
IMG_WIDTH, IMG_HEIGHT = 28, 28

# Lists to store images and labels
images = []
labels = []
```

```

# Load images from the folder
for index, row in tqdm(df.iterrows()):
    img_path = os.path.join(image_folder, row['image'])
    img = Image.open(img_path).convert("L") # Convert to grayscale # Read as
    ↪ grayscale
    img = img.resize((IMG_WIDTH, IMG_HEIGHT)) # Resize to fixed size
    img = np.array(img) # Convert to NumPy array
    images.append(img)
    labels.append(row['label'])

# Convert lists to numpy arrays
images = np.array(images)
labels = np.array(labels)

# Normalize pixel values (0-255 → 0-1)
images = images / 255.0

# Reshape images for CNN input (Add channel dimension)
images = images.reshape(-1, IMG_WIDTH, IMG_HEIGHT, 1)

# Print shape of dataset
print(f"Images shape: {images.shape}, Labels shape: {labels.shape}")

```

0it [00:00, ?it/s]

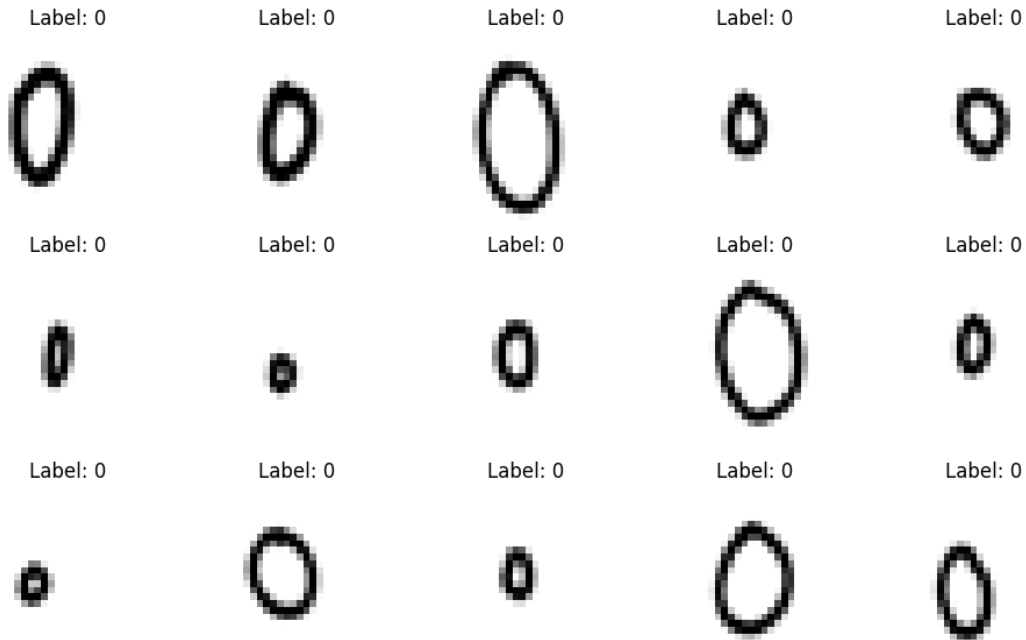
Images shape: (3410, 28, 28, 1), Labels shape: (3410,)

Visualize Sample Images

```

[12]: # Display some images with labels
fig, axes = plt.subplots(3, 5, figsize=(10, 6))
axes = axes.ravel()
for i in range(15):
    axes[i].imshow(images[i].reshape(IMG_WIDTH, IMG_HEIGHT), cmap='gray')
    axes[i].set_title(f"Label: {labels[i]}")
    axes[i].axis('off')
plt.tight_layout()
plt.show()

```



Preprocess the Data

```
[14]: from sklearn.preprocessing import LabelEncoder
# Encode labels into numerical values
label_encoder = LabelEncoder()
labels_encoded = label_encoder.fit_transform(labels)

# Convert labels to one-hot encoding
labels_onehot = to_categorical(labels_encoded)

# Split into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(images, labels_onehot,
    ↪test_size=0.2, random_state=42)

# Print dataset shapes
print(f"Train images: {X_train.shape}, Train labels: {y_train.shape}")
print(f"Test images: {X_test.shape}, Test labels: {y_test.shape}")
```

Train images: (2728, 28, 28, 1), Train labels: (2728, 62)

Test images: (682, 28, 28, 1), Test labels: (682, 62)

Build the CNN Model

```
[19]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
    ↪Dropout
```

```

# Define CNN model
model = Sequential([
    Conv2D(32, (3,3), activation='relu', input_shape=(IMG_WIDTH, IMG_HEIGHT, 1)),
    MaxPooling2D((2,2)),

    Conv2D(64, (3,3), activation='relu'),
    MaxPooling2D((2,2)),

    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(len(label_encoder.classes_), activation='softmax') # Output layer
    with number of unique labels
])

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

# Print summary
model.summary()

```

/usr/local/lib/python3.11/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)
```

Model: "sequential_1"

Layer (type)	Output Shape	
Param #		
conv2d_2 (Conv2D)	(None, 26, 26, 32)	
320		
max_pooling2d_2 (MaxPooling2D)	(None, 13, 13, 32)	
0		
conv2d_3 (Conv2D)	(None, 11, 11, 64)	
18,496		

```

max_pooling2d_3 (MaxPooling2D)      (None, 5, 5, 64)
↳ 0

flatten_1 (Flatten)                 (None, 1600)
↳ 0

dense_2 (Dense)                     (None, 128)
↳ 204,928

dropout_1 (Dropout)                 (None, 128)
↳ 0

dense_3 (Dense)                     (None, 62)
↳ 7,998

```

Total params: 231,742 (905.24 KB)

Trainable params: 231,742 (905.24 KB)

Non-trainable params: 0 (0.00 B)

Train the Model

```

[20]: # Train the model
      history = model.fit(X_train, y_train, epochs=20, validation_data=(X_test,
      ↳ y_test), batch_size=32)

```

```

Epoch 1/20
86/86      5s 37ms/step -
accuracy: 0.0203 - loss: 4.1378 - val_accuracy: 0.0528 - val_loss: 4.0898
Epoch 2/20
86/86      3s 31ms/step -
accuracy: 0.0597 - loss: 4.0053 - val_accuracy: 0.1672 - val_loss: 3.5043
Epoch 3/20
86/86      3s 31ms/step -
accuracy: 0.1495 - loss: 3.3749 - val_accuracy: 0.3475 - val_loss: 2.7568
Epoch 4/20
86/86      3s 37ms/step -
accuracy: 0.2387 - loss: 2.8261 - val_accuracy: 0.4677 - val_loss: 2.2335
Epoch 5/20
86/86      5s 31ms/step -
accuracy: 0.3472 - loss: 2.4013 - val_accuracy: 0.5264 - val_loss: 1.9648
Epoch 6/20
86/86      5s 31ms/step -
accuracy: 0.4014 - loss: 2.1252 - val_accuracy: 0.5821 - val_loss: 1.6830

```

Epoch 7/20
86/86 3s 38ms/step -
accuracy: 0.4630 - loss: 1.9006 - val_accuracy: 0.6349 - val_loss: 1.5014
Epoch 8/20
86/86 4s 30ms/step -
accuracy: 0.5026 - loss: 1.7061 - val_accuracy: 0.6510 - val_loss: 1.3994
Epoch 9/20
86/86 3s 31ms/step -
accuracy: 0.5771 - loss: 1.4755 - val_accuracy: 0.6657 - val_loss: 1.2902
Epoch 10/20
86/86 6s 40ms/step -
accuracy: 0.5739 - loss: 1.4005 - val_accuracy: 0.6745 - val_loss: 1.2308
Epoch 11/20
86/86 4s 44ms/step -
accuracy: 0.5885 - loss: 1.3178 - val_accuracy: 0.6818 - val_loss: 1.1859
Epoch 12/20
86/86 3s 30ms/step -
accuracy: 0.6450 - loss: 1.1686 - val_accuracy: 0.6833 - val_loss: 1.1255
Epoch 13/20
86/86 5s 31ms/step -
accuracy: 0.6539 - loss: 1.1237 - val_accuracy: 0.7009 - val_loss: 1.0775
Epoch 14/20
86/86 4s 42ms/step -
accuracy: 0.6577 - loss: 1.0677 - val_accuracy: 0.7126 - val_loss: 1.0538
Epoch 15/20
86/86 4s 40ms/step -
accuracy: 0.7046 - loss: 0.9691 - val_accuracy: 0.7126 - val_loss: 1.0283
Epoch 16/20
86/86 4s 31ms/step -
accuracy: 0.6777 - loss: 0.9527 - val_accuracy: 0.7141 - val_loss: 1.0144
Epoch 17/20
86/86 6s 39ms/step -
accuracy: 0.7203 - loss: 0.9063 - val_accuracy: 0.7229 - val_loss: 0.9943
Epoch 18/20
86/86 4s 45ms/step -
accuracy: 0.7233 - loss: 0.8293 - val_accuracy: 0.7214 - val_loss: 0.9759
Epoch 19/20
86/86 3s 30ms/step -
accuracy: 0.7472 - loss: 0.8140 - val_accuracy: 0.7346 - val_loss: 0.9553
Epoch 20/20
86/86 3s 31ms/step -
accuracy: 0.7395 - loss: 0.7772 - val_accuracy: 0.7361 - val_loss: 0.9545

Evaluate the Model

```
[23]: # Evaluate model on test data
test_loss, test_acc = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_acc:.4f}")
```

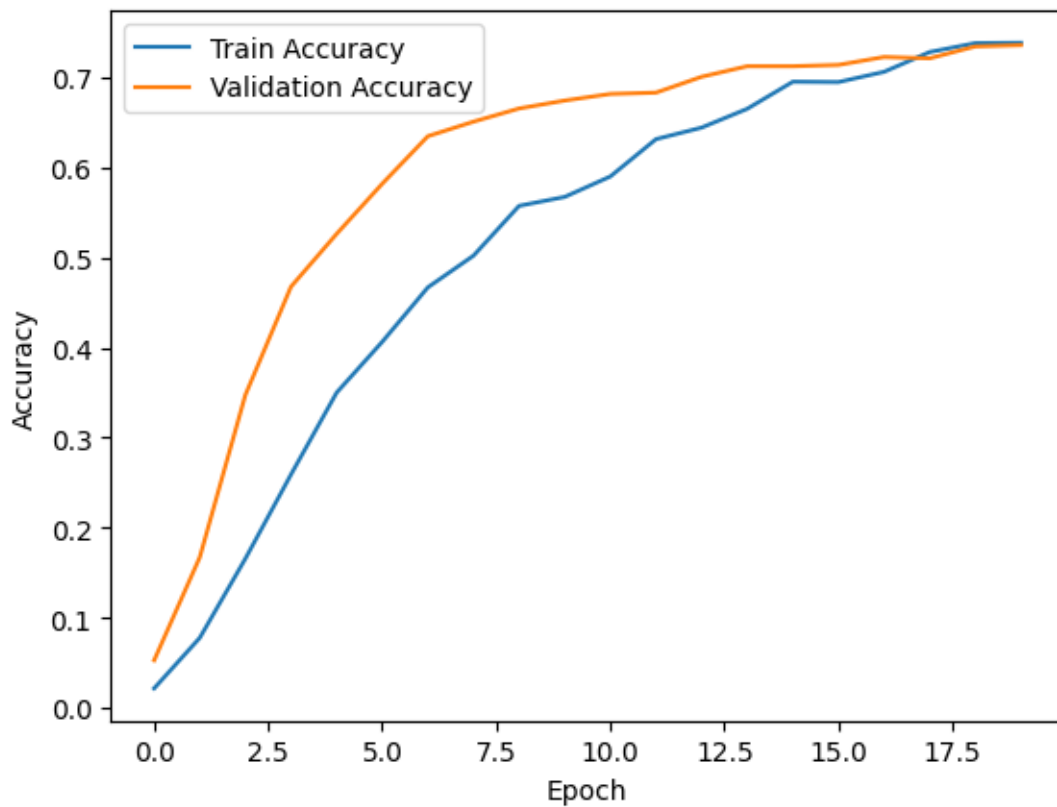
```

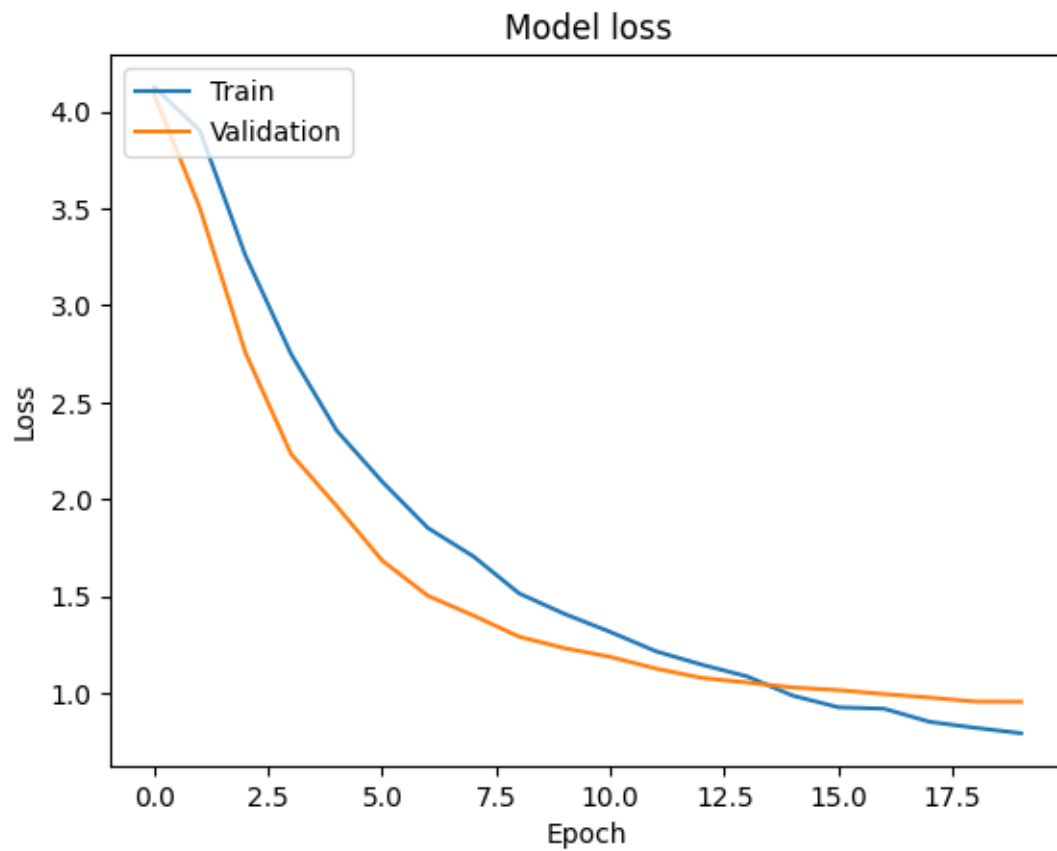
# Plot training history
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Plot training & validation loss values
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'], loc='upper left')
plt.show()

```

22/22 0s 14ms/step -
accuracy: 0.7059 - loss: 0.9695
Test Accuracy: 0.7361





Save the Model

```
[25]: model.save("handwritten_character_model.keras")
```