

Classify English Handwritten Characters through CNN

```
In [ ]: import numpy as np
import pandas as pd

import os
for dirname, _, filenames in os.walk('archive'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

archive\english.csv
archive\Img\img001-001.png
archive\Img\img001-002.png
archive\Img\img001-003.png
archive\Img\img001-004.png
archive\Img\img001-005.png
archive\Img\img001-006.png
archive\Img\img001-007.png
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archive\Img\img001-042.png
archive\Img\img001-043.png
archive\Img\img001-044.png
archive\Img\img001-045.png
archive\Img\img001-046.png
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archive\Img\img062-005.png
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archive\Img\img062-027.png
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archive\Img\img062-029.png
archive\Img\img062-030.png
archive\Img\img062-031.png
archive\Img\img062-032.png
archive\Img\img062-033.png
archive\Img\img062-034.png
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archive\Img\img062-040.png
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archive\Img\img062-049.png
archive\Img\img062-050.png
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archive\Img\img062-055.png

Problem statement

The dataset contains 3410 images containing handwritten letters (0-9 numbers, a-z alphabets small and in caps) The goal is to train the model to recognize and predict the characters efficiently and categorize between 62 unique characters

I'm trying the classification through CNN

import the libraries

```
In [ ]: import pandas
import random
import tensorflow as tf
from keras_preprocessing.image import ImageDataGenerator
import matplotlib.image as img
import matplotlib.pyplot as plt
```

Split the dataset

In this step, we'll split the data into 3 datasets - training set, validation test and test set

Out of total 3410 images, 2910 to training set, 490 added to validation set, 5 to test set

Removed the images added to validation, test set from training set to test its accuracy

```
In [ ]: data_path = r"archive"

dataset = pandas.read_csv(data_path + '/english.csv')
rand = random.sample(range(len(dataset)), 500)
validation_set = pandas.DataFrame(dataset.iloc[rand, :].values, columns=['image'
# remove the added data
dataset.drop(rand, inplace=True)

rand = random.sample(range(len(validation_set)), 12)
test_set = pandas.DataFrame(validation_set.iloc[rand, :].values, columns=['image'
# remove the added data
validation_set.drop(rand, inplace=True)

print(test_set)
```

	image	label
0	Img/img004-043.png	3
1	Img/img029-039.png	S
2	Img/img023-048.png	M
3	Img/img006-017.png	5
4	Img/img020-027.png	J
5	Img/img020-043.png	J
6	Img/img023-046.png	M
7	Img/img059-028.png	w
8	Img/img060-029.png	x
9	Img/img009-020.png	8
10	Img/img027-050.png	Q
11	Img/img029-053.png	S

Data preprocessing

Now that the data is split, let's start with the preprocessing step

Load the images through **flow_from_dataframe** method. This method is convenient since the data file (english.csv) contains the image names along with the classification class details

```
In [ ]: train_data_generator = ImageDataGenerator(rescale=1/255, shear_range=0.2, zoom_r
data_generator = ImageDataGenerator(rescale=1/255)
training_data_frame = train_data_generator.flow_from_dataframe(dataframe=dataset
                                                                target_size=(64,
validation_data_frame = data_generator.flow_from_dataframe(dataframe=validation_
                                                                target_size=(64, 64),
test_data_frame = data_generator.flow_from_dataframe(dataframe=test_set, directo
                                                                target_size=(64, 64), class
```

Found 2910 validated image filenames belonging to 62 classes.

Found 488 validated image filenames belonging to 62 classes.

Found 12 validated image filenames belonging to 9 classes.

Building the CNN model

We are about to build a CNN model using libraries provided through **TensorFlow**

Code block breakdown:

- Create Convolution layer: to read/process the image, one feature or one part at a time
- Create Pooling layer: used to reduce the spatial size of convolved image
- Create Flattening layer: used to flatten the result, whose output would be the input for the neural network

We can create multiple convolution and pooling layers depending upon the need/complexity of the dataset

```
In [ ]: cnn = tf.keras.models.Sequential()

# add convolutional and pooling layer
cnn.add(tf.keras.layers.Conv2D(filters=30, kernel_size=3, activation='relu', inp
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

cnn.add(tf.keras.layers.Conv2D(filters=30, kernel_size=3, activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

cnn.add(tf.keras.layers.Conv2D(filters=30, kernel_size=3, activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

cnn.add(tf.keras.layers.Flatten())
```

Building, compiling and training the neural network

From the above step we have received the flattened matrix of the images that we processed. We are going to feed it to our neural network and train it.

In this section, we created a fully connected Neural network aka Dense network, chosen sigmoid function for activation type. In below, the model will learn from the training set and predicts the data from validation set.

The model accuracy improves as the epochs iteration progresses.

```
In [ ]: # add full connection, output layer
cnn.add(tf.keras.layers.Dense(units=600, activation='relu'))
cnn.add(tf.keras.layers.Dense(units=62, activation='sigmoid'))

# compile cnn
cnn.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
cnn.fit(x=training_data_frame, validation_data=validation_data_frame, epochs=30)
```

Epoch 1/30
91/91 [=====] - 49s 523ms/step - loss: 3.7126 - accuracy: 0.1058 - val_loss: 2.6056 - val_accuracy: 0.3525
Epoch 2/30
91/91 [=====] - 35s 382ms/step - loss: 1.8850 - accuracy: 0.5055 - val_loss: 1.5906 - val_accuracy: 0.5799
Epoch 3/30
91/91 [=====] - 34s 370ms/step - loss: 1.1412 - accuracy: 0.6845 - val_loss: 1.3657 - val_accuracy: 0.6639
Epoch 4/30
91/91 [=====] - 35s 380ms/step - loss: 0.8307 - accuracy: 0.7491 - val_loss: 1.3678 - val_accuracy: 0.6455
Epoch 5/30
91/91 [=====] - 34s 376ms/step - loss: 0.6413 - accuracy: 0.7997 - val_loss: 1.2448 - val_accuracy: 0.6783
Epoch 6/30
91/91 [=====] - 36s 399ms/step - loss: 0.4814 - accuracy: 0.8546 - val_loss: 1.2550 - val_accuracy: 0.6885
Epoch 7/30
91/91 [=====] - 36s 393ms/step - loss: 0.3842 - accuracy: 0.8777 - val_loss: 1.2418 - val_accuracy: 0.7234
Epoch 8/30
91/91 [=====] - 37s 407ms/step - loss: 0.2803 - accuracy: 0.9117 - val_loss: 1.2328 - val_accuracy: 0.7070
Epoch 9/30
91/91 [=====] - 36s 399ms/step - loss: 0.2674 - accuracy: 0.9137 - val_loss: 1.3054 - val_accuracy: 0.7090
Epoch 10/30
91/91 [=====] - 34s 378ms/step - loss: 0.2088 - accuracy: 0.9357 - val_loss: 1.2232 - val_accuracy: 0.7418
Epoch 11/30
91/91 [=====] - 36s 396ms/step - loss: 0.2107 - accuracy: 0.9344 - val_loss: 1.3556 - val_accuracy: 0.7070
Epoch 12/30
91/91 [=====] - 39s 435ms/step - loss: 0.1824 - accuracy: 0.9419 - val_loss: 1.4141 - val_accuracy: 0.6967
Epoch 13/30
91/91 [=====] - 46s 502ms/step - loss: 0.1518 - accuracy: 0.9522 - val_loss: 1.5065 - val_accuracy: 0.7275
Epoch 14/30
91/91 [=====] - 52s 573ms/step - loss: 0.1732 - accuracy: 0.9385 - val_loss: 1.2945 - val_accuracy: 0.7131
Epoch 15/30
91/91 [=====] - 63s 692ms/step - loss: 0.1509 - accuracy: 0.9519 - val_loss: 1.3216 - val_accuracy: 0.7172
Epoch 16/30
91/91 [=====] - 52s 570ms/step - loss: 0.1179 - accuracy: 0.9605 - val_loss: 1.6675 - val_accuracy: 0.7029
Epoch 17/30
91/91 [=====] - 38s 415ms/step - loss: 0.1285 - accuracy: 0.9581 - val_loss: 1.6104 - val_accuracy: 0.7070
Epoch 18/30
91/91 [=====] - 43s 471ms/step - loss: 0.1058 - accuracy: 0.9653 - val_loss: 1.5495 - val_accuracy: 0.7295
Epoch 19/30
91/91 [=====] - 43s 479ms/step - loss: 0.1103 - accuracy: 0.9643 - val_loss: 1.6781 - val_accuracy: 0.7193
Epoch 20/30
91/91 [=====] - 34s 371ms/step - loss: 0.1255 - accuracy: 0.9625 - val_loss: 1.4071 - val_accuracy: 0.7336

```

Epoch 21/30
91/91 [=====] - 43s 471ms/step - loss: 0.1093 - accuracy: 0.9656 - val_loss: 1.7305 - val_accuracy: 0.7254
Epoch 22/30
91/91 [=====] - 50s 556ms/step - loss: 0.0947 - accuracy: 0.9722 - val_loss: 1.5441 - val_accuracy: 0.7439
Epoch 23/30
91/91 [=====] - 42s 465ms/step - loss: 0.1103 - accuracy: 0.9649 - val_loss: 1.7748 - val_accuracy: 0.7172
Epoch 24/30
91/91 [=====] - 47s 514ms/step - loss: 0.1093 - accuracy: 0.9663 - val_loss: 1.7726 - val_accuracy: 0.7254
Epoch 25/30
91/91 [=====] - 50s 548ms/step - loss: 0.0823 - accuracy: 0.9711 - val_loss: 1.7765 - val_accuracy: 0.6988
Epoch 26/30
91/91 [=====] - 48s 528ms/step - loss: 0.0872 - accuracy: 0.9759 - val_loss: 1.5370 - val_accuracy: 0.7377
Epoch 27/30
91/91 [=====] - 46s 506ms/step - loss: 0.0770 - accuracy: 0.9766 - val_loss: 1.5058 - val_accuracy: 0.7459
Epoch 28/30
91/91 [=====] - 38s 422ms/step - loss: 0.0713 - accuracy: 0.9753 - val_loss: 1.7650 - val_accuracy: 0.7172
Epoch 29/30
91/91 [=====] - 44s 482ms/step - loss: 0.0555 - accuracy: 0.9804 - val_loss: 1.6092 - val_accuracy: 0.7254
Epoch 30/30
91/91 [=====] - 46s 512ms/step - loss: 0.0646 - accuracy: 0.9804 - val_loss: 1.7664 - val_accuracy: 0.7131

```

```
Out[ ]: <keras.src.callbacks.History at 0x2cac9a80150>
```

Predicting the testset images

Since the model is trained, let's pass the testset images and see how well our model predicts. The `class_indices` function gives us the neural network mapping for our 62 characters.

The result image's name is the predicted character by our model.

```

In [ ]: print("Prediction mapping: ", training_data_frame.class_indices)
        pred = cnn.predict(test_data_frame)

        # switcher shows our network mapping to the prediction
        switcher = {
            0: "0", 1: "1", 2: "2", 3: "3", 4: "4", 5: "5", 6: "6", 7: "7", 8: "8",
            9: "9", 10: "A", 11: "B", 12: "C", 13: "D", 14: "E", 15: "F", 16: "G", 17: "H", 18: "I",
            19: "J", 20: "K", 21: "L", 22: "M", 23: "N", 24: "O", 25: "P", 26: "Q", 27: "R", 28: "S",
            29: "T", 30: "U", 31: "V", 32: "W", 33: "X", 34: "Y", 35: "Z", 36: "a", 37: "b", 38: "c",
            39: "d", 40: "e", 41: "f", 42: "g", 43: "h", 44: "i", 45: "j", 46: "k", 47: "l", 48: "m",
            49: "n", 50: "o", 51: "p", 52: "q", 53: "r", 54: "s", 55: "t", 56: "u", 57: "v", 58: "w",
            59: "x", 60: "y", 61: "z"}

        outputDf = pandas.DataFrame(pred)
        maxIndex = list(outputDf.idxmax(axis=1))
        print("Max index: ", maxIndex)
        for i in range(len(test_set)):

```



```

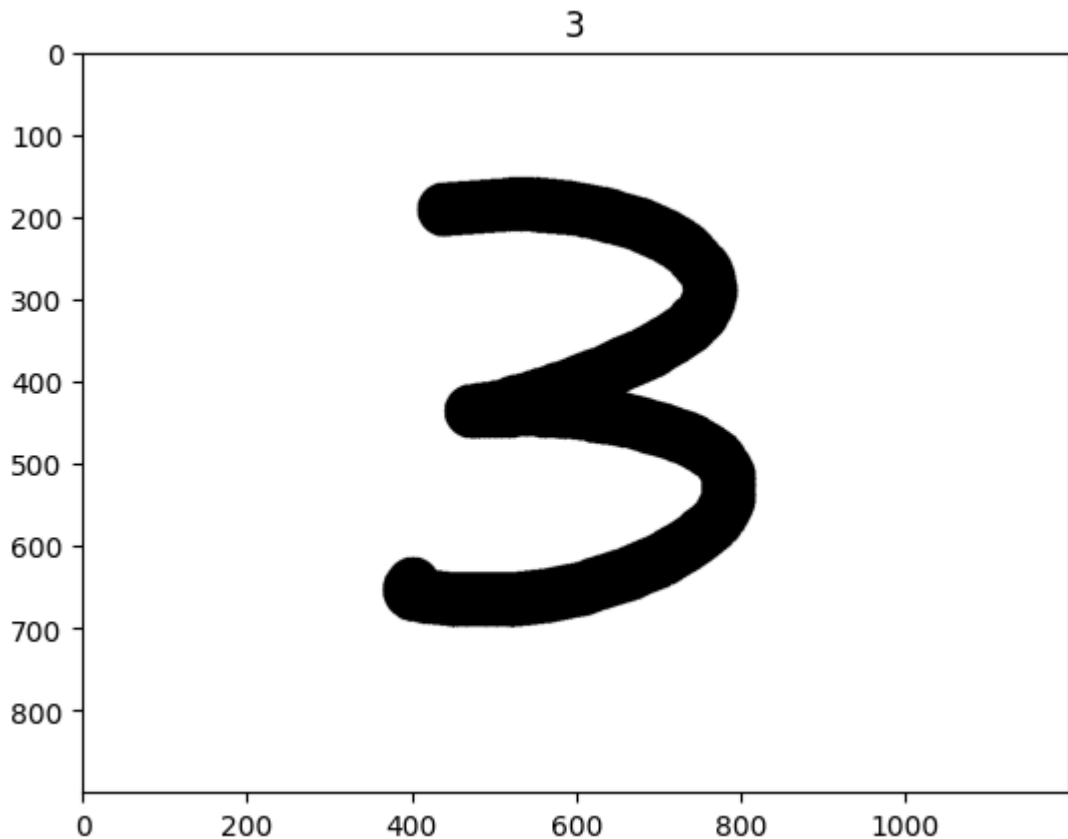
image = img.imread(data_path + '/' + test_set.at[i, 'image'])
plt.title(chooser.get(maxIndex[i], "error"))
plt.imshow(image)
plt.show()

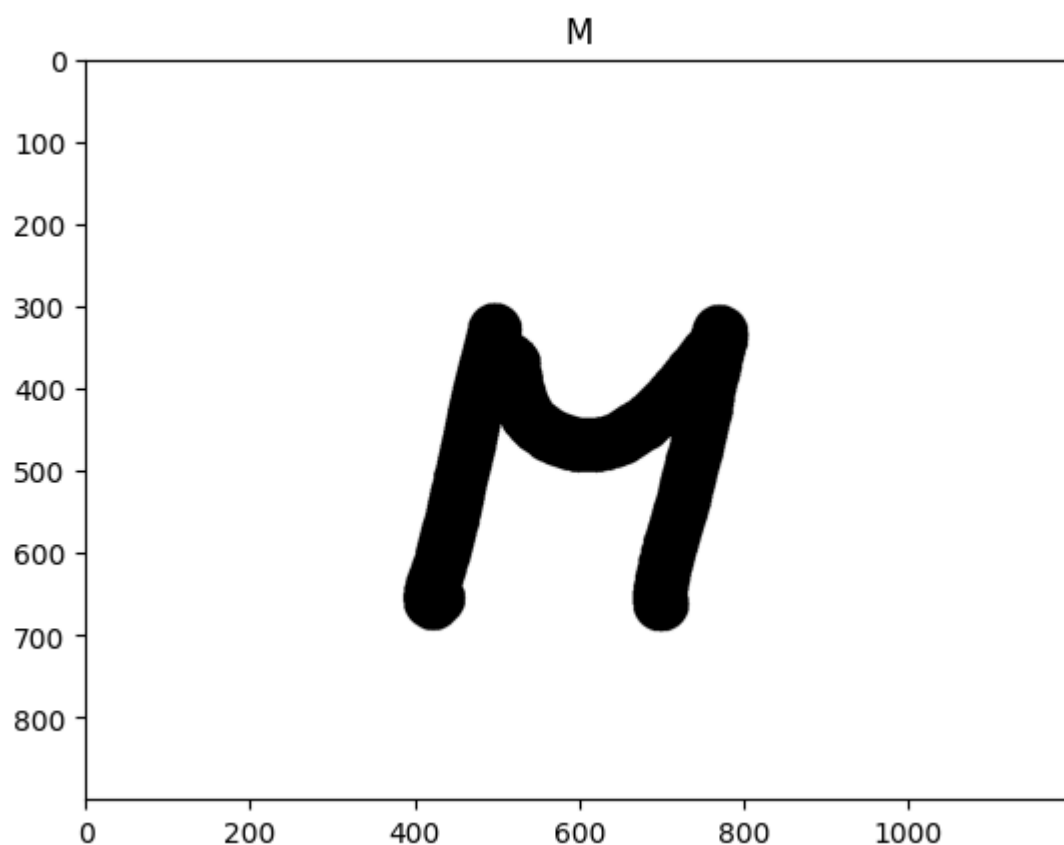
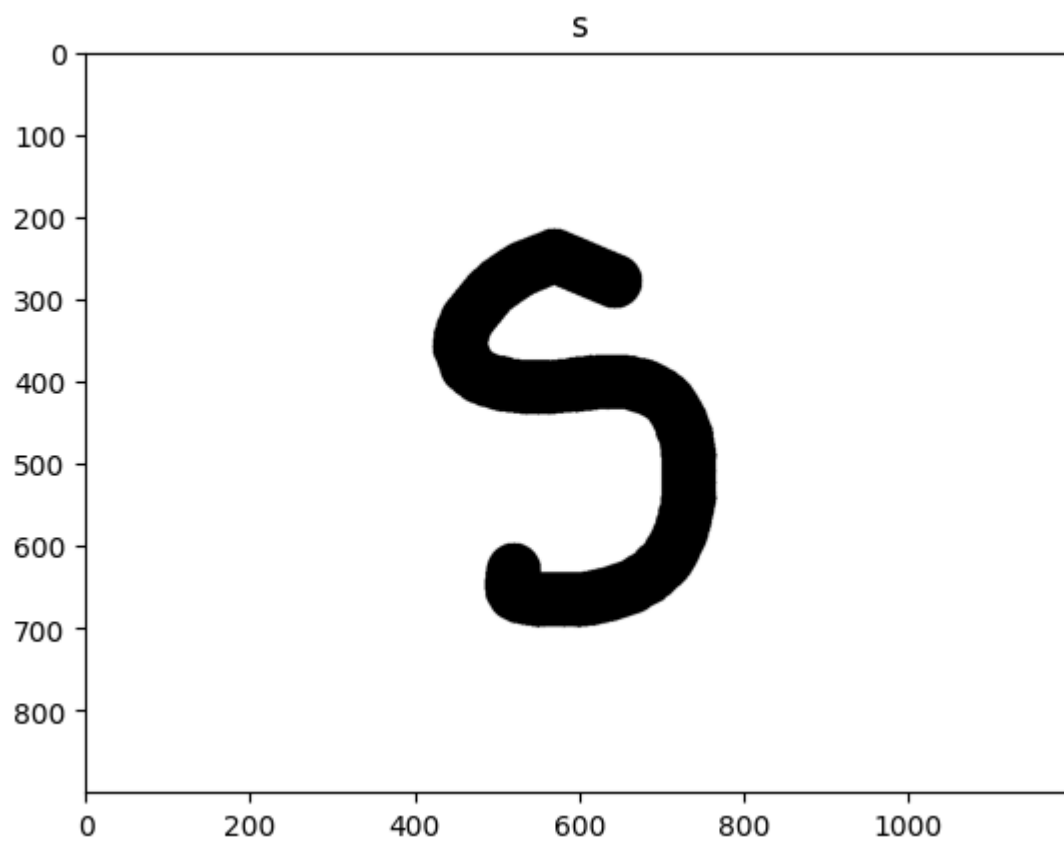
```

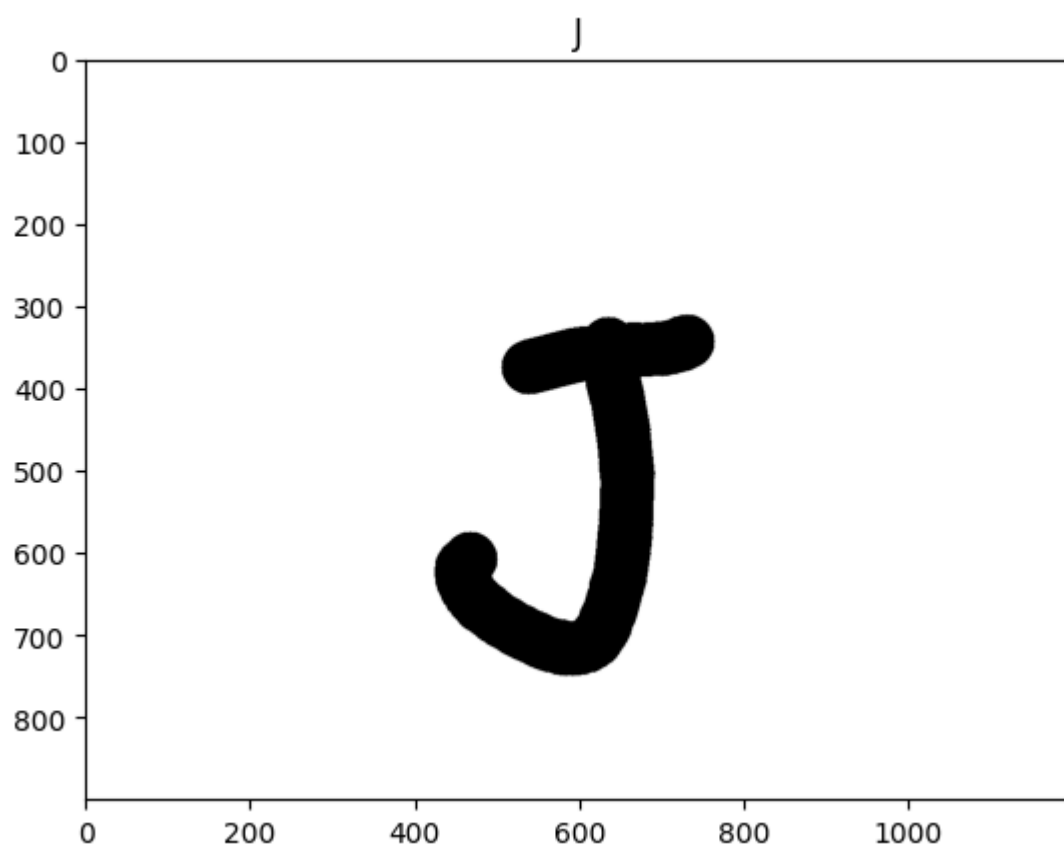
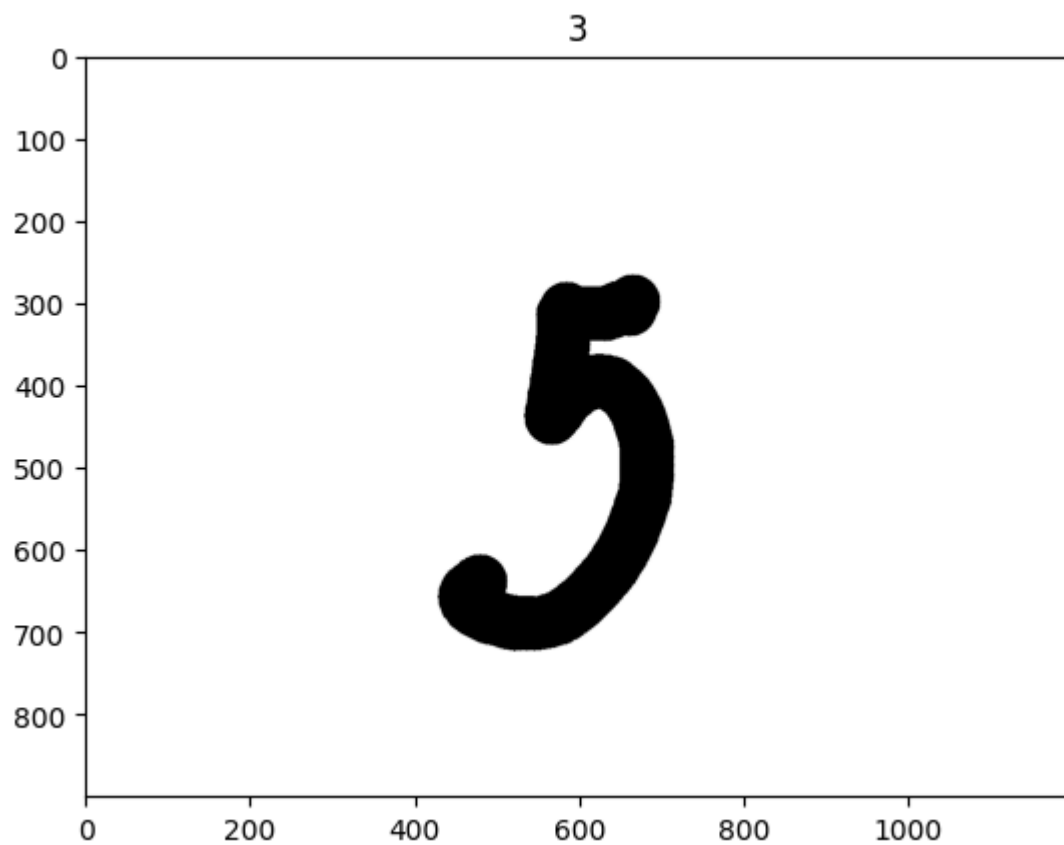
Prediction mapping: {'0': 0, '1': 1, '2': 2, '3': 3, '4': 4, '5': 5, '6': 6, '7': 7, '8': 8, '9': 9, 'A': 10, 'B': 11, 'C': 12, 'D': 13, 'E': 14, 'F': 15, 'G': 16, 'H': 17, 'I': 18, 'J': 19, 'K': 20, 'L': 21, 'M': 22, 'N': 23, 'O': 24, 'P': 25, 'Q': 26, 'R': 27, 'S': 28, 'T': 29, 'U': 30, 'V': 31, 'W': 32, 'X': 33, 'Y': 34, 'Z': 35, 'a': 36, 'b': 37, 'c': 38, 'd': 39, 'e': 40, 'f': 41, 'g': 42, 'h': 43, 'i': 44, 'j': 45, 'k': 46, 'l': 47, 'm': 48, 'n': 49, 'o': 50, 'p': 51, 'q': 52, 'r': 53, 's': 54, 't': 55, 'u': 56, 'v': 57, 'w': 58, 'x': 59, 'y': 60, 'z': 61}

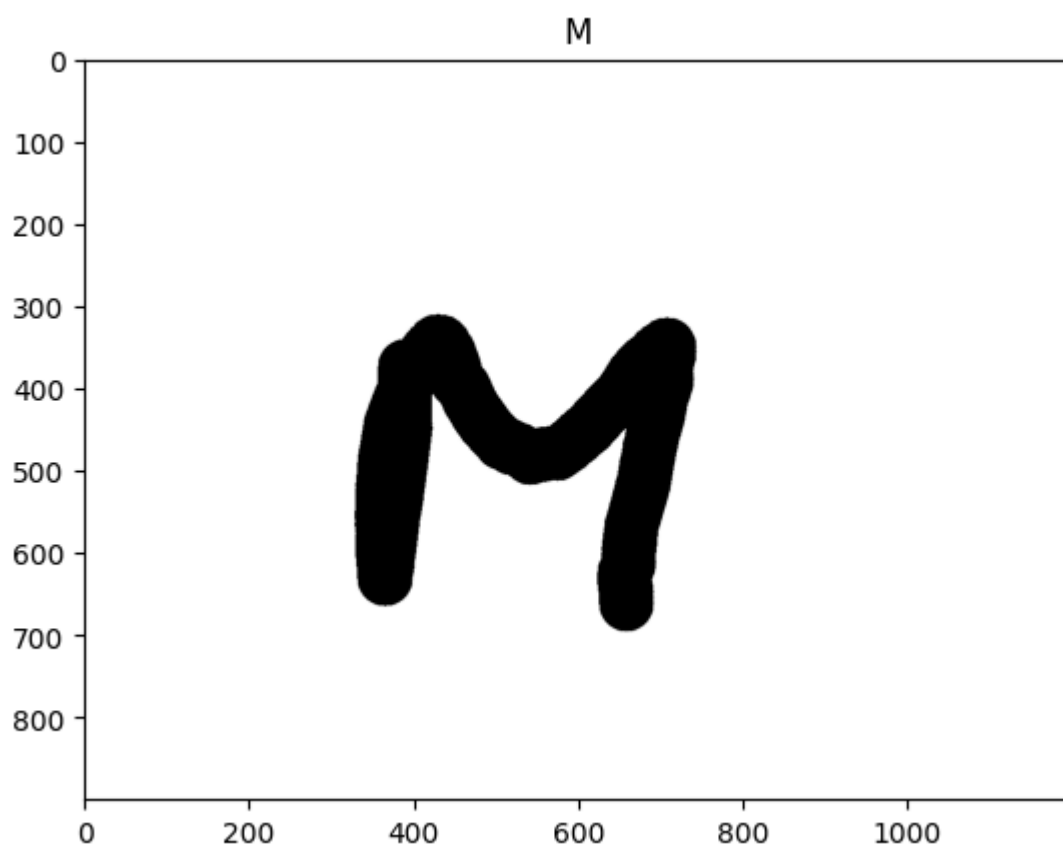
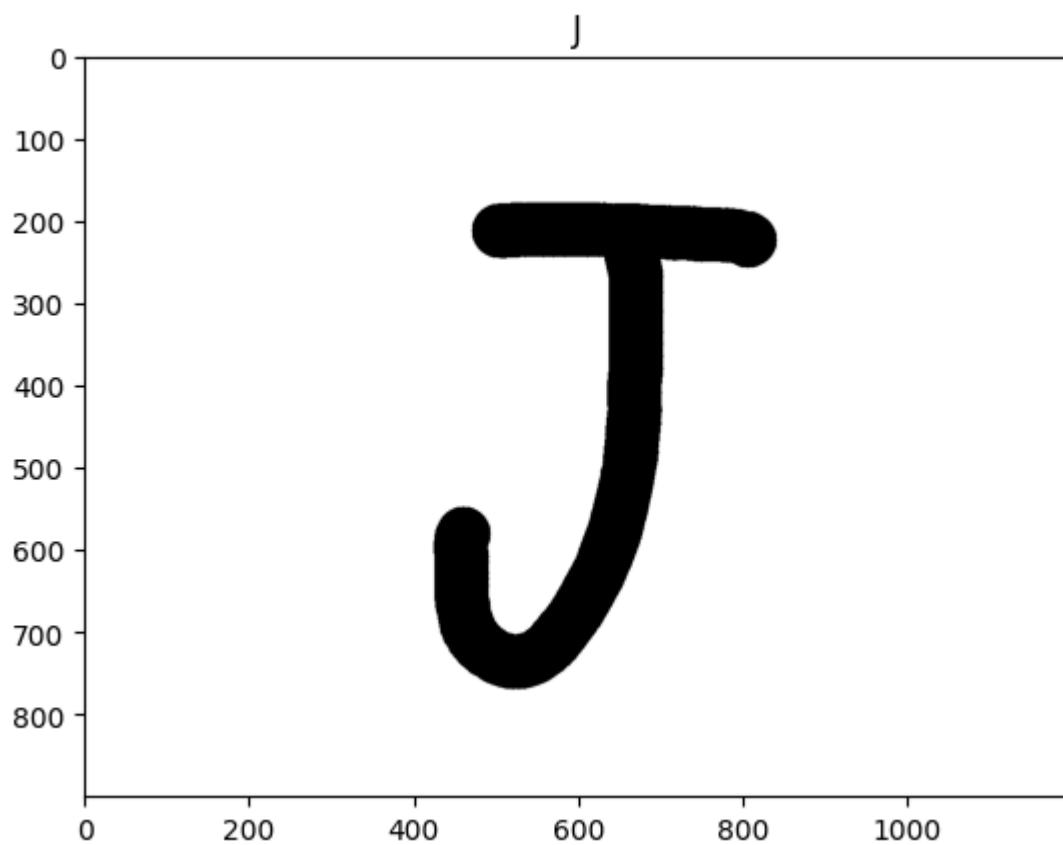
1/1 [=====] - 0s 246ms/step

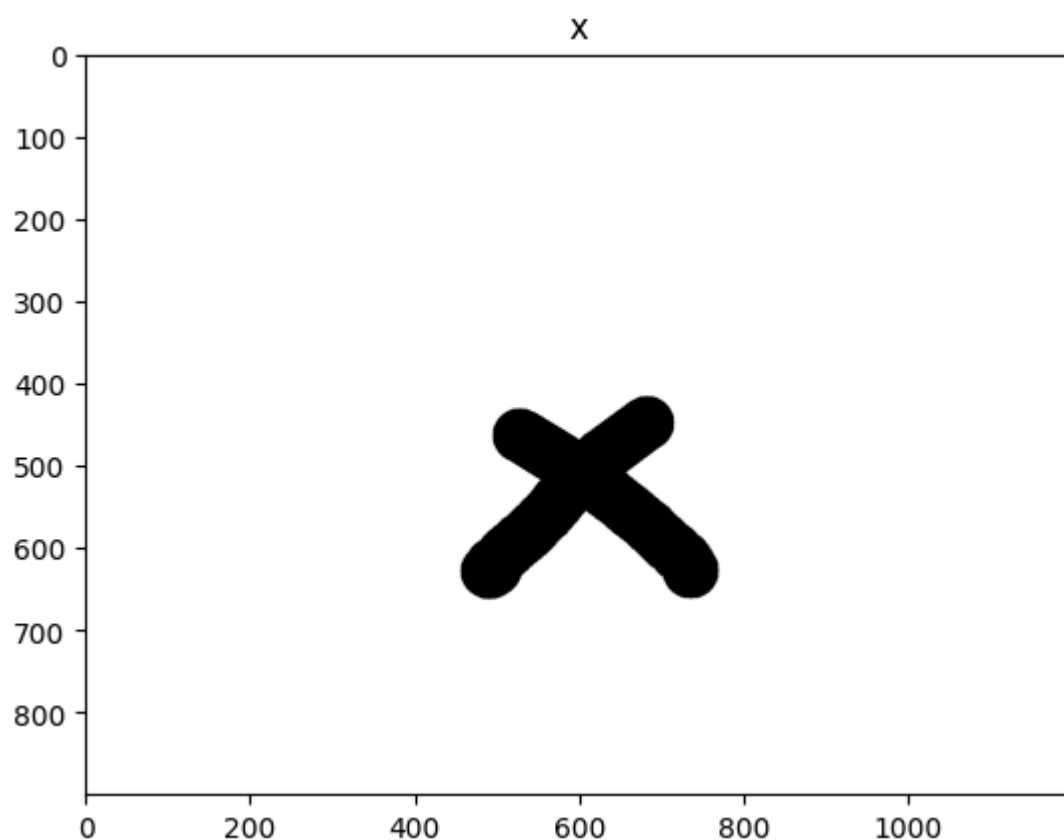
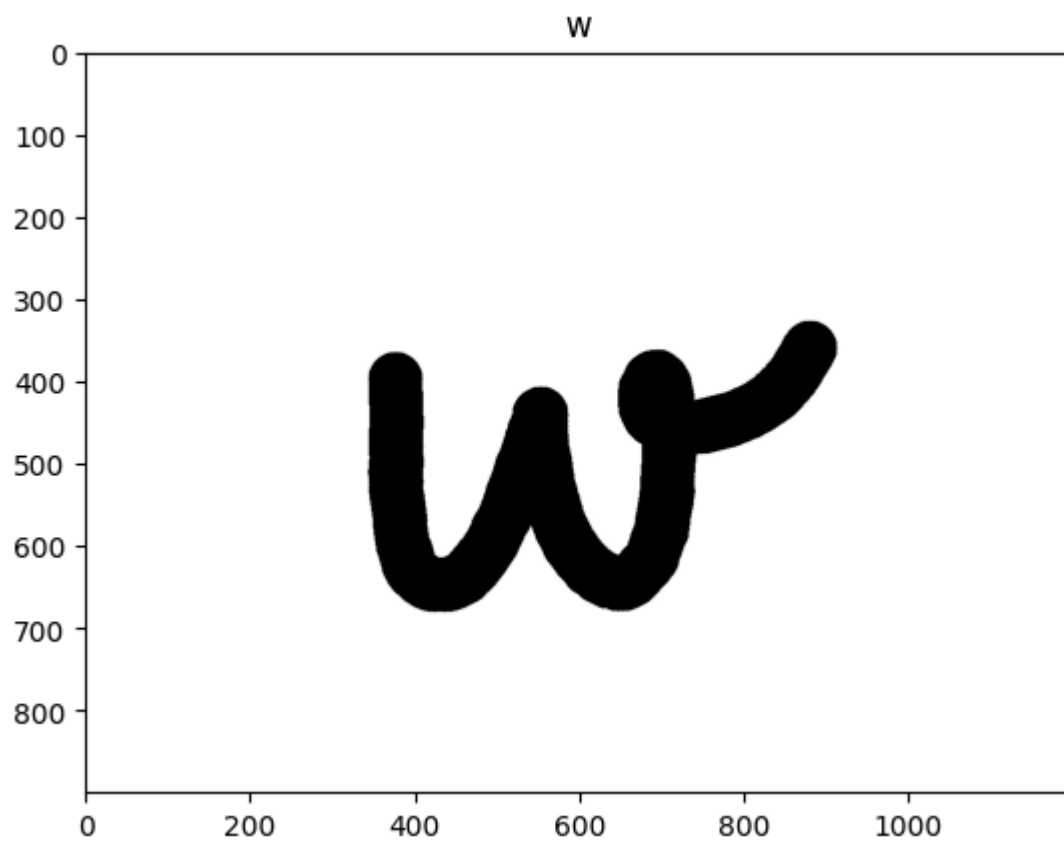
Max index: [3, 54, 22, 3, 19, 19, 22, 3, 59, 8, 26, 28]

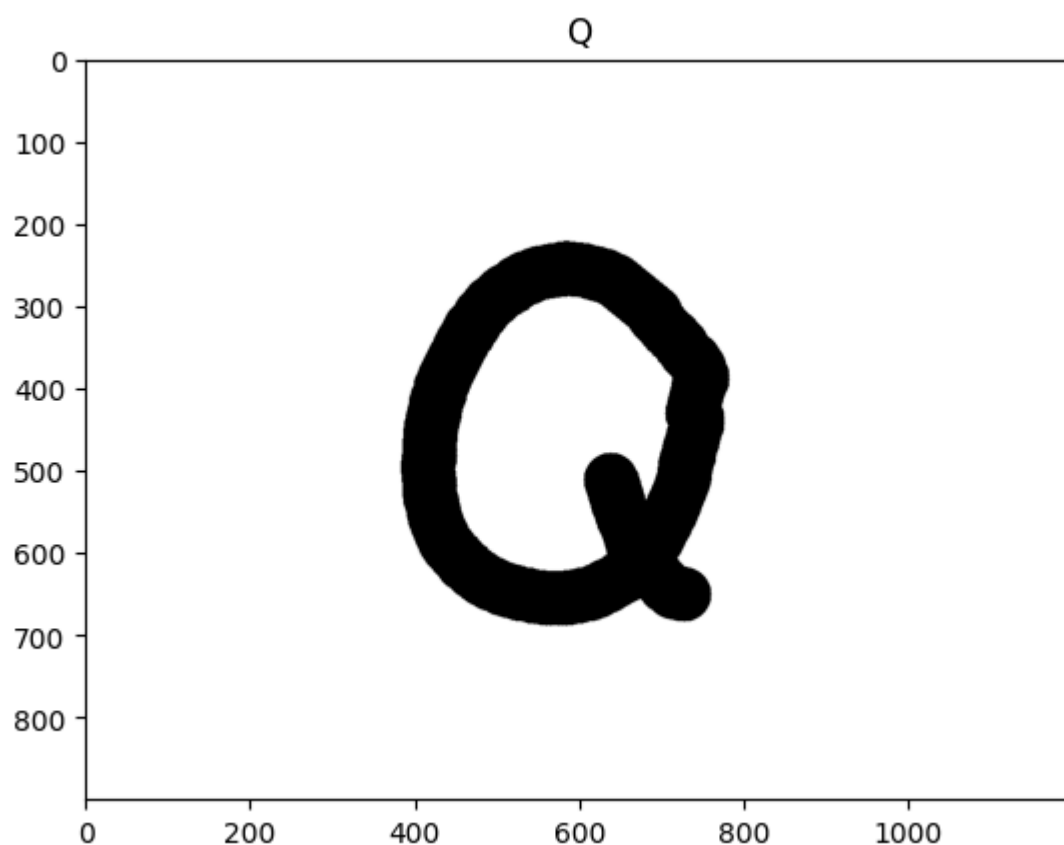
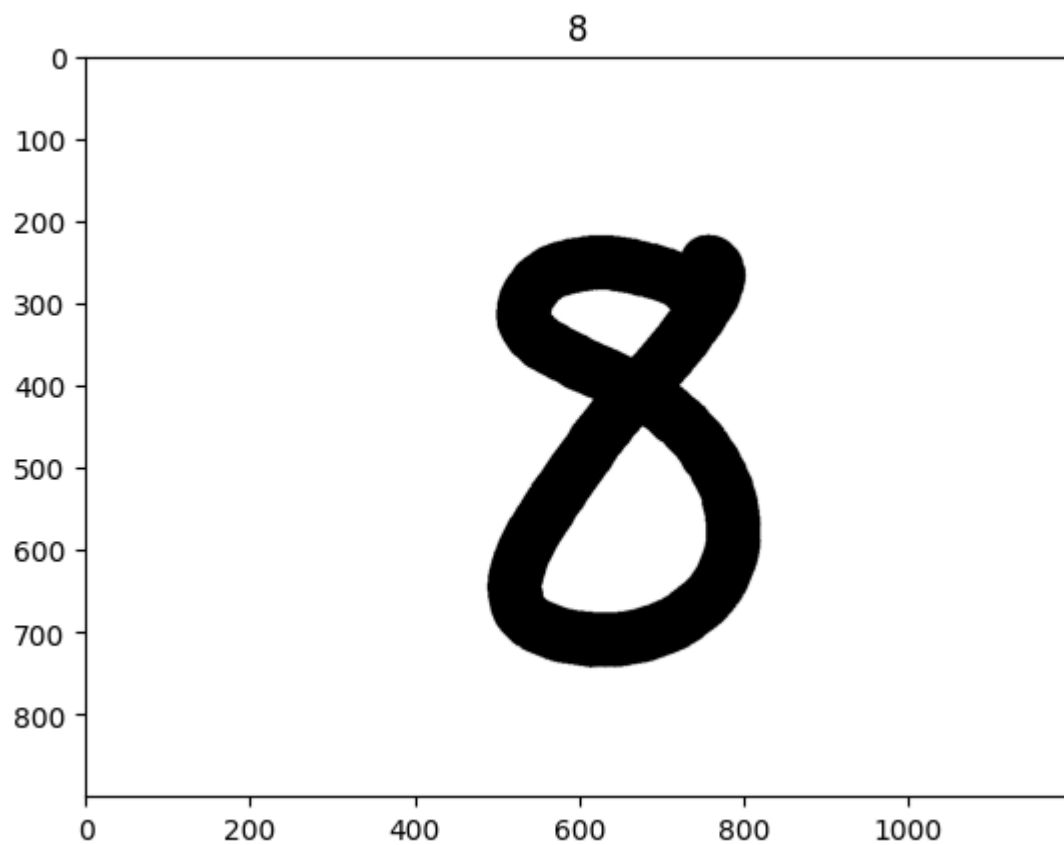


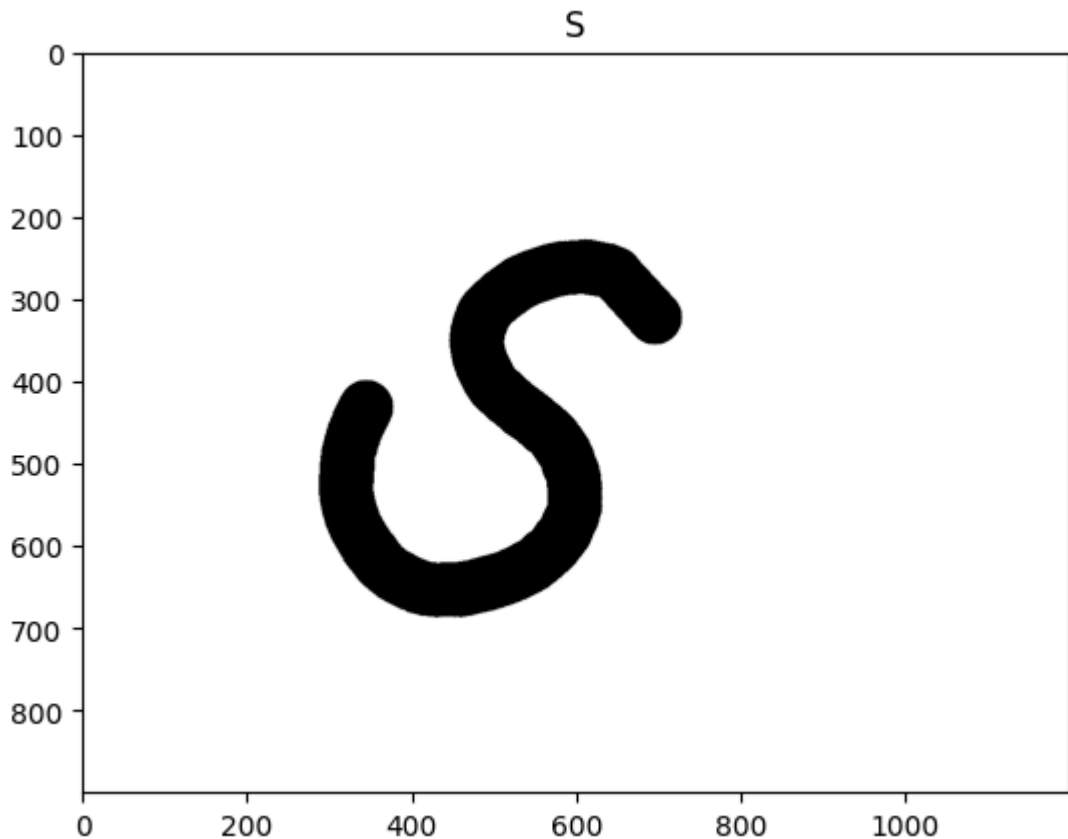












```
In [ ]: from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
import numpy as np

# Function to convert labels to one-hot encoding
def convert_to_one_hot(labels, num_classes):
    one_hot_labels = np.zeros((len(labels), num_classes))
    for i in range(len(labels)):
        one_hot_labels[i, labels[i]] = 1
    return one_hot_labels

# Convert labels to one-hot encoding for training and test sets
train_labels_one_hot = convert_to_one_hot(training_data_frame.classes, 62)
test_labels_one_hot = convert_to_one_hot(test_data_frame.classes, 62)

# Predict probabilities for the test set
test_pred_prob = cnn.predict(test_data_frame)

# Calculate ROC curve and AUC for each class
fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(62):
    fpr[i], tpr[i], _ = roc_curve(test_labels_one_hot[:, i], test_pred_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC curve for each class
plt.figure(figsize=(10, 8))
for i in range(62):
    plt.plot(fpr[i], tpr[i], label='Class {} (AUC = {:.2f})'.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], linestyle='--', color='gray', label='Random')
```

```
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for each class')
plt.legend()
plt.show()
```

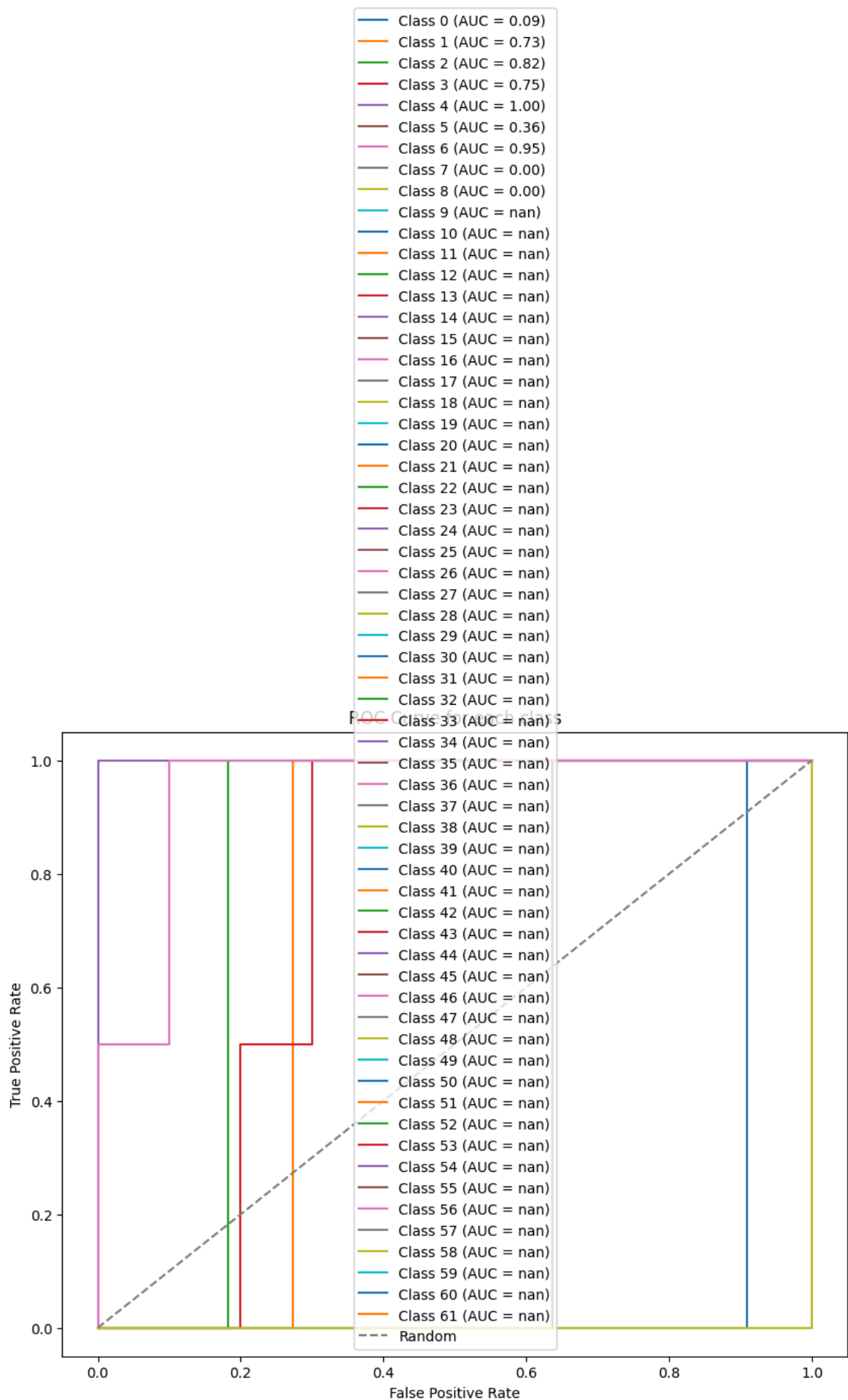
1/1 [=====] - 0s 153ms/step

[illegible]

[illegible]

[illegible]

[illegible]



```
In [ ]: from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
```

```

import numpy as np

def convert_to_one_hot(labels, num_classes):
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# Predict probabilities for the test set
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# Calculate ROC curve and AUC for each class
fpr = dict()
tpr = dict()
roc_auc = dict()

plt.figure(figsize=(10, 8))

for i in range(62):
    fpr[i], tpr[i], _ = roc_curve(test_labels_one_hot[:, i], test_pred_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

    # Plot ROC curve for each class
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

# Plot the random classifier
plt.plot([0, 1], [0, 1], linestyle='--', color='gray', label='Random')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for each class')
plt.legend()
plt.show()

```

1/1 [=====] - 0s 179ms/step

[illegible]

[illegible]

[illegible]

[illegible]

