RELEVENT LIBRARIES IMPORTED

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing import image
from tensorflow.keras.optimizers import RMSprop
import matplotlib.pyplot as plt
import tensorflow as tf
import numpy as np
import cv2
import os
```

MOUNT THE GOOGLE DRIVE

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

CHANGING THE CURRENT WORKING DIRECTORY

```
os.chdir("/content/drive/My Drive/Colab Notebooks/Mini Project PS2019246/")
os.getcwd()
```

```
'/content/drive/My Drive/Colab Notebooks/Mini Project PS2019246'
```

LOAD AND DISPLAY A IMAGE FROM A SPECIFIED PATH

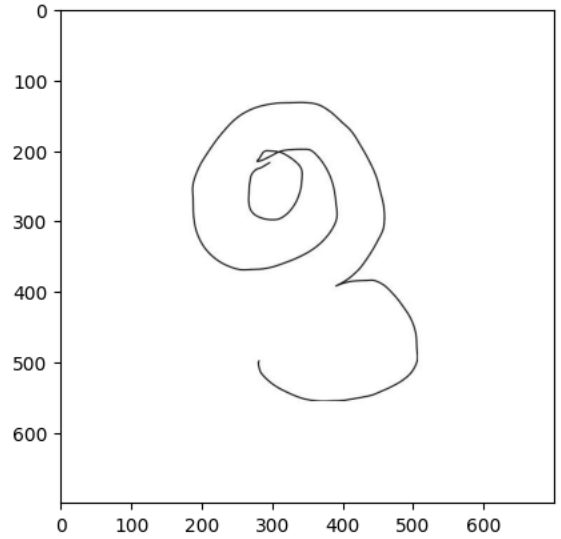
Specify the path to the image and load the image using load_img from Keras

```
img = image.load_img("Training/e/1.jpg")
```

Display the image using matplotlib

```
#Display the image using matplotlib
plt.imshow(img)
```

```
<matplotlib.image.AxesImage at 0x7c1869c910f0>
```



Read the image using OpenCV (cv2) and retrieve its shape

```
cv2.imread("Training/e/1.jpg").shape
```

```
(700, 700, 3)
```

```
# Create an ImageDataGenerator for training data with pixel value rescaling
train = ImageDataGenerator(rescale = 1/255)
# Create an ImageDataGenerator for validation data with pixel value rescaling
validation = ImageDataGenerator(rescale = 1/255)
```

CREATE TRAINING AND VALIDATION DATASETS USING ImageDataGenerator

```
# Create a training dataset generator using the training ImageDataGenerator
train_dataset = train.flow_from_directory('Training/',
                                          target_size = (200,200),
                                          batch_size = 3,
                                          class_mode = 'binary')
# Create a validation dataset generator using the validation ImageDataGenerator
validation_dataset = validation.flow_from_directory('Validation/',
                                                    target_size = (200,200),
                                                    batch_size = 3,
                                                    class_mode = 'binary')
```

```
Found 80 images belonging to 2 classes.
Found 80 images belonging to 2 classes.
```

```
# Retrieve the mapping of class names to their indices in the training dataset
train_dataset.class_indices
```

```
{'e': 0, 'ta': 1}
```

```
# Retrieve the array of class indices for each sample in the training dataset
train_dataset.classes
```

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1], dtype=int32)
```

SPECIFYING THE CNN ARCHITECTURE

```
# Create a Sequential model
# Convolutional layer with 16 filters, each of size (3, 3), and ReLU activation
model = tf.keras.models.Sequential([tf.keras.layers.Conv2D(16,(3,3),activation = 'relu',input_shape = (200,200,3)),
                                    # MaxPooling layer with pool size (2, 2)
                                     tf.keras.layers.MaxPool2D(2,2),
                                    # Convolutional layer with 32 filters, each of size (3, 3), and ReLU activation
                                     tf.keras.layers.Conv2D(32,(3,3),activation = 'relu'),
                                     tf.keras.layers.MaxPool2D(2,2),
                                    # Convolutional layer with 64 filters, each of size (3, 3), and ReLU activation
                                     tf.keras.layers.Conv2D(64,(3,3),activation = 'relu'),
                                     tf.keras.layers.MaxPool2D(2,2),
                                    # Flatten layer to convert 3D feature maps to 1D feature vectors
                                     tf.keras.layers.Flatten(),
                                    # Dense (fully connected) layer with 512 units and ReLU activation
                                     tf.keras.layers.Dense(512,activation = 'relu'),
                                    # Output layer with 1 unit and sigmoid activation for binary classification
                                     tf.keras.layers.Dense(1,activation = 'sigmoid')
                                     ])
```

```
# Compile the model with binary crossentropy loss, RMSprop optimizer, and accuracy metric
model.compile(loss = 'binary_crossentropy',
              optimizer = RMSprop(lr=0.001),
              metrics = ['accuracy'])
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use the legacy optimizer, e.g.,tf.keras.optimizers.leg
```

TRAINING THE MODEL

```
# Train the model using the training dataset and validate on the validation dataset
model_fit = model.fit(train_dataset,
                      steps_per_epoch = 5,
                      epochs = 30,
                      validation_data = validation_dataset)
```

```
Epoch 1/30
5/5 [==============================] - 36s 8s/step - loss: 8.1285 - accuracy: 0.4667 - val_loss: 0.9937 - val_accuracy: 0.5000
Epoch 2/30
5/5 [==============================] - 9s 2s/step - loss: 1.2297 - accuracy: 0.6429 - val_loss: 0.7205 - val_accuracy: 0.5000
Epoch 3/30
5/5 [==============================] - 5s 1s/step - loss: 0.8156 - accuracy: 0.5714 - val_loss: 0.6628 - val_accuracy: 0.5000
Epoch 4/30
5/5 [==============================] - 6s 1s/step - loss: 0.7565 - accuracy: 0.3333 - val_loss: 0.6311 - val_accuracy: 1.0000
Epoch 5/30
5/5 [==============================] - 5s 1s/step - loss: 0.6090 - accuracy: 0.8667 - val_loss: 0.5299 - val_accuracy: 0.8375
Epoch 6/30
5/5 [==============================] - 6s 1s/step - loss: 0.7734 - accuracy: 0.6000 - val_loss: 0.4431 - val_accuracy: 0.8375
Epoch 7/30
5/5 [==============================] - 6s 1s/step - loss: 0.5716 - accuracy: 0.6000 - val_loss: 0.2600 - val_accuracy: 1.0000
Epoch 8/30
5/5 [==============================] - 5s 1s/step - loss: 0.1655 - accuracy: 1.0000 - val_loss: 0.1450 - val_accuracy: 0.9750
Epoch 9/30
5/5 [==============================] - 6s 1s/step - loss: 0.2251 - accuracy: 0.9333 - val_loss: 0.0920 - val_accuracy: 1.0000
Epoch 10/30
5/5 [==============================] - 5s 1s/step - loss: 0.0406 - accuracy: 1.0000 - val_loss: 0.0180 - val_accuracy: 1.0000
Epoch 11/30
5/5 [==============================] - 7s 1s/step - loss: 0.0311 - accuracy: 1.0000 - val_loss: 0.0054 - val_accuracy: 1.0000
Epoch 12/30
5/5 [==============================] - 5s 1s/step - loss: 0.0033 - accuracy: 1.0000 - val_loss: 0.0043 - val_accuracy: 1.0000
Epoch 13/30
5/5 [==============================] - 5s 1s/step - loss: 0.0024 - accuracy: 1.0000 - val_loss: 0.0014 - val_accuracy: 1.0000
Epoch 14/30
5/5 [==============================] - 4s 905ms/step - loss: 3.9165e-04 - accuracy: 1.0000 - val_loss: 0.0011 - val_accuracy: 1.0000
Epoch 15/30
5/5 [==============================] - 5s 984ms/step - loss: 1.8889e-04 - accuracy: 1.0000 - val_loss: 0.0010 - val_accuracy: 1.0000
Epoch 16/30
5/5 [==============================] - 7s 1s/step - loss: 0.0023 - accuracy: 1.0000 - val_loss: 0.0025 - val_accuracy: 1.0000
Epoch 17/30
5/5 [==============================] - 5s 1s/step - loss: 2.8844e-04 - accuracy: 1.0000 - val_loss: 0.0018 - val_accuracy: 1.0000
Epoch 18/30
5/5 [==============================] - 5s 1s/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 5.2245e-04 - val_accuracy: 1.0000
Epoch 19/30
5/5 [==============================] - 5s 1s/step - loss: 1.2745e-04 - accuracy: 1.0000 - val_loss: 4.8946e-04 - val_accuracy: 1.0000
Epoch 20/30
5/5 [==============================] - 6s 1s/step - loss: 1.3140e-04 - accuracy: 1.0000 - val_loss: 4.6050e-04 - val_accuracy: 1.0000
Epoch 21/30
5/5 [==============================] - 5s 1s/step - loss: 5.2939e-04 - accuracy: 1.0000 - val_loss: 2.6116e-04 - val_accuracy: 1.0000
Epoch 22/30
5/5 [==============================] - 6s 1s/step - loss: 1.4275e-04 - accuracy: 1.0000 - val_loss: 5.3583e-04 - val_accuracy: 1.0000
Epoch 23/30
5/5 [==============================] - 4s 952ms/step - loss: 2.3227e-04 - accuracy: 1.0000 - val_loss: 1.5151e-04 - val_accuracy: 1.0
Epoch 24/30
5/5 [==============================] - 5s 1s/step - loss: 1.3093e-04 - accuracy: 1.0000 - val_loss: 6.3010e-04 - val_accuracy: 1.0000
Epoch 25/30
5/5 [==============================] - 5s 1s/step - loss: 2.7713e-04 - accuracy: 1.0000 - val_loss: 1.9404e-04 - val_accuracy: 1.0000
Epoch 26/30
5/5 [==============================] - 5s 1s/step - loss: 9.9213e-05 - accuracy: 1.0000 - val_loss: 1.1431e-04 - val_accuracy: 1.0000
Epoch 27/30
5/5 [==============================] - 5s 1s/step - loss: 5.3542e-04 - accuracy: 1.0000 - val_loss: 1.2126e-04 - val_accuracy: 1.0000
Epoch 28/30
5/5 [==============================] - 4s 975ms/step - loss: 1.6137e-04 - accuracy: 1.0000 - val_loss: 4.5646e-05 - val_accuracy: 1.0
Epoch 29/30
```

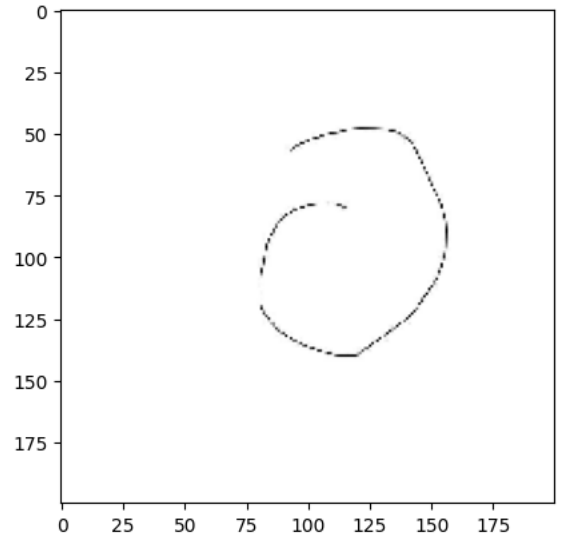
Retrieve the mapping of class names to their indices in the validation dataset

```
validation_dataset.class_indices
```

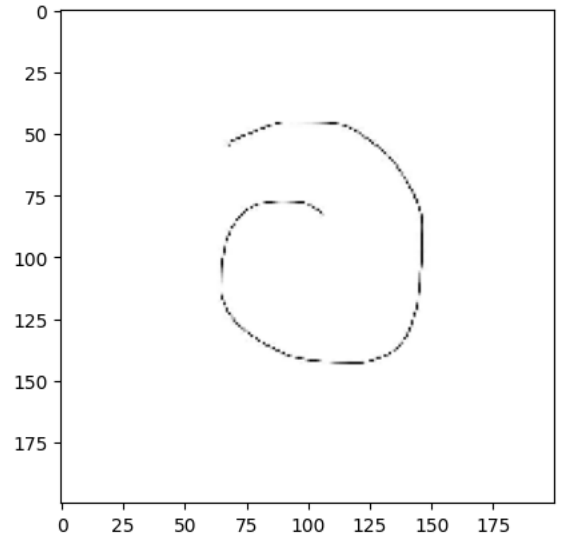
```
{'e': 0, 'ta': 1}
```

TESTING

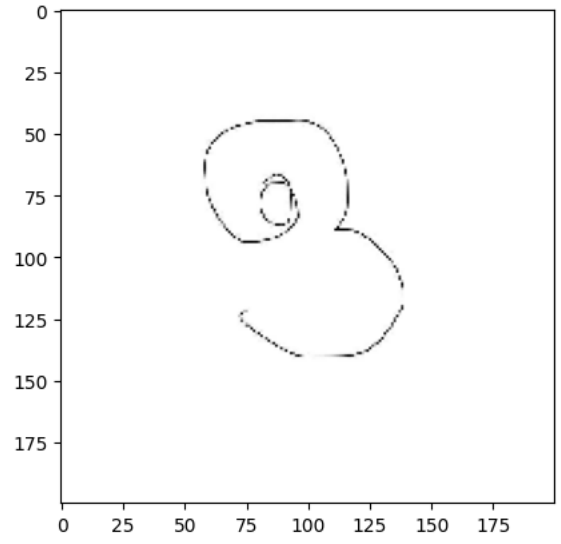
```
# Directory path containing the testing images
dir_path = 'Testing/'

# Loop over each file in the directory
for file_name in os.listdir(dir_path):
    # Concatenate the directory path and the file name
    file_path = os.path.join(dir_path, file_name)

    # Check if the item is a file (not a directory)
    if os.path.isfile(file_path):
        # Load the image and resize it to the target size
        img = image.load_img(file_path, target_size=(200, 200))
        # Display the image using matplotlib
        plt.imshow(img)
        plt.show()

        # Convert the image to a NumPy array and add an extra dimension
        X = image.img_to_array(img)
        X = np.expand_dims(X, axis=0)
        # Stack the array vertically to create a batch of images
        images = np.vstack([X])
        # Make a prediction using the trained model
        val = model.predict(images)
        # Check the predicted value and print the corresponding class label
        if val == 0:
            print("This is Letter 'E' in Sinhala")
        else:
            print("This is Letter 'Ta' in Sinhala")
```



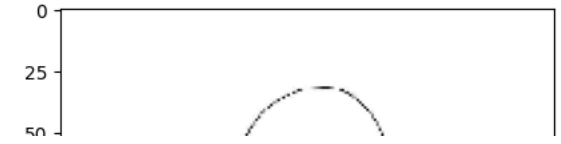
```
1/1 [==============================] - 0s 42ms/step
This is Letter 'Ta' in Sinhala
```

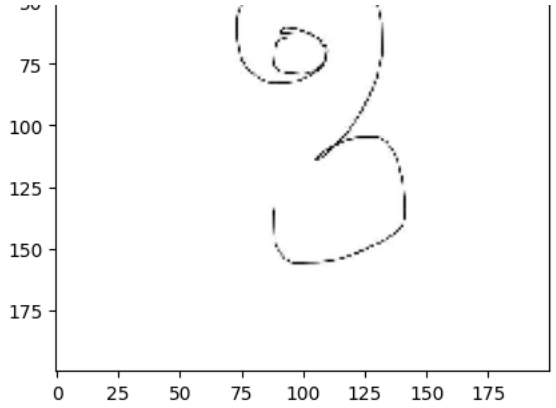


```
1/1 [==============================] - 0s 39ms/step
This is Letter 'Ta' in Sinhala
```

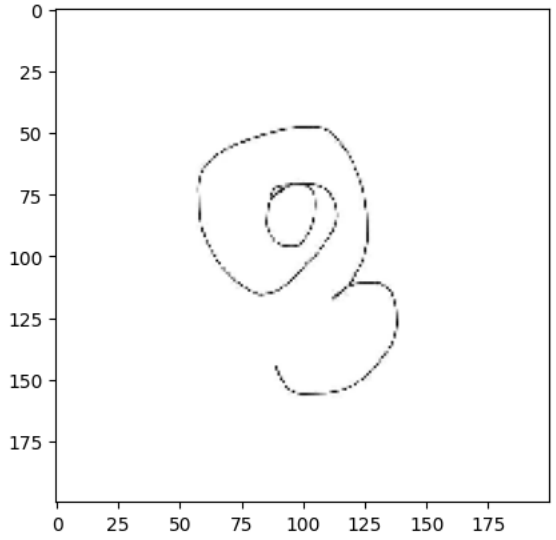


```
1/1 [==============================] - 0s 41ms/step
This is Letter 'E' in Sinhala
```

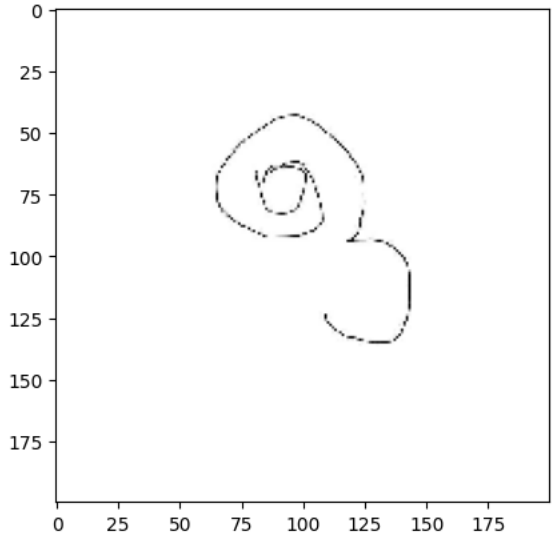




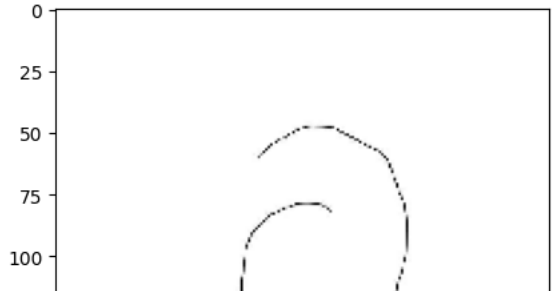
```
1/1 [==============================] - 0s 39ms/step
This is Letter 'E' in Sinhala
```

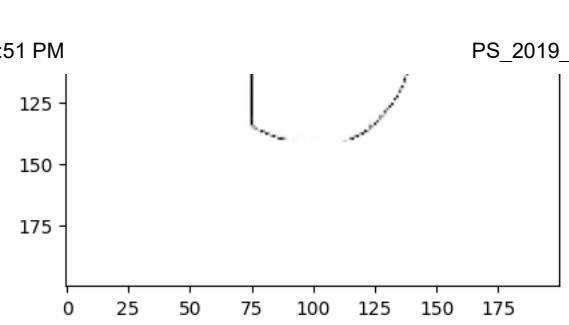


```
1/1 [==============================] - 0s 42ms/step
This is Letter 'E' in Sinhala
```

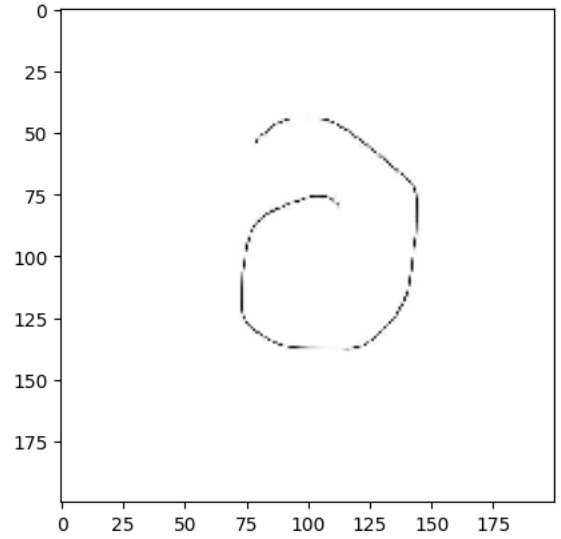


```
1/1 [==============================] - 0s 42ms/step
This is Letter 'E' in Sinhala
```

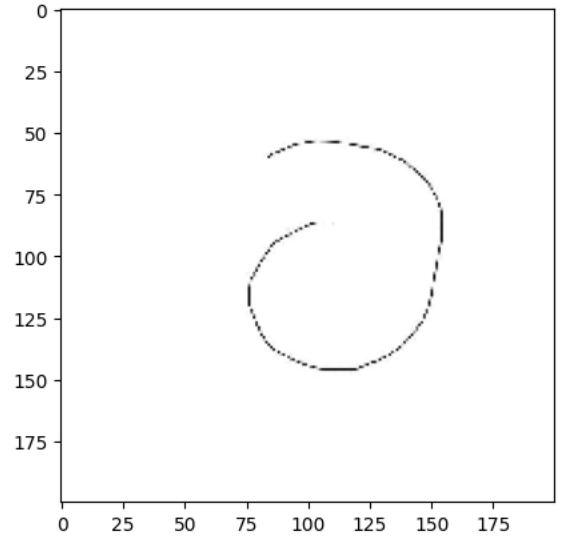




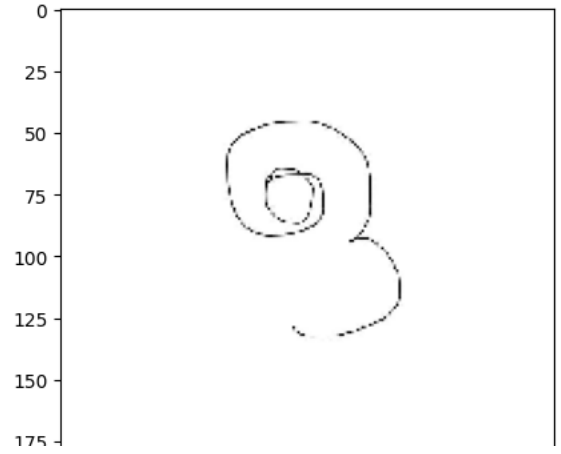
```
1/1 [==============================] - 0s 39ms/step
This is Letter 'Ta' in Sinhala
```

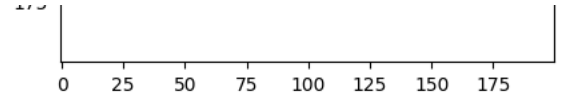


```
1/1 [==============================] - 0s 45ms/step
This is Letter 'Ta' in Sinhala
```

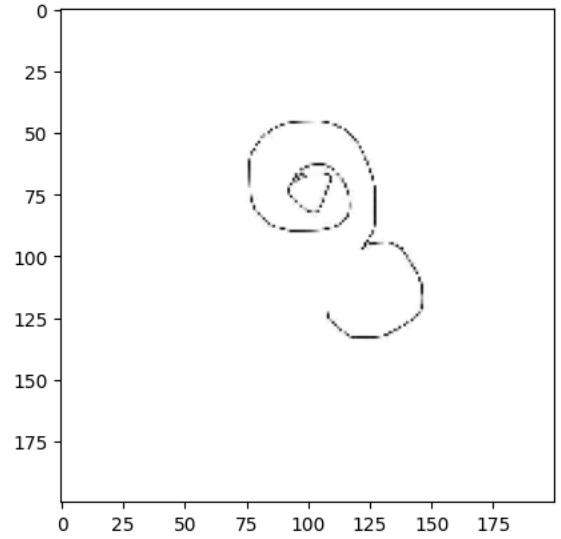


```
1/1 [==============================] - 0s 40ms/step
This is Letter 'Ta' in Sinhala
```

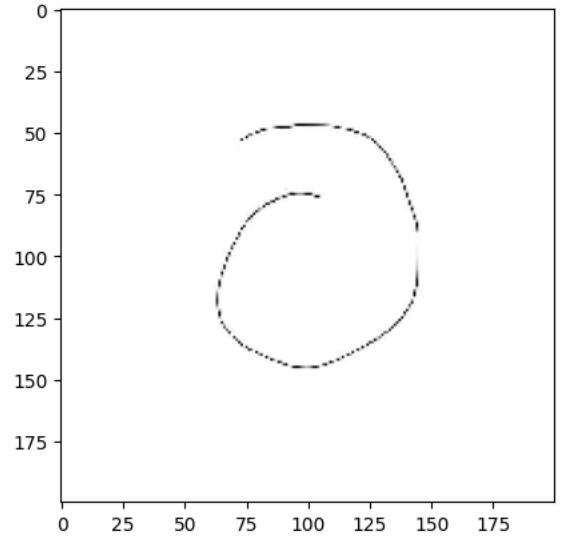




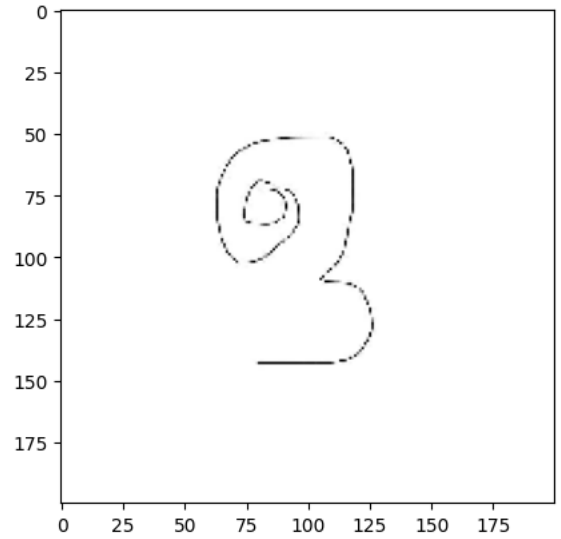

```
1/1 [==============================] - 0s 36ms/step
This is Letter 'E' in Sinhala
```



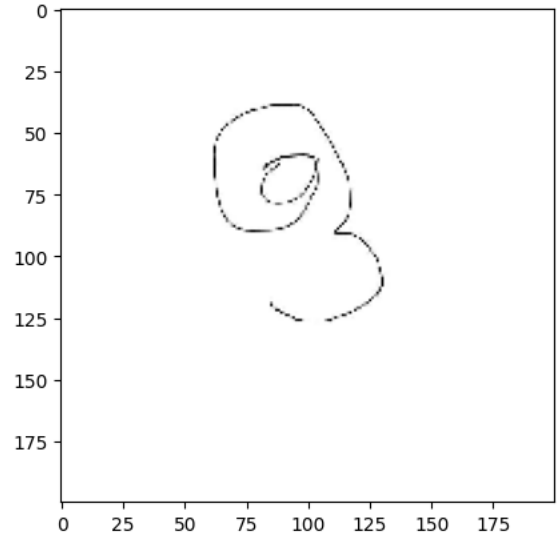

```
1/1 [==============================] - 0s 40ms/step
This is Letter 'E' in Sinhala
```



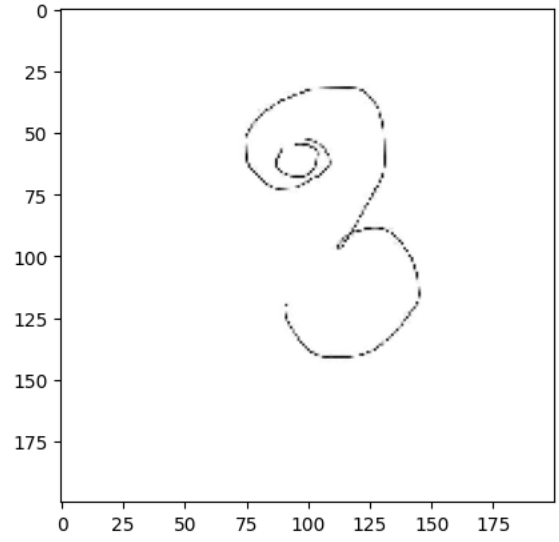

```
1/1 [==============================] - 0s 43ms/step
This is Letter 'Ta' in Sinhala
```



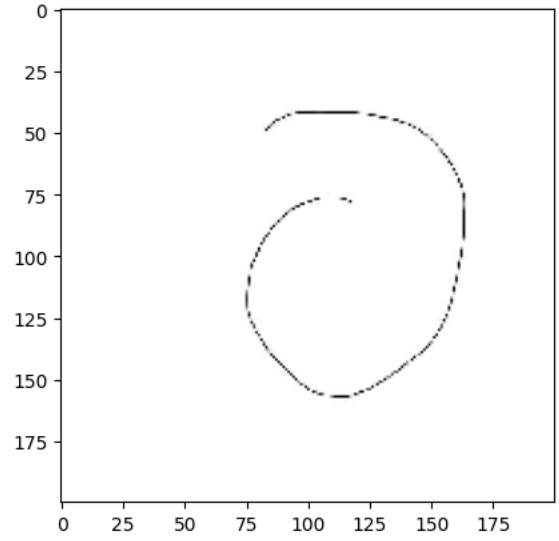

```
1/1 [==============================] - 0s 54ms/step
This is Letter 'E' in Sinhala
```



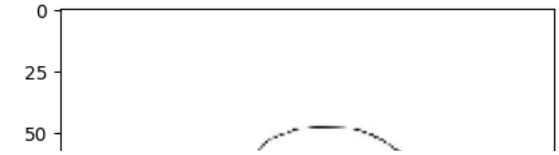
```
1/1 [==============================] - 0s 36ms/step
This is Letter 'E' in Sinhala
```

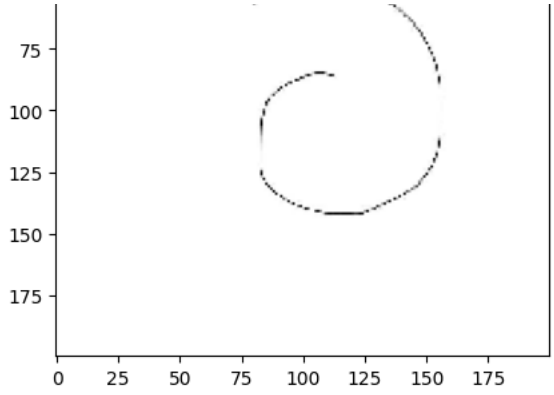


```
1/1 [==============================] - 0s 35ms/step
This is Letter 'E' in Sinhala
```

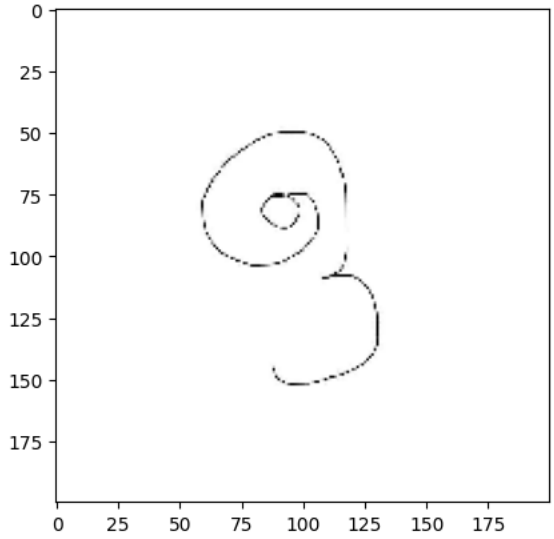


```
1/1 [==============================] - 0s 75ms/step
This is Letter 'Ta' in Sinhala
```






```
1/1 [==============================] - 0s 59ms/step
This is Letter 'Ta' in Sinhala
```




```
1/1 [==============================] - 0s 59ms/step
This is Letter 'E' in Sinhala
```