Challenge 4

CY6740 – Machine Learning in CyberSecurity

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Siamese Networks

Solution:

We have a dataset with 64 sets of real and forged signature images as training data and 21 sets of real and forged signatures as test dataset. Each set containing from minimum of 8 to maximum of 24 samples of images. The training set has 239 real signatures and 639 forged signatures in total, while the test dataset has 252 real signatures and 248 forged signatures overall.

1. As a part of preprocessing the images we apply the following for every image that we read:
    - Convert them into gray scale images
    - Resize them into a fixed dimension of 100 * 100 pixels. Here, various trial and error experiments were conducted inorder to achieve the best accuracy, and it seemed to me that at a fixed image size of 100*100 we could achieve a best optimized model.
2. As mentioned in the challenge, we prepare the data for Siamese network by creating real – real image pairs and real – forged dissimilar image pairs. All pairs possible combinations are considered while generating these pairs.
3. In the training dataset:
    - We have 6301 pairs of similar pairs (real – real)
    - We have 8813 pairs of dissimilar pairs (real-forged)
    - In total we have 6301 + 8813 pairs = 15114 pairs of images as training samples set.

3.b. For testing phase,

- We have 1386 similar pairs (real-real)

- We have 2752 pairs of dissimilar pairs (real-forged)
- In total we have 1386 + 2752 pairs = 4138 pairs.

4. I used Keras to develop the base Siamese Network. Used a total of 2 convolutional 2D layers and 2 Dense layers after flattening the nodes. Used Kernel Size of 3 * 3 with striding length of 1. Used “same” padding of size 1 for all input images. Also, used “Relu” activation function for all the layers. Used “Average Pooling” of size 2*2 to all images to reduce their spatial size.
5. Used 5-Fold cross validation and the,
   - Mean Accuracy = 0.967
   - Predictive Error Mean = Mean of all difference scores between the pairs of images = 1.1078988
   - Predictive error Median = 0.8049226
   - Predictive error standard deviation = 1.1090828

6. We then used the trained model to test on the test set of 4138 pairs. We have an overall accuracy of 0.979 if we use optimal threshold of 0.485 from difference score.
   That is, if difference score > 0.485 then they are real and forged pair, whereas if score < 0.485 then they both are similar (real – real) pair.

   Below are some of the results:


```
Difference Score =  1.3013374
Its a Forged Signature
```


```
Difference Score =  0.017931737
Its a Genuine Signature
```


```
Difference Score =  0.18574136
Its a Genuine Signature
```


```
Difference Score =  7.557686
Its a Forged Signature
```

Using Siamese Network to differentiate between Real Signatures and Forged Signatures

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Import all the necessery modules

In [1]:
```
import sys
import numpy as np
import os
import matplotlib.pyplot as plt

import cv2
import itertools
import random

from sklearn.utils import shuffle

import tensorflow as tf
from keras.models import Sequential
from keras.optimizers import Adam, RMSprop
from keras.layers import Conv2D, AveragePooling2D, Activation, Input, conca
from keras.models import Model

from keras.layers.normalization import BatchNormalization
from keras.layers.pooling import MaxPooling2D
from keras.layers.merge import Concatenate
from keras.layers.core import Lambda, Flatten, Dense

from keras.engine.topology import Layer
from keras.regularizers import l2
from keras import backend as K
```

In [2]:
```
## Mount the google drive to colab
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, ca
ll drive.mount("/content/drive", force_remount=True).
```

In [3]:
```
path = "/content/drive/My Drive/Signatures_2/Train_Set/"
os.chdir(path)
!ls
```

```
001  005  009  013  017  021  025  029  033  037  041  045  049  053  057
061
002  006  010  014  018  022  026  030  034  038  042  046  050  054  058
062
003  007  011  015  019  023  027  031  035  039  043  047  051  055  059
063
004  008  012  016  020  024  028  032  036  040  044  048  052  056  060
064
```

In [4]:
```
#dir_list = '001', '002'...
dir_list = next(os.walk(path))[1]
#print (os.listdir(path))
```

Read all the Paths for the data from folder for each image

In [5]:
```
## Read the data
real_groups, forg_groups = [], []
rlen, flen = [], []
for directory in dir_list:

    ## Read all Image names
    real_images = os.listdir(path+'/' +directory+'/Real')
    forg_images = os.listdir(path+ '/' + directory+ '/Forged')

    ## Create a full_path for each image in the directory and add in a list
    real_image_paths = [path+directory+'/Real/'+x for x in real_images]
    forged_image_paths = [path+directory+'/Forged/'+x for x in forg_images]

    ## Check how many images are in each path and store the number for refe
    rlen.append(len(real_image_paths))
    flen.append(len(forged_image_paths))

    ## Append the list of paths into a parent list.
    real_groups.append(real_image_paths)
    forg_groups.append(forged_image_paths)
```

In [6]:
```
### Define Fixed Params:
img_height = 100
img_width = 100
```

In [7]:

```
# A function to generate batches with the available groups of images
def generate_batch(real_groups, forg_groups, batch_size = 30):


    while True:
        #### Create pairs
        real_pairs = []          # Real - Real image pair
        forg_pairs = []          # Real - Forged image pair
        all_pairs = []
        all_labels = []


        for real, forg in zip(real_groups, forg_groups):  #64 each
            real_pairs.extend(list(itertools.combinations(real, 2)))
            for i in range(len(forg)):
                forg_pairs.extend(list(itertools.product(real[i:i+1], rando

        # Label for real-real pairs is 1
        # Label for real-forged pairs is 0
        real_real_labels = [1]*len(real_pairs)
        real_for_labels = [0]*len(forg_pairs)



        # Concatenate all the pairs together along with their labels and sh
        all_pairs = real_pairs + forg_pairs
        all_labels = real_real_labels + real_for_labels
        all_pairs, all_labels = shuffle(all_pairs, all_labels)




        ## Read the images from the paths, resize them, convert to 1D np ar
        k = 0
        pairs=[np.zeros((batch_size, img_height, img_width, 1)) for i in ra
        targets=np.zeros((batch_size,))

        for ix, pair in enumerate(all_pairs):
            ## Read Images
            img1 = cv2.imread(pair[0], 0)
            img2 = cv2.imread(pair[1], 0)

            # Resize
            img1 = cv2.resize(img1, (img_width, img_height))
            img2 = cv2.resize(img2, (img_width, img_height))

            ## Convert to np arrays
            img1 = np.array(img1, dtype = np.float64)
            img2 = np.array(img2, dtype = np.float64)
            img1 /= 255
            img2 /= 255

            ## Add a third axis, make it into shape = (250, 250, 1)
            img1 = img1[..., np.newaxis]
            img2 = img2[..., np.newaxis]
```

```
            ## Convert them into a 1D array
            pairs[0][k, :, :, :] = img1
            pairs[1][k, :, :, :] = img2

            ## Store the corresponding labels
            targets[k] = all_labels[ix]
            k += 1

            ## If batch is full, then yeild the batch
            if k == batch_size:
                yield pairs, targets

                # Reset Params for next batch
                k = 0
                pairs=[np.zeros((batch_size, img_height, img_width, 1)) for
                targets=np.zeros((batch_size,))
```

In [8]:

```
### Defining a Base Siamese Network for both images
def Base_Siamese_Network(input_shape):
    '''Base Siamese Network'''

    seq = Sequential()
    seq.add(Conv2D(96, kernel_size=(3, 3), activation='relu', name='conv1_1
                   input_shape= input_shape))
    seq.add(AveragePooling2D((2,2), strides=(2, 2), padding = 'same'))

    seq.add(Conv2D(200, kernel_size=(3, 3), activation='relu', name='conv2_
    seq.add(AveragePooling2D((2,2), strides=(2, 2), padding = 'same'))
    #seq.add(Dropout(0.3))# added extra
    seq.add(ZeroPadding2D((1, 1)))


    #seq.add(Dropout(0.3))# added extra
    seq.add(Flatten(name='flatten'))
    seq.add(Dense(128, activation='relu'))
    seq.add(Dense(128, activation='relu'))

    return seq
```

In [9]:
```
### Defining functions for loss functions and distance measures
def euclidean_distance(vects):
    '''Compute Euclidean Distance between two vectors'''
    x, y = vects
    return K.sqrt(K.sum(K.square(x - y), axis=1, keepdims=True))

def eucl_dist_output_shape(shapes):
    shape1, shape2 = shapes
    return (shape1[0], 1)


def contrastive_loss(y_true, y_pred):
    margin = 1
    return K.mean(y_true * K.square(y_pred) + (1 - y_true) * K.square(K.max
```

In [10]:
```
#### Divide val and Train
real_train, real_val = real_groups[:50], real_groups[50:]
forg_train, forg_val = forg_groups[:50], forg_groups[50:]
```

In [11]:
```

### A function to return the length of train and test samples for the avail
def len_of_all_pairs(real_groups, forg_groups):

    #### Create pairs
    real_pairs = []           # Real - Real image pair
    forg_pairs = []           # Real - Forged image pair
    all_pairs = []
    all_labels = []


    for real, forg in zip(real_groups, forg_groups):  #64 each
        real_pairs.extend(list(itertools.combinations(real, 2)))
        for i in range(len(forg)):
            forg_pairs.extend(list(itertools.product(real[i:i+1], random.sa

    # Label for real-real pairs is 1
    # Label for real-forged pairs is 0
    real_real_labels = [1]*len(real_pairs)
    real_for_labels = [0]*len(forg_pairs)



    # Concatenate all the pairs together along with their labels and shuffl
    all_pairs = real_pairs + forg_pairs
    all_labels = real_real_labels + real_for_labels
    all_pairs, all_labels = shuffle(all_pairs, all_labels)

    return(len(all_pairs))
```

In [12]:

```
## Calcualte length of samples for train and test case
num_train_samples = len_of_all_pairs(real_train, forg_train)
num_val_samples = len_of_all_pairs(real_val, forg_val)
batch_sz = 30
```

In [13]:

```
# network definition
input_shape = (img_height, img_width, 1)
base_network = Base_Siamese_Network(input_shape)

input_a = Input(shape=(input_shape))
input_b = Input(shape=(input_shape))

processed_a = base_network(input_a)
processed_b = base_network(input_b)

# Compute the Euclidean distance between the two vectors in the latent spac
distance = Lambda(euclidean_distance, output_shape=eucl_dist_output_shape)(

model = Model(inputs=[input_a, input_b], outputs=distance)
```

In [14]:

```
### Fit the model with the training data and validate it on validation data
rms = RMSprop()
model.compile(loss=contrastive_loss, optimizer=rms)


results = model.fit_generator(generate_batch(real_train, forg_train, batch_
                              steps_per_epoch = num_train_samples//batch_sz
                              epochs = 20,
                              validation_data = generate_batch(real_val, fo
                              validation_steps = num_val_samples//batch_sz)
```

```
WARNING:tensorflow:From <ipython-input-14-1a5c576ff73b>:10: Model.fit_
generator (from tensorflow.python.keras.engine.training) is deprecated
and will be removed in a future version.
Instructions for updating:
Please use Model.fit, which supports generators.
Epoch 1/20
418/418 [==============================] - 174s 417ms/step - loss: 0.0
846 - val_loss: 0.0591
Epoch 2/20
418/418 [==============================] - 170s 406ms/step - loss: 0.0
144 - val_loss: 0.0526
Epoch 3/20
418/418 [==============================] - 166s 397ms/step - loss: 0.0
068 - val_loss: 0.0432
Epoch 4/20
418/418 [==============================] - 168s 401ms/step - loss: 0.0
047 - val_loss: 0.0551
Epoch 5/20
418/418 [==============================] - 166s 396ms/step - loss: 0.0
035 - val_loss: 0.0565
Epoch 6/20
418/418 [==============================] - 162s 388ms/step - loss: 0.0
026 - val_loss: 0.0503
Epoch 7/20
418/418 [==============================] - 160s 383ms/step - loss: 0.0
024 - val_loss: 0.0462
Epoch 8/20
418/418 [==============================] - 161s 385ms/step - loss: 0.0
021 - val_loss: 0.0486
Epoch 9/20
418/418 [==============================] - 160s 382ms/step - loss: 0.0
017 - val_loss: 0.0382
Epoch 10/20
418/418 [==============================] - 160s 382ms/step - loss: 0.0
016 - val_loss: 0.0447
Epoch 11/20
418/418 [==============================] - 160s 382ms/step - loss: 0.0
014 - val_loss: 0.0555
Epoch 12/20
418/418 [==============================] - 159s 381ms/step - loss: 0.0
012 - val_loss: 0.0476
Epoch 13/20
418/418 [==============================] - 159s 380ms/step - loss: 0.0
011 - val_loss: 0.0575
```

```
Epoch 14/20
418/418 [==============================] - 158s 377ms/step - loss: 0.0
010 - val_loss: 0.0331
Epoch 15/20
418/418 [==============================] - 158s 378ms/step - loss: 9.9
861e-04 - val_loss: 0.0573
Epoch 16/20
418/418 [==============================] - 157s 377ms/step - loss: 0.0
011 - val_loss: 0.0571
Epoch 17/20
418/418 [==============================] - 158s 377ms/step - loss: 8.7
150e-04 - val_loss: 0.0412
Epoch 18/20
418/418 [==============================] - 157s 376ms/step - loss: 0.0
013 - val_loss: 0.0712
Epoch 19/20
418/418 [==============================] - 158s 378ms/step - loss: 9.7
285e-04 - val_loss: 0.0348
Epoch 20/20
418/418 [==============================] - 157s 377ms/step - loss: 8.3
732e-04 - val_loss: 0.0604
```

In [14]:

In [15]:

```python
## A function to compute accuracy and optimal threshold for prediction analy
def compute_accuracy_roc(predictions, labels):
    '''Compute ROC accuracy with a range of thresholds on distances.
    '''
    dmax = np.max(predictions)
    dmin = np.min(predictions)
    nsame = np.sum(labels == 1)
    ndiff = np.sum(labels == 0)

    step = 0.01
    max_acc = 0
    best_thresh = -1

    for d in np.arange(dmin, dmax+step, step):
        idx1 = predictions.ravel() <= d
        idx2 = predictions.ravel() > d

        tpr = float(np.sum(labels[idx1] == 1)) / nsame
        tnr = float(np.sum(labels[idx2] == 0)) / ndiff
        acc = 0.5 * (tpr + tnr)
#       print ('ROC', acc, tpr, tnr)

        if (acc > max_acc):
            max_acc, best_thresh = acc, d

    return max_acc, best_thresh
```

In [16]:
```
## Generate a test batch to check its validation accuracy
test_gen = generate_batch(real_val, forg_val, 1)
pred, tr_y = [], []
for i in range(num_val_samples):
    (img1, img2), label = next(test_gen)
    tr_y.append(label)
    pred.append(model.predict([img1, img2])[0][0])
```

In [17]:
```
# Print validation accuracy and threshold
tr_acc, threshold = compute_accuracy_roc(np.array(pred), np.array(tr_y))
tr_acc, threshold
```

Out[17]:
```
(0.9670788770053476, 0.2799162214994431)
```

In [18]:
```
## A function to display samples and their result of classification.
def predict_score():
    '''Predict distance score and classify test images as Genuine or Forged
    test_point, test_label = next(test_gen)
    img1, img2 = test_point[0], test_point[1]

    fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (10, 10))
    ax1.imshow(np.squeeze(img1), cmap='gray')
    ax2.imshow(np.squeeze(img2), cmap='gray')
    ax1.set_title('Genuine')
    if test_label == 1:
        ax2.set_title('Genuine')
    else:
        ax2.set_title('Forged')
    ax1.axis('off')
    ax2.axis('off')
    plt.show()
    result = model.predict([img1, img2])
    diff = result[0][0]
    print("Difference Score = ", diff)
    if diff > threshold:
        print("Its a Forged Signature")
    else:
        print("Its a Genuine Signature")
```

In [19]:

```
# Validation set examples
predict_score()
```

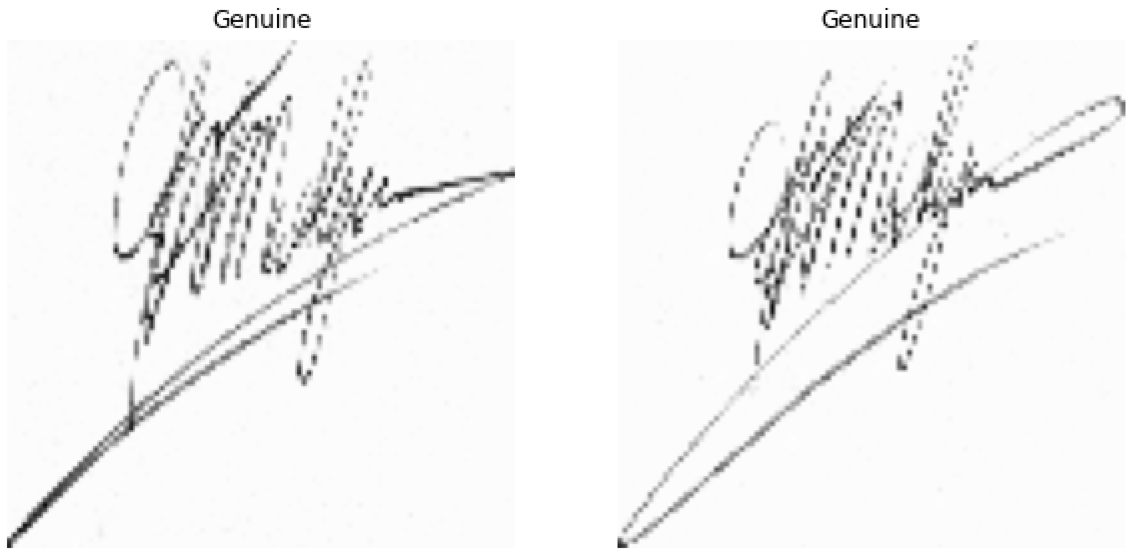
Genuine

Genuine

```
Difference Score =  0.14578772
Its a Genuine Signature
```

In [20]:

```
predict_score()
```




```
Difference Score =  0.059697773
Its a Genuine Signature
```

In [21]:

```
predict_score()
```


```
Difference Score =  0.2604548
Its a Genuine Signature
```

In [22]:

```
predict_score()
```


```
Difference Score =  0.2147054
Its a Genuine Signature
```

In [23]:

```
predict_score()
```


```
Difference Score =  0.1094851
Its a Genuine Signature
```

In [24]:
```
predict_score()
```

Genuine Genuine

```
Difference Score =  0.18574136
Its a Genuine Signature
```

In [25]:
```
predict_score()
```

Genuine Forged

```
Difference Score =  7.557686
Its a Forged Signature
```

Now do the same analysis for testing

In [26]:
```
### Apply the trained model on Test Set!!!
path = "/content/drive/My Drive/Signatures_2/Test_Set/"

#dir_list = '001', '002'...
dir_list = next(os.walk(path))[1]
```

In [27]:
```
## Read the data
real_groups_test, forg_groups_test = [], []
for directory in dir_list:

    ## Read all Image names
    real_images = os.listdir(path+'/' +directory+'/Real')
    forg_images = os.listdir(path+ '/' + directory+ '/Forged')

    ## Create a full_path for each image in the directory and add in a list
    real_image_paths = [path+directory+'/Real/'+x for x in real_images]
    forged_image_paths = [path+directory+'/Forged/'+x for x in forg_images]

    ## Append the list of paths into a parent list.
    real_groups_test.append(real_image_paths)
    forg_groups_test.append(forged_image_paths)
```

In [28]:
```
num_of_test_samples = len_of_all_pairs(real_groups_test, forg_groups_test)

test_gen = generate_batch(real_groups_test, forg_groups_test, 1)
pred_test, tr_y_test = [], []
for i in range(num_of_test_samples):
    (img1, img2), label = next(test_gen)
    tr_y_test.append(label)
    pred_test.append(model.predict([img1, img2])[0][0])
```

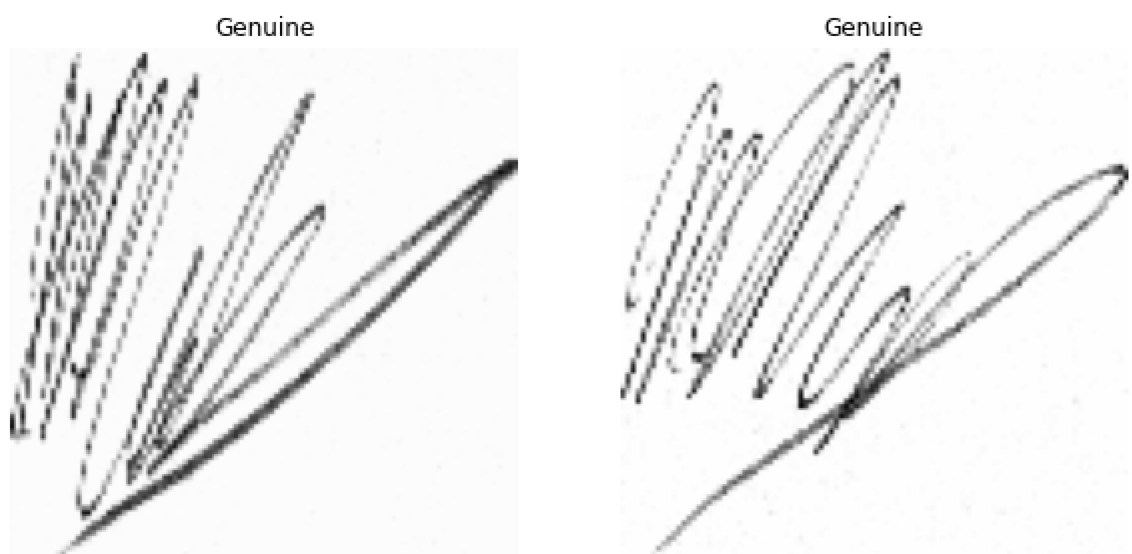
In [29]:
```
# Printing Training Accuracy
tr_acc_test, threshold_test = compute_accuracy_roc(np.array(pred_test), np.
print('Training Accuracy: ', tr_acc_test)
```

```
Training Accuracy:  0.9791821348870768
```

In [30]:
```python
## A function to print the test images and their results.
def predict_test():
    '''Predict distance score and classify test images as Genuine or Forged
    test_point, test_label = next(test_gen)
    img1, img2 = test_point[0], test_point[1]

    fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (10, 10))
    ax1.imshow(np.squeeze(img1), cmap='gray')
    ax2.imshow(np.squeeze(img2), cmap='gray')
    ax1.set_title('Genuine')
    if test_label == 1:
        ax2.set_title('Genuine')
    else:
        ax2.set_title('Forged')
    ax1.axis('off')
    ax2.axis('off')
    plt.show()
    result = model.predict([img1, img2])
    diff = result[0][0]
    print("Difference Score = ", diff)
    if diff > threshold:
        print("Its a Forged Signature")
    else:
        print("Its a Genuine Signature")
```

In [31]:
```python
### Printing a test sample with their results
predict_test()
```




```
Difference Score =  0.09506219
Its a Genuine Signature
```

In [32]:

```
predict_test()
```


```
Difference Score =  1.3013374
Its a Forged Signature
```

In [33]:

```
predict_test()
```


```
Difference Score =  0.017931737
Its a Genuine Signature
```

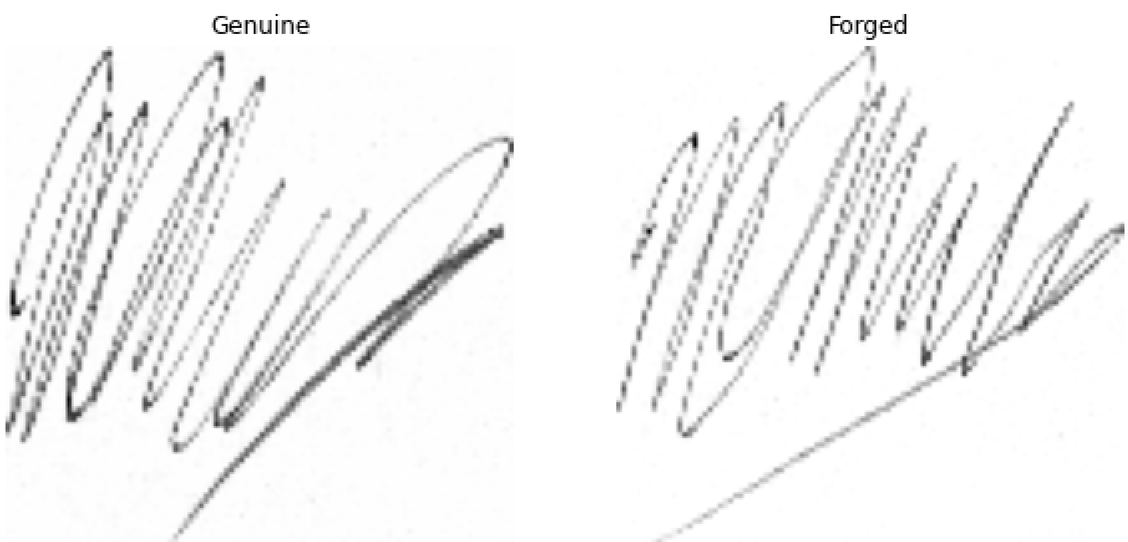
In [34]:

```
predict_test()
```


```
Difference Score =  0.1044879
Its a Genuine Signature
```

In [35]:

```
predict_test()
```




```
Difference Score =  0.49496564
Its a Forged Signature
```

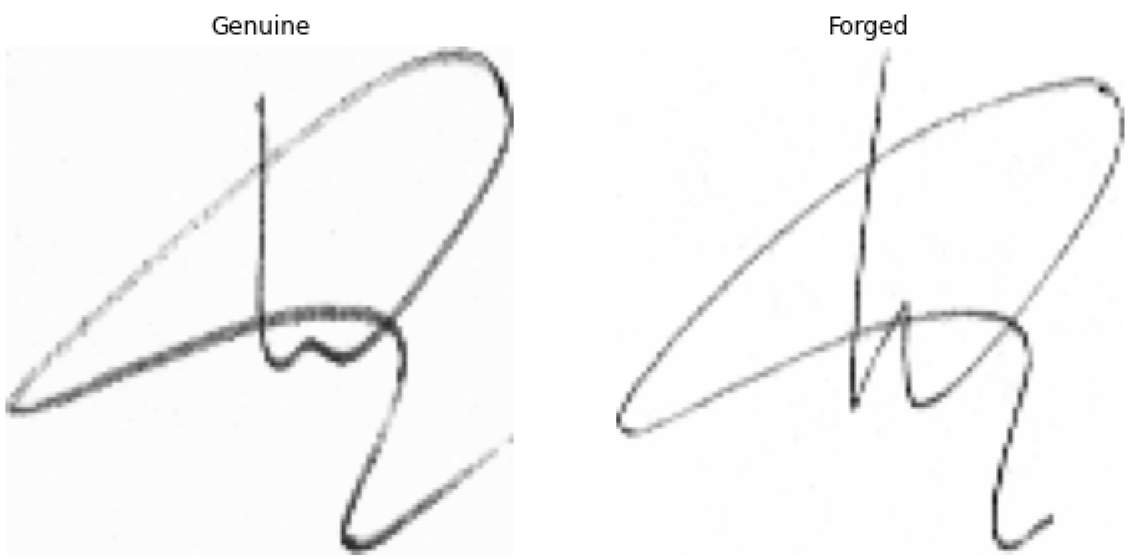
In [36]:

```
predict_test()
```


```
Difference Score =  1.2296127
Its a Forged Signature
```

In [37]:

```
predict_test()
```




```
Difference Score =  1.3465387
Its a Forged Signature
```

In [37]:

```

```