Offline Handwritten Signature Recognition

1. Aditya Lakshmanan - 2019103003
2. Kavya Sridhar - 2019103027
3. Ishwarya S - 2019103528

INTRODUCTION

Handwritten signature is one of the most important forms of biometric authorizations that are used universally to authorize and verify documents. However, they are among the more vulnerable metrics since they can be easily forged thereby leading to drastic effects such as identity theft, information theft, etc. Thus, a need for identifying the genuineness of a signature is essential.

The primary difficulty faced by signature recognition system is the intra-class variation, i.e., an individual’s original sign may not be the same each time they sign it because several external and internal factors affect it, such as, the pen used, the surface used, etc. Thus any model that aims at performing signature recognition must account for these variations.

Online and Offline Signatures:

There are two ways to identify the signatures, off-line signature recognition and on-line signature recognition. On-line signature assesses the parameters such as speed of writing, the force employed on the signing instrument, the position of the hand, etc., all of which are physical factors that are outside the scope of this project. Off-line signature verification essentially treats the signature as an image and uses Neural Networks to identify the validity of the signature.

We will be designing an offline signature verification system for our project.

Writer Dependent and Writer Independent

In a ***writer dependent*** model characteristics included are writer dependent threshold, features and classifiers. This model is based on writer dependent features which are selected based on a score computed for each feature of the respective writer, thereby resulting in selection of different set of features for different writers.

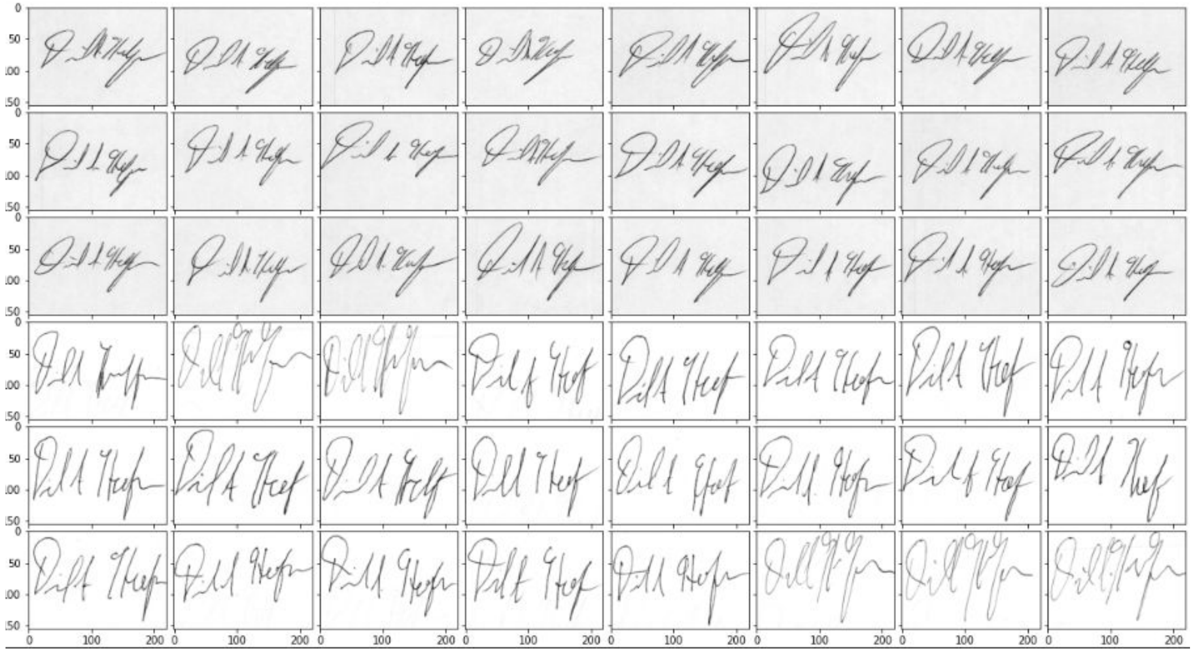
However, this model is not sufficient since a new neural network would have to be trained for each and every individual writer, which is highly inefficient and ineffective.

The neural network proposed by the base paper, is a Siamese Neural Network, i.e., a network which consists of twin convolutional networks accepting two distinct signature images that are either similar or dissimilar. This makes the neural network ***writer independent*** and requires a genuine signature to be passed along with the sample signature to determine its validity.

This project explores both these categories.

Dataset:

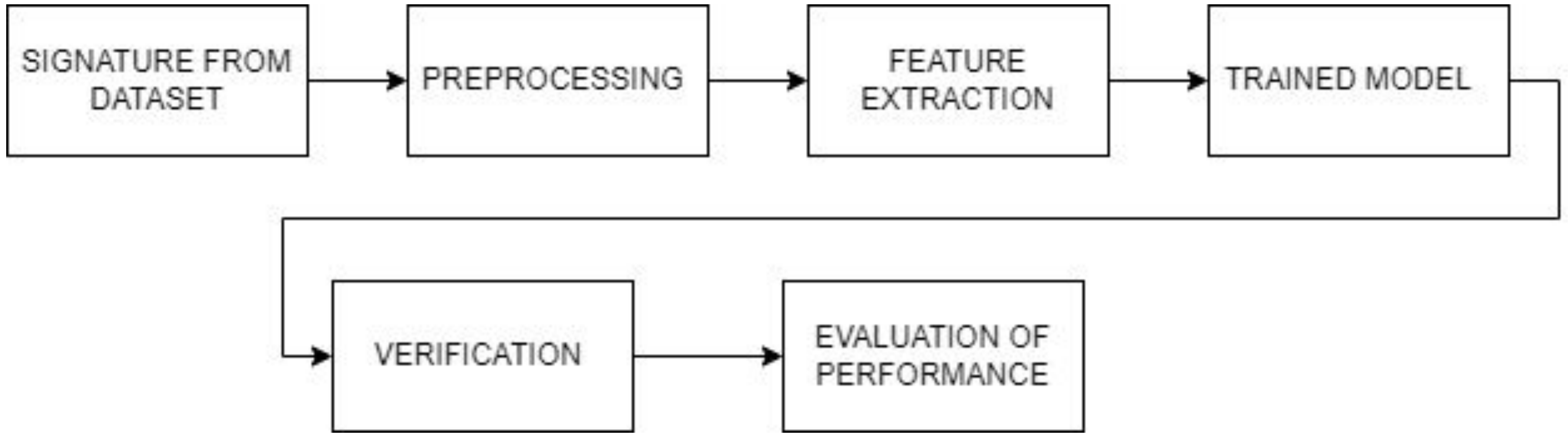
CEDAR Signature is a database of off-line signatures for signature verification. Each of 55 individuals contributed 24 signatures thereby creating 1,320 genuine signatures. Some were asked to forge three other writers' signatures, eight times per subject, thus creating 1,320 forgeries. The database has 24 genuines and 24 forgeries available for each writer.



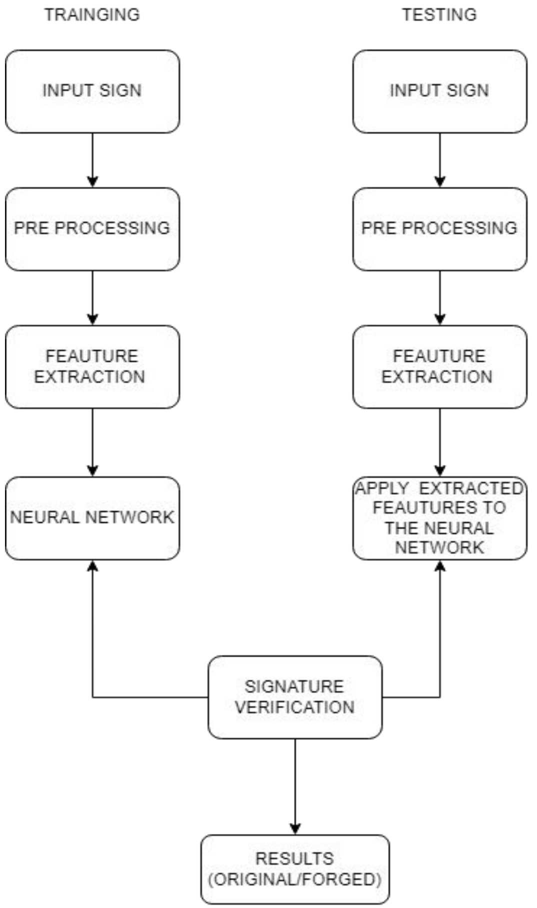
Sample sign from dataset with first 3 rows as original signatures and last 3 rows as forged signatures.

MODEL 1 : WRITER DEPENDENT

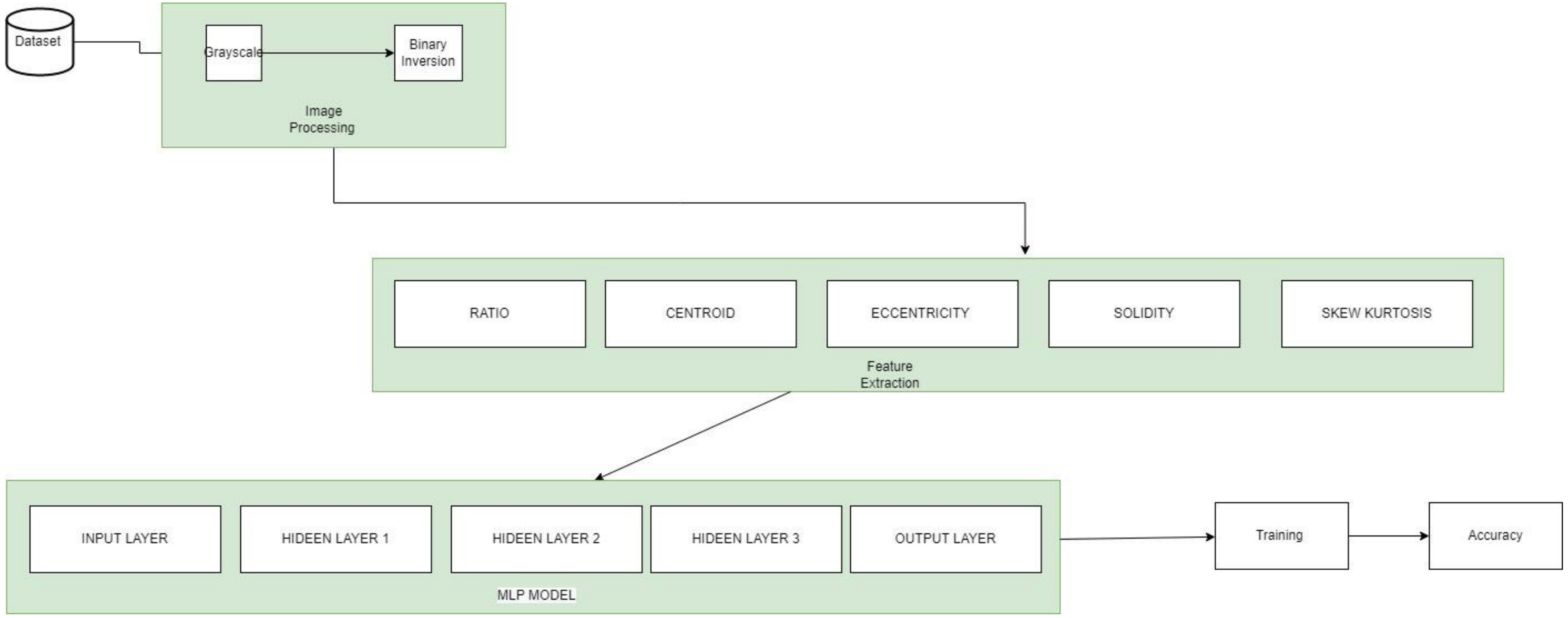
BLOCK DIAGRAM



FLOW CHART


TRAINGING
TESTING
INPUT SIGN
PRE PROCESSING
FEAUTURE EXTRACTION
NEURAL NETWORK
INPUT SIGN
PRE PROCESSING
FEAUTURE EXTRACTION
APPLY EXTRACTED FEAUTURES TO THE NEURAL NETWORK
SIGNATURE VERIFICATION
RESULTS (ORIGINAL/FORGED)

Detailed Block Diagram

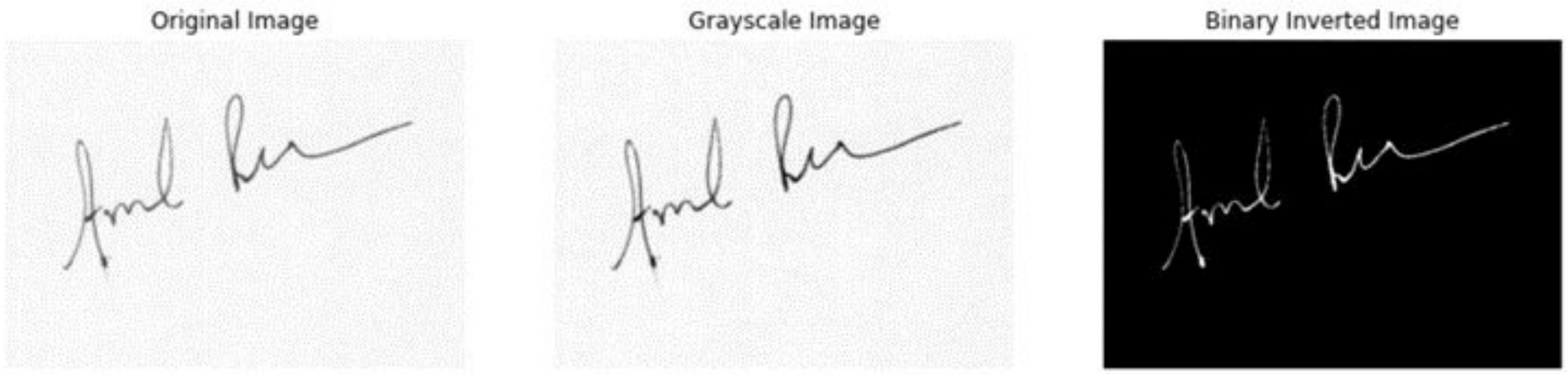


MODULES

- Pre Processing
- Feature Extraction
- Training & Testing
- Verification Result

PRE PROCESSING

- BINARY INVERSION
- GRAY SCALE CONVERSION



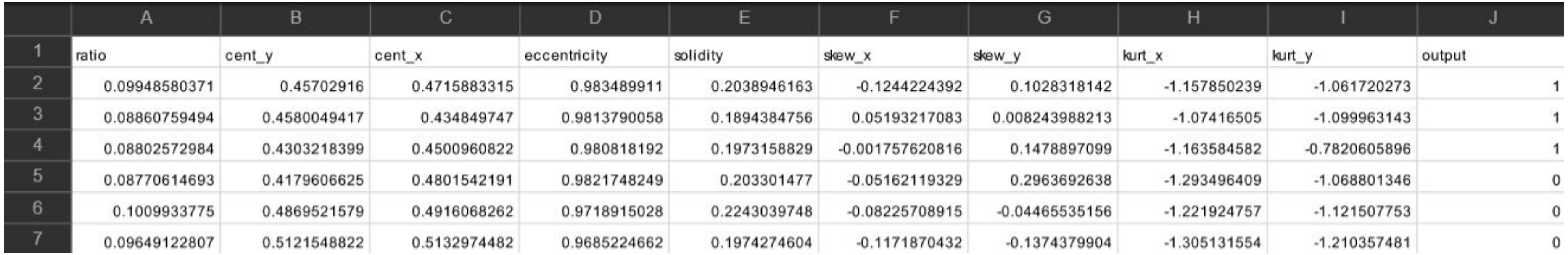
FEATURE EXTRACTION

- ***Ratio***
  - It is the ratio of area of signature image to the area of signature enclosed in a bounding box. Area of a signature is the number of pixels comprising it.
- ***Centroid***
  - To find the centroid of a group of pixels in a binary image you must calculate the average coordinate. In case of a grayscale image you can use the pixels' gray values to calculate the weighted average position.
- ***Eccentricity***
  - Eccentricity measures the shortest length of the paths from a given vertex v to reach any other vertex w of a connected graph.
  - Computed for every vertex v it transforms the connectivity structure of the graph into a set of values. For a connected region of a digital image it is defined through its neighbourhood graph and the given metric.
  - This transform assigns to each element of a region a value that depends on its location inside the region and the region’s shape.

- ***Solidity***
  - Solidity is area fraction of the region as compared to its convex hull.
  - Solidity is what fraction of the actual area your region is.
- ***Skew***
  - Skewness is a measure of (lack of) symmetry . For instance, if the skewness is negative, the histogram is negatively skewed. That means its left tail is longer or fatter than its right one. Therefore, the frequency over the darker intensities (closer to zero) is wider spread (less concentrated, but not necessarily less frequent than the right tail!). The positive skewness is the opposite.
- ***Kurtosis***
  - It is the average (or expected value) of the standardized data raised to the fourth power. Any standardized values that are less than 1 (i.e., data within one standard deviation of the mean, where the "peak" would be), contribute virtually nothing to kurtosis, since raising a number that is less than 1 to the fourth power makes it close to zero. The only data values (observed or observable) that contribute to kurtosis in any meaningful way are those outside the region of the peak; i.e., the outliers. Therefore kurtosis measures outliers only; it measures nothing about the "peak."

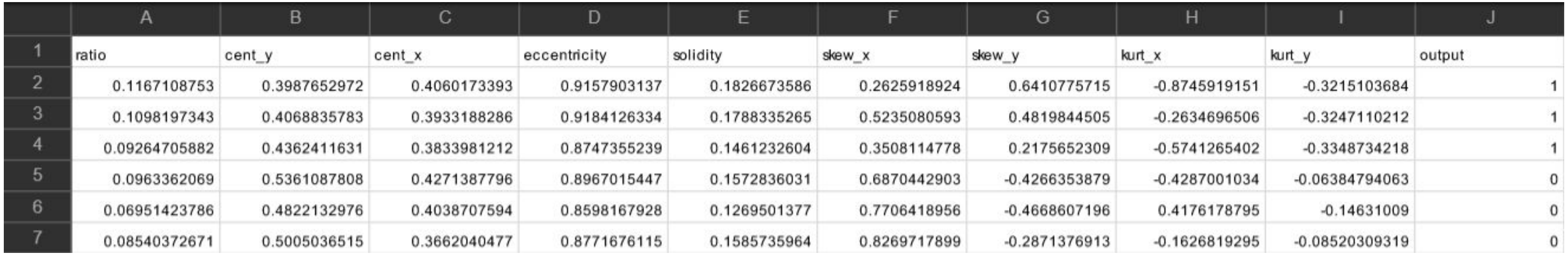
EXTRACTED FEATURES

The below is the csv file containing extracted features of person-001.



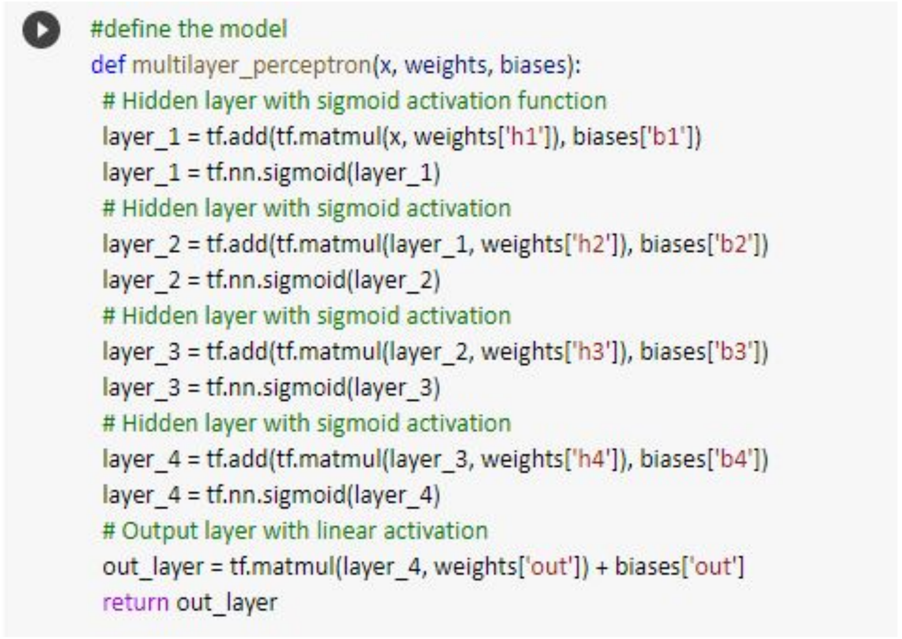
	A	B	C	D	E	F	G	H	I	J
1	ratio	cent_y	cent_x	eccentricity	solidity	skew_x	skew_y	kurt_x	kurt_y	output
2	0.09948580371	0.45702916	0.4715883315	0.983489911	0.2038946163	-0.1244224392	0.1028318142	-1.157850239	-1.061720273	1
3	0.08860759494	0.4580049417	0.434849747	0.9813790058	0.1894384756	0.05193217083	0.008243988213	-1.07416505	-1.099963143	1
4	0.08802572984	0.4303218399	0.4500960822	0.980818192	0.1973158829	-0.001757620816	0.1478897099	-1.163584582	-0.7820605896	1
5	0.08770614693	0.4179606625	0.4801542191	0.9821748249	0.203301477	-0.05162119329	0.2963692638	-1.293496409	-1.068801346	0
6	0.1009933775	0.4869521579	0.4916068262	0.9718915028	0.2243039748	-0.08225708915	-0.04465535156	-1.221924757	-1.121507753	0
7	0.09649122807	0.5121548822	0.5132974482	0.9685224662	0.1974274604	-0.1171870432	-0.1374379904	-1.305131554	-1.210357481	0

The below is the csv file containing extracted features of person-005.

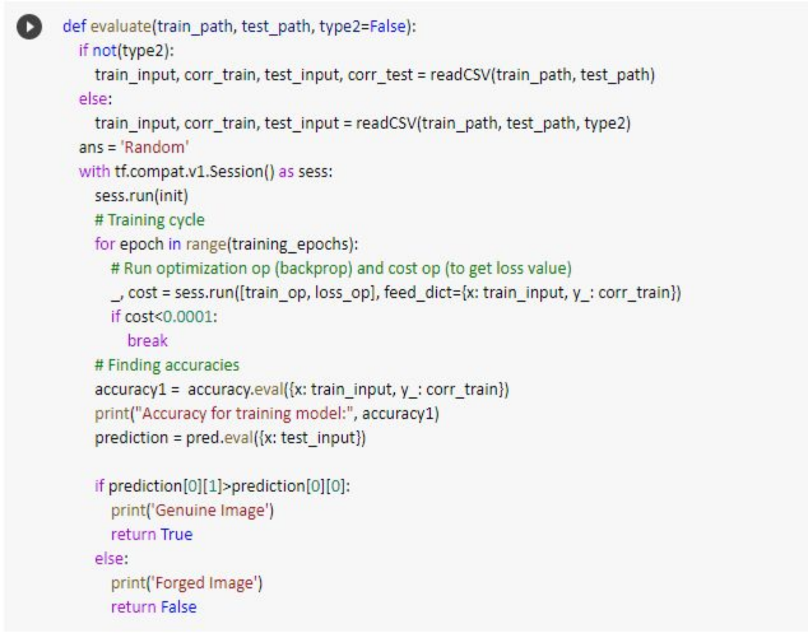


	A	B	C	D	E	F	G	H	I	J
1	ratio	cent_y	cent_x	eccentricity	solidity	skew_x	skew_y	kurt_x	kurt_y	output
2	0.1167108753	0.3987652972	0.4060173393	0.9157903137	0.1826673586	0.2625918924	0.6410775715	-0.8745919151	-0.3215103684	1
3	0.1098197343	0.4068835783	0.3933188286	0.9184126334	0.1788335265	0.5235080593	0.4819844505	-0.2634696506	-0.3247110212	1
4	0.09264705882	0.4362411631	0.3833981212	0.8747355239	0.1461232604	0.3508114778	0.2175652309	-0.5741265402	-0.3348734218	1
5	0.0963362069	0.5361087808	0.4271387796	0.8967015447	0.1572836031	0.6870442903	-0.4266353879	-0.4287001034	-0.06384794063	0
6	0.06951423786	0.4822132976	0.4038707594	0.8598167928	0.1269501377	0.7706418956	-0.4668607196	0.4176178795	-0.14631009	0
7	0.08540372671	0.5005036515	0.3662040477	0.8771676115	0.1585735964	0.8269717899	-0.2871376913	-0.1626819295	-0.08520309319	0

TRAINING & TESTING



```python
#define the model
def multilayer_perceptron(x, weights, biases):
    # Hidden layer with sigmoid activation function
    layer_1 = tf.add(tf.matmul(x, weights['h1']), biases['b1'])
    layer_1 = tf.nn.sigmoid(layer_1)
    # Hidden layer with sigmoid activation
    layer_2 = tf.add(tf.matmul(layer_1, weights['h2']), biases['b2'])
    layer_2 = tf.nn.sigmoid(layer_2)
    # Hidden layer with sigmoid activation
    layer_3 = tf.add(tf.matmul(layer_2, weights['h3']), biases['b3'])
    layer_3 = tf.nn.sigmoid(layer_3)
    # Hidden layer with sigmoid activation
    layer_4 = tf.add(tf.matmul(layer_3, weights['h4']), biases['b4'])
    layer_4 = tf.nn.sigmoid(layer_4)
    # Output layer with linear activation
    out_layer = tf.matmul(layer_4, weights['out']) + biases['out']
    return out_layer
```



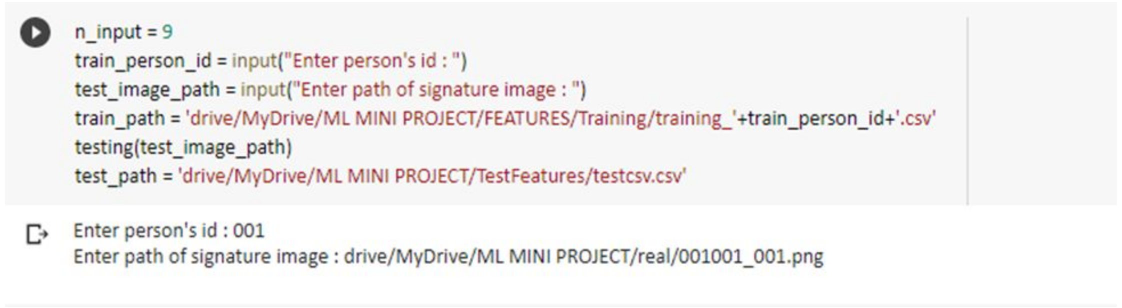
```python
def evaluate(train_path, test_path, type2=False):
    if not(type2):
        train_input, corr_train, test_input, corr_test = readCSV(train_path, test_path)
    else:
        train_input, corr_train, test_input = readCSV(train_path, test_path, type2)
    ans = 'Random'
    with tf.compat.v1.Session() as sess:
        sess.run(init)
        # Training cycle
        for epoch in range(training_epochs):
            # Run optimization op (backprop) and cost op (to get loss value)
            _, cost = sess.run([train_op, loss_op], feed_dict={x: train_input, y_: corr_train})
            if cost<0.0001:
                break
        # Finding accuracies
        accuracy1 =  accuracy.eval({x: train_input, y_: corr_train})
        print("Accuracy for training model:", accuracy1)
        prediction = pred.eval({x: test_input})

        if prediction[0][1]>prediction[0][0]:
            print('Genuine Image')
            return True
        else:
            print('Forged Image')
            return False
```

VERIFICATION RESULT

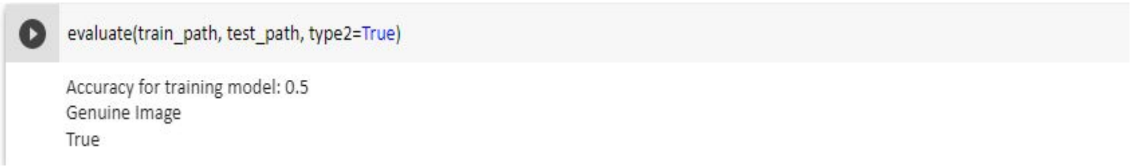
For Person with id 001

1. When a real signature is given.



```
n_input = 9
train_person_id = input("Enter person's id : ")
test_image_path = input("Enter path of signature image : ")
train_path = 'drive/MyDrive/ML MINI PROJECT/FEATURES/Training/training_'+train_person_id+'.csv'
testing(test_image_path)
test_path = 'drive/MyDrive/ML MINI PROJECT/TestFeatures/testcsv.csv'
```

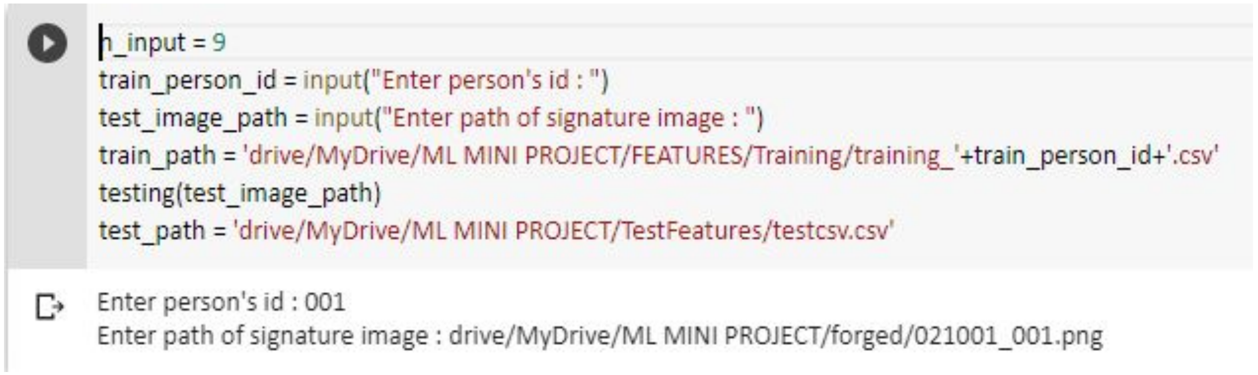
```
Enter person's id : 001
Enter path of signature image : drive/MyDrive/ML MINI PROJECT/real/001001_001.png
```



```
evaluate(train_path, test_path, type2=True)
```

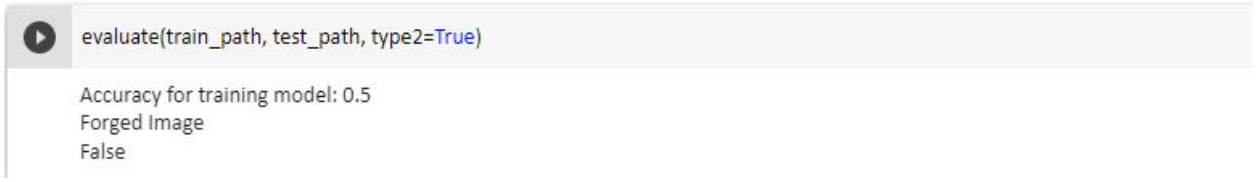
```
Accuracy for training model: 0.5
Genuine Image
True
```

2. When forged signature is given.



```
n_input = 9
train_person_id = input("Enter person's id : ")
test_image_path = input("Enter path of signature image : ")
train_path = 'drive/MyDrive/ML MINI PROJECT/FEATURES/Training/training_'+train_person_id+'.csv'
testing(test_image_path)
test_path = 'drive/MyDrive/ML MINI PROJECT/TestFeatures/testcsv.csv'
```

```
Enter person's id : 001
Enter path of signature image : drive/MyDrive/ML MINI PROJECT/forged/021001_001.png
```

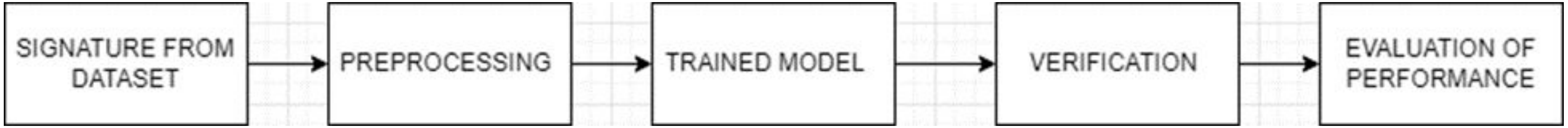


```
evaluate(train_path, test_path, type2=True)
```

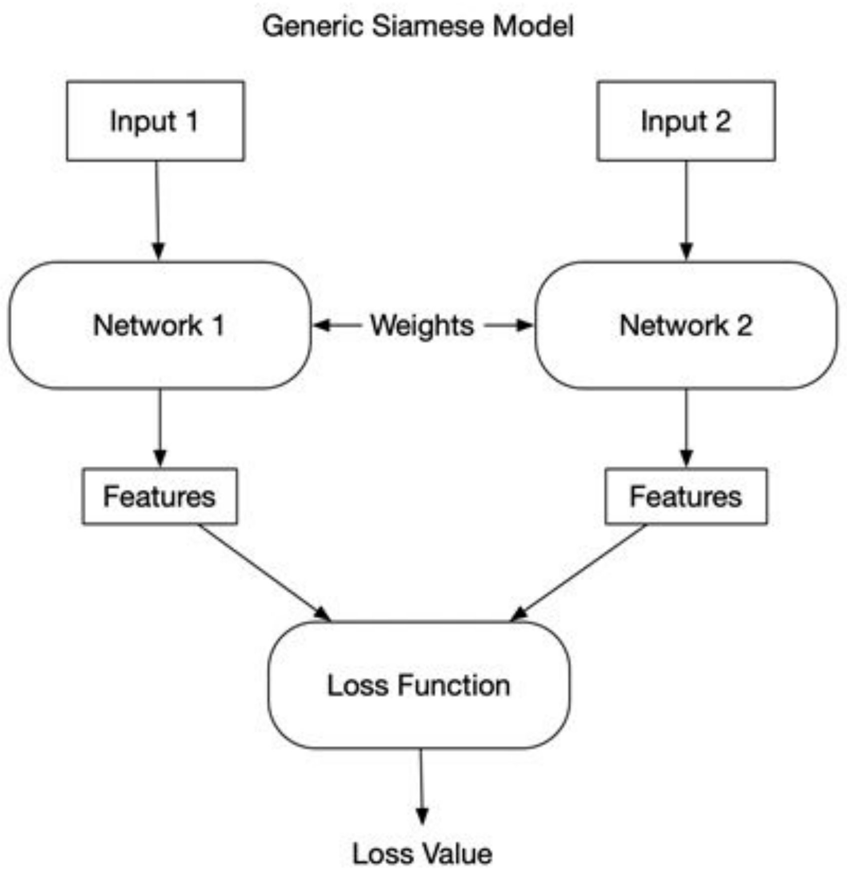
```
Accuracy for training model: 0.5
Forged Image
False
```

MODEL 2 : WRITER INDEPENDENT

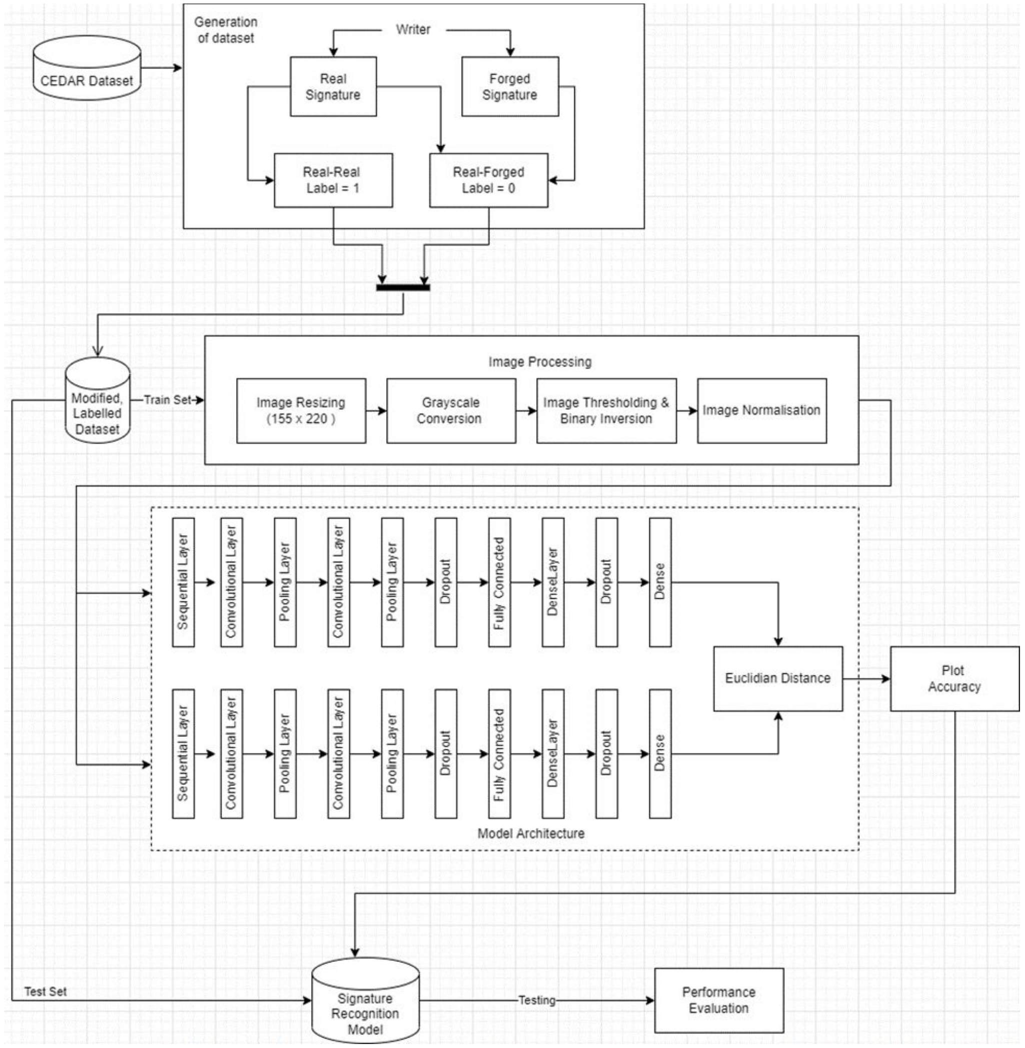
BLOCK DIAGRAM:



FLOW CHART


Generic Siamese Model
Input 1
Input 2
Network 1
Weights
Network 2
Features
Features
Loss Function
Loss Value

Detailed Block Diagram:



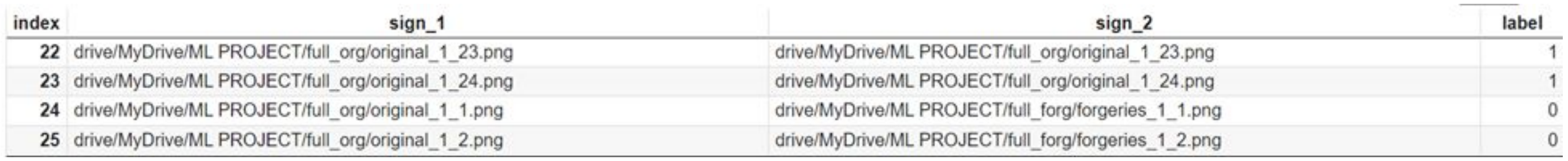
MODULES

1. Dataset preprocessing
   1.1. Generation of Labelled Dataset
   1.2. Image Processing
2. Model Development
   2.1. Model summary
   2.2. Training the model
3. Testing and Performance Evaluation

Module 1.1: Generation of Labelled Dataset

A labelled dataset is generated from the original dataset, consisting of rows of pairs of images along with the label.

Two kinds of pairs created, a real-real with label 1, and a real-forged with label 0.

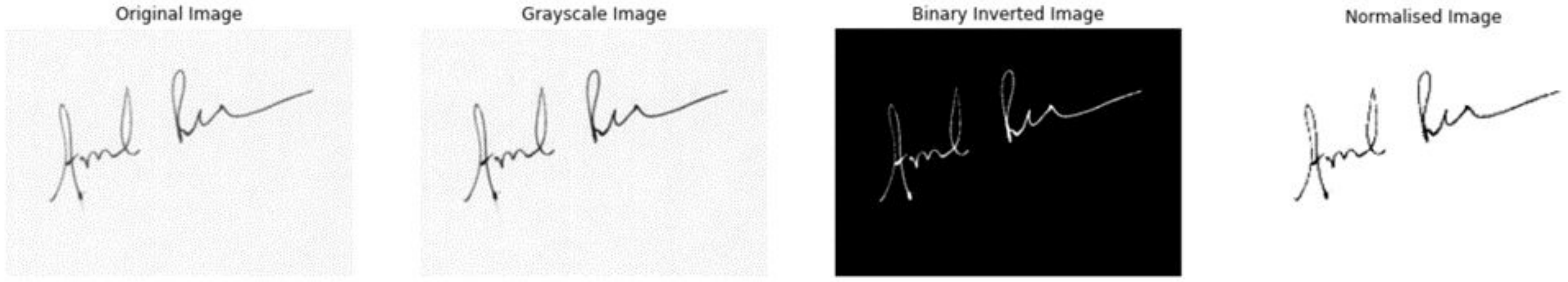


index	sign_1	sign_2	label
22	drive/MyDrive/ML PROJECT/full_org/original_1_23.png	drive/MyDrive/ML PROJECT/full_org/original_1_23.png	1
23	drive/MyDrive/ML PROJECT/full_org/original_1_24.png	drive/MyDrive/ML PROJECT/full_org/original_1_24.png	1
24	drive/MyDrive/ML PROJECT/full_org/original_1_1.png	drive/MyDrive/ML PROJECT/full_forg/forgeries_1_1.png	0
25	drive/MyDrive/ML PROJECT/full_org/original_1_2.png	drive/MyDrive/ML PROJECT/full_forg/forgeries_1_2.png	0

Module 1.2: Image Processing

The images are preprocessed using the OpenCV library and the following are the steps:

1. Resizing: the images are resized to 220 x 155 pixels using bilinear interpolation
2. Gray Scale Conversion: colored images are converted to grayscale
3. Image thresholding and binary inversion: that finds the optimal threshold value, to invert the image
4. Normalization: the images are normalized by 255



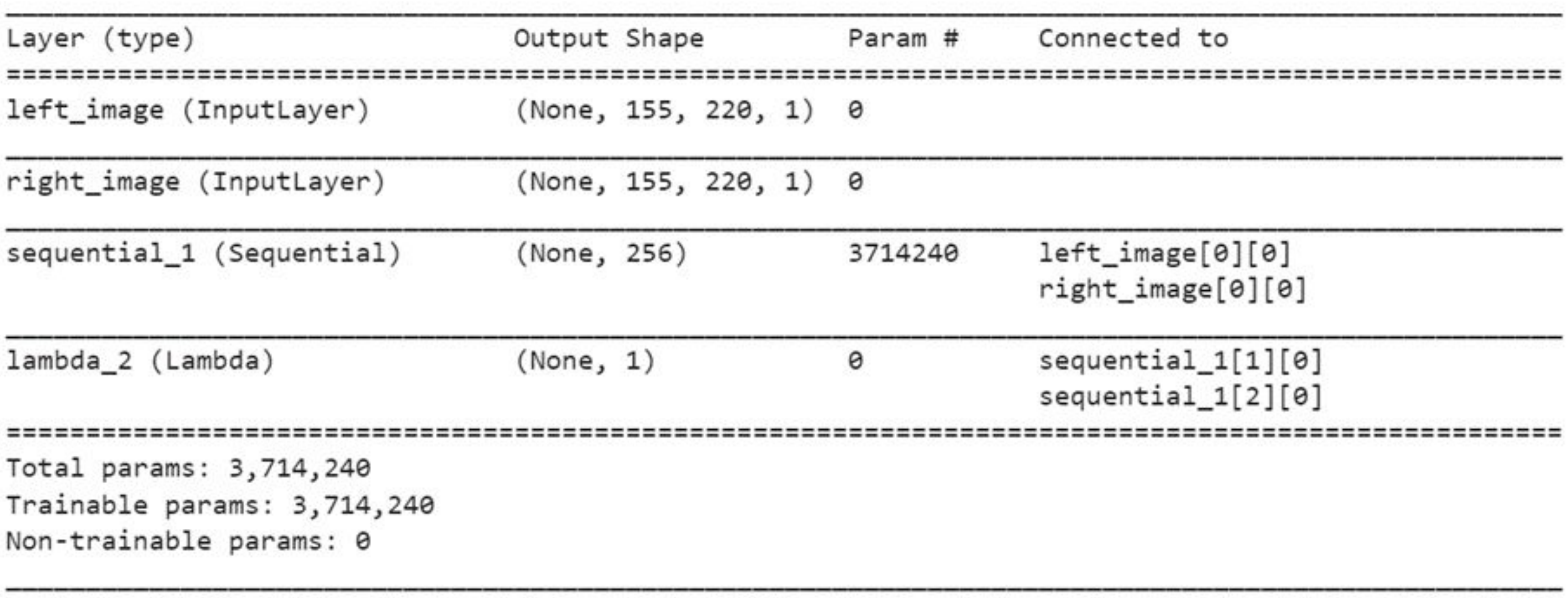
Module 2:MODEL DEVELOPMENT:

The input accepted by the model is (155,220,1) and both the images are passed to the model, where they now split into left_image and right_image. They are trained separately to extract the features using the layers described below:

- Sequential
- Convolutional
- MaxPooling
- DropOut
- Flatten
- Dense

They are then combined and passed to the Model() where the dense layers produced on both sides of the Siamese network is measured by a similarity metric containing Euclidean distance.

2.1 Model summary



```
____________________________________________________________________________________________________
Layer (type)                     Output Shape          Param #     Connected to
====================================================================================================
left_image (InputLayer)          (None, 155, 220, 1)  0
____________________________________________________________________________________________________
right_image (InputLayer)         (None, 155, 220, 1)  0
____________________________________________________________________________________________________
sequential_1 (Sequential)        (None, 256)           3714240     left_image[0][0]
                                                                   right_image[0][0]
____________________________________________________________________________________________________
lambda_2 (Lambda)                (None, 1)             0           sequential_1[1][0]
                                                                   sequential_1[2][0]
====================================================================================================
Total params: 3,714,240
Trainable params: 3,714,240
Non-trainable params: 0
____________________________________________________________________________________________________
```

2.2 TRAINING THE MODEL

Contrastive Loss Function is used as the loss function of the model. It aims at dimensionality reduction by learning an invariant mapping that produces high to low dimensional space maps similar input vectors to nearby points on the output manifold and dissimilar vectors to distant points.

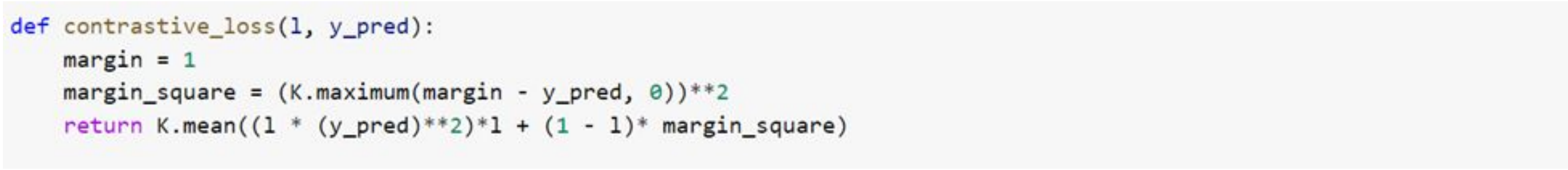
Contrastive loss takes the output of the network for a positive example and calculates its distance to an example of the same class and contrasts that with the distance to negative examplesThus, the loss is low if positive samples are encoded to similar (closer) representations and negative examples are encoded to different (farther) representations.

For two inputs X1 and X2, contrastive loss function is calculated as such:

$$D_W(\vec{X_1}, \vec{X_2}) = \|G_W(\vec{X_1}) - G_W(\vec{X_2})\|_2$$

$$\mathcal{L}(W) = \sum_{i=1}^{P} L(W, (Y, \vec{X_1}, \vec{X_2})^i) \qquad (2)$$

$$L(W, (Y, \vec{X_1}, \vec{X_2})^i) = (1 - Y) L_S \left(D_W^i\right) + Y L_D \left(D_W^i\right) \qquad (3)$$



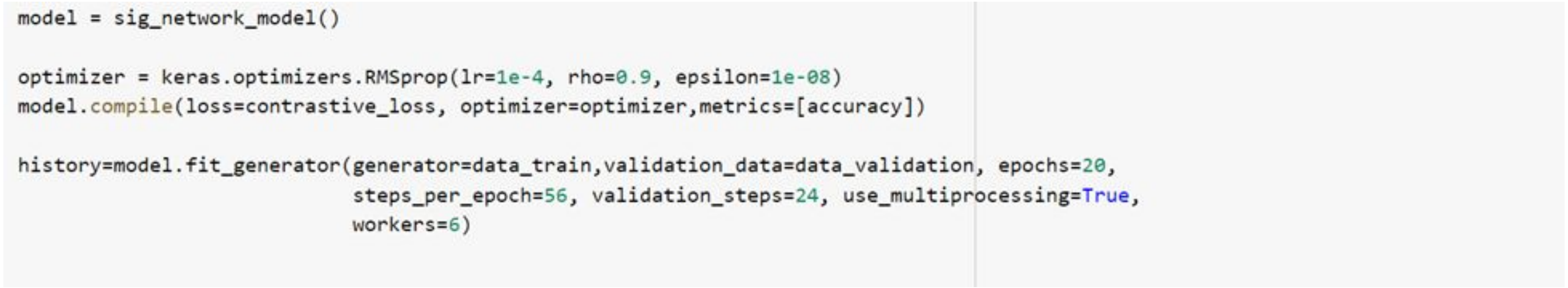
```python
def contrastive_loss(l, y_pred):
    margin = 1
    margin_square = (K.maximum(margin - y_pred, 0))**2
    return K.mean((l * (y_pred)**2)*l + (1 - l)* margin_square)
```

RMS Prop is used as the optimizer for the model.

The gist of RMSprop is to:

- Maintain a moving (discounted) average of the square of gradients
- Divide the gradient by the root of this average

This implementation of RMSprop uses plain momentum.

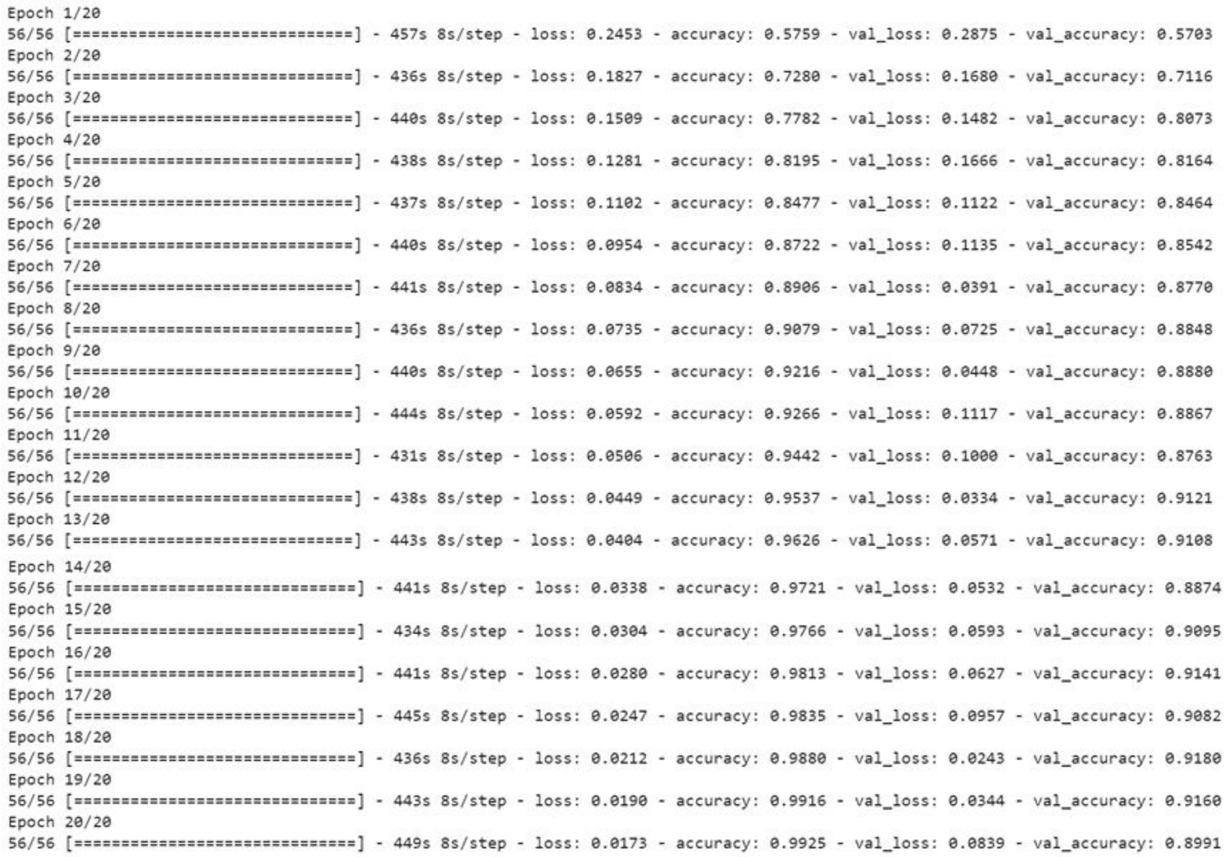


```python
model = sig_network_model()

optimizer = keras.optimizers.RMSprop(lr=1e-4, rho=0.9, epsilon=1e-08)
model.compile(loss=contrastive_loss, optimizer=optimizer,metrics=[accuracy])

history=model.fit_generator(generator=data_train,validation_data=data_validation, epochs=20,
                            steps_per_epoch=56, validation_steps=24, use_multiprocessing=True,
                            workers=6)
```

OUTPUT



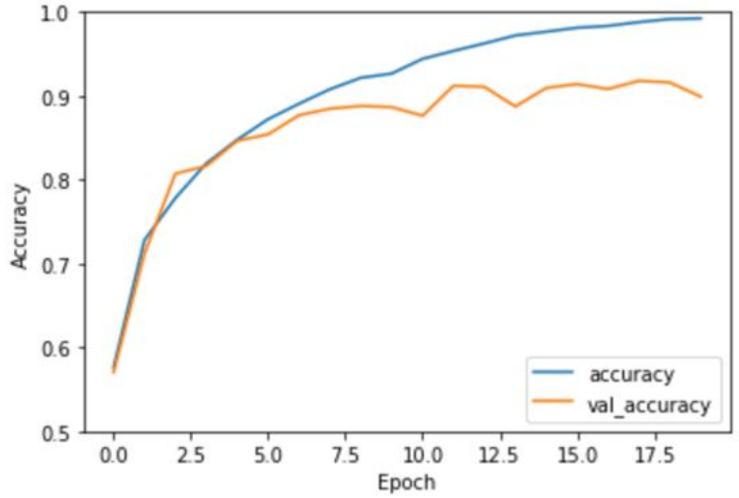
```
Epoch 1/20
56/56 [==============================] - 457s 8s/step - loss: 0.2453 - accuracy: 0.5759 - val_loss: 0.2875 - val_accuracy: 0.5703
Epoch 2/20
56/56 [==============================] - 436s 8s/step - loss: 0.1827 - accuracy: 0.7280 - val_loss: 0.1680 - val_accuracy: 0.7116
Epoch 3/20
56/56 [==============================] - 440s 8s/step - loss: 0.1509 - accuracy: 0.7782 - val_loss: 0.1482 - val_accuracy: 0.8073
Epoch 4/20
56/56 [==============================] - 438s 8s/step - loss: 0.1281 - accuracy: 0.8195 - val_loss: 0.1666 - val_accuracy: 0.8164
Epoch 5/20
56/56 [==============================] - 437s 8s/step - loss: 0.1102 - accuracy: 0.8477 - val_loss: 0.1122 - val_accuracy: 0.8464
Epoch 6/20
56/56 [==============================] - 440s 8s/step - loss: 0.0954 - accuracy: 0.8722 - val_loss: 0.1135 - val_accuracy: 0.8542
Epoch 7/20
56/56 [==============================] - 441s 8s/step - loss: 0.0834 - accuracy: 0.8906 - val_loss: 0.0391 - val_accuracy: 0.8770
Epoch 8/20
56/56 [==============================] - 436s 8s/step - loss: 0.0735 - accuracy: 0.9079 - val_loss: 0.0725 - val_accuracy: 0.8848
Epoch 9/20
56/56 [==============================] - 440s 8s/step - loss: 0.0655 - accuracy: 0.9216 - val_loss: 0.0448 - val_accuracy: 0.8880
Epoch 10/20
56/56 [==============================] - 444s 8s/step - loss: 0.0592 - accuracy: 0.9266 - val_loss: 0.1117 - val_accuracy: 0.8867
Epoch 11/20
56/56 [==============================] - 431s 8s/step - loss: 0.0506 - accuracy: 0.9442 - val_loss: 0.1000 - val_accuracy: 0.8763
Epoch 12/20
56/56 [==============================] - 438s 8s/step - loss: 0.0449 - accuracy: 0.9537 - val_loss: 0.0334 - val_accuracy: 0.9121
Epoch 13/20
56/56 [==============================] - 443s 8s/step - loss: 0.0404 - accuracy: 0.9626 - val_loss: 0.0571 - val_accuracy: 0.9108
Epoch 14/20
56/56 [==============================] - 441s 8s/step - loss: 0.0338 - accuracy: 0.9721 - val_loss: 0.0532 - val_accuracy: 0.8874
Epoch 15/20
56/56 [==============================] - 434s 8s/step - loss: 0.0304 - accuracy: 0.9766 - val_loss: 0.0593 - val_accuracy: 0.9095
Epoch 16/20
56/56 [==============================] - 441s 8s/step - loss: 0.0280 - accuracy: 0.9813 - val_loss: 0.0627 - val_accuracy: 0.9141
Epoch 17/20
56/56 [==============================] - 445s 8s/step - loss: 0.0247 - accuracy: 0.9835 - val_loss: 0.0957 - val_accuracy: 0.9082
Epoch 18/20
56/56 [==============================] - 436s 8s/step - loss: 0.0212 - accuracy: 0.9880 - val_loss: 0.0243 - val_accuracy: 0.9180
Epoch 19/20
56/56 [==============================] - 443s 8s/step - loss: 0.0190 - accuracy: 0.9916 - val_loss: 0.0344 - val_accuracy: 0.9160
Epoch 20/20
56/56 [==============================] - 449s 8s/step - loss: 0.0173 - accuracy: 0.9925 - val_loss: 0.0839 - val_accuracy: 0.8991
```

The validation accuracy improved from 0.5703 to a maximum of 0.9180.

Training Curve

```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

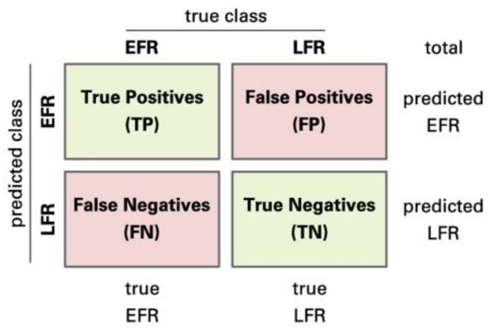
```
<matplotlib.legend.Legend at 0x7fac767a3310>
```



The training and validation accuracies are plotted as shown and it evident that the model doesn’t overfit or underfit the data.

Module 3: Testing and Performance Evaluation

CONFUSION MATRIX



		true class		
		EFR	LFR	total
predicted class	EFR	True Positives (TP)	False Positives (FP)	predicted EFR
	LFR	False Negatives (FN)	True Negatives (TN)	predicted LFR
		true EFR	true LFR	

$$\mathrm{PR} = \frac{\mathrm{TP}}{\mathrm{TP+FP}}$$

$$\mathrm{RE} = \frac{\mathrm{TP}}{\mathrm{TP+FN}}$$

$$\mathrm{CA} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}$$

$$\mathrm{F}_1 = \frac{2\mathrm{TP}}{2\mathrm{TP+FP+FN}}$$

PRECISION

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

RECALL

$$\text{Recall} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Negative}}$$

ACCURACY

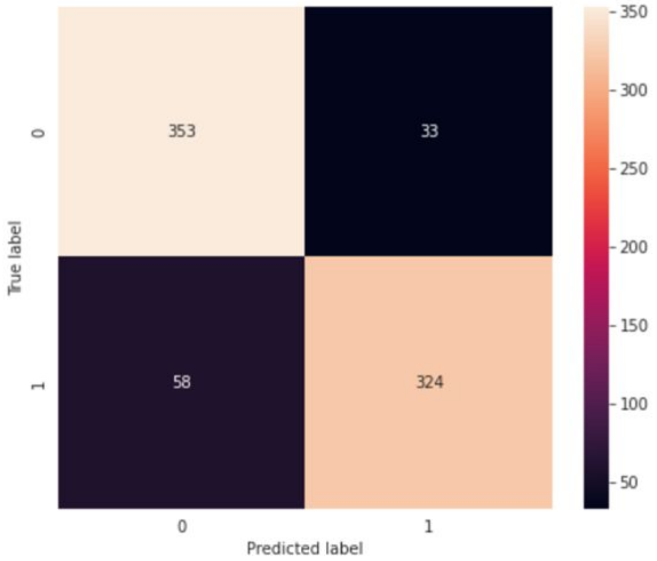
$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})}$$

F1 SCORE

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

```
PERFORMANCE OF MODEL ON TESTING DATA
Best Threshold:0.713634087042883

Confusion Matrix:
 [[353  33]
 [ 58 324]]
```



```
Accuracy 0.8815104166666666


Classification Report
              precision    recall  f1-score   support

           0       0.86      0.91      0.89       386
           1       0.91      0.85      0.88       382

    accuracy                           0.88       768
   macro avg       0.88      0.88      0.88       768
weighted avg       0.88      0.88      0.88       768
```

References:

1. Handwritten Signature Recognition : A Convolutional Neural Network Approach [IEEE XPLORE]

2. An Offline System for Handwritten Signature Recognition [IEEE XPLORE]

3. Dey, Sounak & Dutta, Anjan & Toledo, J. & Ghosh, Suman & Lladós, Josep & Pal, Umapada. (2017). SigNet: Convolutional Siamese Network for Writer Independent Offline Signature Verification.

4. R. Hadsell, S. Chopra and Y. LeCun, "Dimensionality Reduction by Learning an Invariant Mapping," 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06), 2006, pp. 1735-1742, doi: 10.1109/CVPR.2006.100.