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Authentication of a User using ECG Signals

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Abstract— The commonality, measurement, individuality, and permanence of all biometric traits make them very desirable than any other forms of authentication. Numerous applications use biometric authentication, including unlocking phones using face recognition and fingerprint verification, using speech recognition to log into bank accounts, etc. . In a very similar way, the electrocardiogram(ECG) signals can potentially be employed as a biometric in order to identify a person. Because the ECG signals are specific to each and every individual and show how alive a person is. This undertaking offers a technique for user authentication using ECG signals. In this project, signals are processed and trained with Siamese Networks, and then models of trained Siamese Networks are used to identify persons. In this research, the Siamese Networks are trained using the ECG-ID dataset taken from the Physionet website in order to recognize specific individuals. 90 people's raw ECG signals can be found in the ECG-ID dataset. The findings of this study can substantiate the claim that ECG signals can be used as biometrics.

Index Terms—Authentication, Biometric, Electrocardio- gram(ECG), Signals, Siamese Networks, Metrics learning.

I. PROBLEM STATEMENT

In the modern world, user identification technology—which establishes a person's identity—is used in a variety of indus- tries, including banking, information technology, communica- tion, medicine, social welfare, administration, access control, and even entertainment. A person's distinctive biometric data and signals are used by biometric technology to enrol and store biometric data in real-time and compare the data that is stored to distinguish the target. Biodata can be found outside the body or on the skin's surface. Based on physical and behavioural traits that remain constant throughout an individual's lifespan, bio-information can be gathered. Physical traits can be used to gather bio-information, such as fingerprint, face, vein, iris and retina data. The Bio-information that can be obtained through behavioural data comprises speech, gait, and signature data. The body produces bio-signals, which include electrocardio- gram (ECG) signals, heart noises, electroencephalograms, and electromyograms. The use of physical features in biometrics exposes users to the possibility of forgeries and/or changes, in- cluding altered voices, disguised faces, fake irises, and phoney fingerprints. Electrocardiogram (ECG) impulses are capable of being employed as biometrics due to their individuality and stability. Deep Learning techniques are used to identify the user based on the ECG readings.

II. LITERATURE SURVEY

[1] ECG Authentication in Post-Exercise Situation, Dong-suk Sung, MyungjunKoh, Jeehoon Kim and Kwang Suk Park, Research gate, 2017.

For the past 10 years, human authentication using an electro- cardiogram (ECG) has been a notable problem. The ECG data that was recorded after the strenuous activity was used in this paper to suggest an authentication mechanism. 55 volunteers participated in this study. Authors came to the conclusion that after a minute of catching one's breath, ECG authentication procedures might be applied.

[2] User Identification System using 2D resized Spectro-gram features of ECG signals, Gyu-Ho Choi, Eun-Sang Bak, and Sung-Bum Pan, IEEE, 2019.

1D data is contained in the ECG lead-I signals that are acquired utilising ECG collection devices. As a result, it is constrained in terms of data analysis and feature extraction. This study presented a user-recognition 4 system that, after transforming the measured ECG into a spectrogram, preserves the original data values while improving calculation time by extracting multi-dimensional features using 2D scaling based on bi-cubic interpolation.

[3] ECG Biometric Authentication: A Comparative Anal-ysis, Mohit Ingale, Renato Cordeiro, Siddartha Thentu, Younghee Park, and Nima IMA Karimian, IEEE, 2020.

The authors of this work made contributions to the devel-opment of a new, sizable collection of off-the-person ECG datasets, which may open up new avenues for the ECG biometric research community. They investigated how ECG biometrics were affected by evaluation metrics for filtering type, segmentation, feature extraction, and health state.

[4] SVM for human identification using the ECG signal, Sihem Hamza and Yassine Ben Ayed, Elsevier, 2020.

In this study, an electrocardiogram (ECG) signal-based per- son identification system was simulated. The feature extraction and classification phases of the authors' two-phase approach for conducting human identification using the ECG data.

[5] A Comprehensive Survey on ECG Signals as New Bio-metric Modality for Human Authentication: Recent

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Advances and Future Challenges, Anthony Ngozichukwuka Uwaechia; Dzati Athiar Ramli, IEEE, 2021.

The authors give thorough reviews of the literature on ECG- based biometric identification systems for user authentication in this survey. By providing a thorough analysis of many ECG- based biometric recognition subjects, this survey paper aims to close the knowledge gap of ECG biometric systems using deep learning for ECG classification and feature extraction, selection, and transformation, databases which are still missing by enabling interested readers to find the desired information quickly.

III. ARCHITECTURE OF THE SYSTEM

Essentially, the system accepts ECG signals as input. Then takes the continuous ECG signals and generates the segments. Siamese networks receive the images of these segments. In the following step, for the purpose of extracting information from ECG segments, convolution neural networks are utilised. A metric learning function is given the feature vectors to determine similarity. Identify the user lastly based on similarity metrics obtained. The approach to this model is represented in Fig. 1.

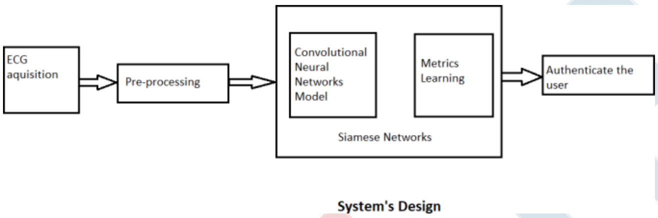

Figure 1. Architecture of the System

As shown above our system architecture is divided in modules

- Pre-processing(Segmentation)
- Siamese Networks
- Identifying user

A. Pre-processing

An electrocardiogram (ECG) is a test that finds and documents the frequency and intensity of our heart's electrical activity. This data is plotted on a graph that depicts the electrical signal's progression through our heart at each phase. The left and right atria contract as a result of the electrical signal, pumping blood into the ventricles. The sinoatrial node, which is located in the right atrium, is where it starts. This electrical impulse appears as the P wave on the ECG. The PR Interval measures the amount of time between the beginning of the P wave and the beginning of the QRS complex in seconds. The electrical signal passes from the atria to the ventricles through the atrioventricular (AV) node. The signal slows down as it passes through this node, allowing the ventricles to fill with blood. This sluggish signal can be seen as a flat line 8 on the ECG between the peak of the P wave and the beginning of the Q wave. The PR segment shows the electrical impulse's delay in the atrioventricular node as well as its conduction through the atria. The signal leaves the atrioventricular (AV) node and proceeds along the bundle of this until it reaches the right and left bundle branches. The heart's ventricles contract in response to the signal, pumping blood to the body's organs and lungs. This signal, or QRS waves, is captured by the ECG. Because of their rapid succession, these waves are usually referred to as the QRS complex. The ventricles then recover to their normal electrical state, as indicated by the T wave. The muscles relax and stop contracting with each heartbeat, enabling the atria to fill with blood. The beginning of the ventricles' electrical recovery is indicated by the ST segment, which connects the QRS complex and the T wave. The time between stimulation and recuperation for the ventricles is represented by the QT interval. At a quicker heart rate, this interval gets shorter, while at a slower one, it gets longer. The P wave and QRS complex T wave are two typical ECG features shown in Fig 2.

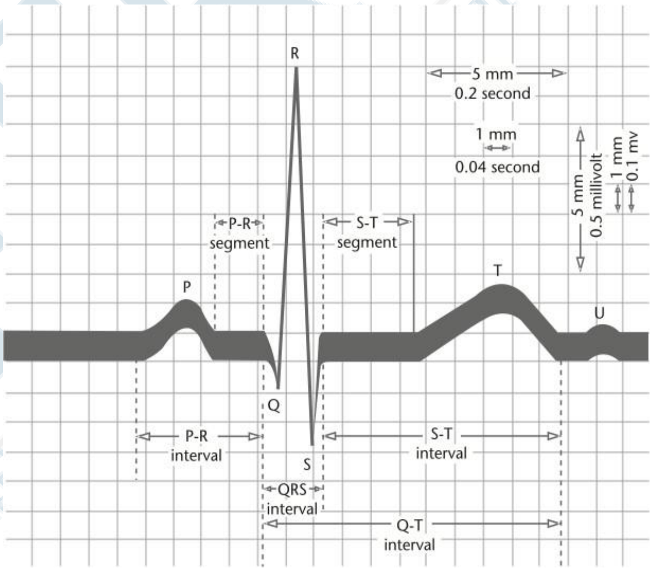

Figure 2. Features of an ECG signal

This study makes use of the physionet ECG-id database. 310 ECG recordings from 90 distinct individuals are stored in the database. Each recording contains the ECG lead I, which was captured for 20 seconds and digitalized at 500 Hz with 12-bit resolution over a nominal 10 mV range; 10 annotated beats (unaudited R- and T-wave peak annotations from an automated detector); and data (in the record's.hea file) containing the patient's age, gender, and the recording date. Volunteers (46 women and 44 men, age group of 13-75, who were the students of authors, acquaintances and coworkers) provided these records[1]. Each participant has between 2 (collected all in one day) and 20 records (collected regularly over a period of six months). Unprocessed ECG readings have some high- and low-frequency noise in them and are generally noisy. Each record contains both filtered and unfiltered signals(raw signals). While Signal 1 is an ECG I filtered signal, Signal 0 is an ECG I raw signal. The ECG-id

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dataset includes a continuous electrocardiogram (ECG) signal for each record. As seen in Fig 3, these continuous signals must be divided into a single pattern. ECG signals are first segmented before QRS complexes are found. The electrocardiogram (ECG) signal can be segmented using a variety of methods, including Christov segmentation, Engelse and Zeelenberg (EZEE) segmentation, P. Hamilton (HAM) segmentation, H. Gamboa (GAMBOA) segmentation, and ECG Slope Sum Function (ESSF) seg- mentation. The Christov segmentation approach is one of these segmentation methods that is employed to find QRS complexes. Christov suggests the following stages for a QRS complex detection algorithm.

The first phase involves addressing power-line interference by using a moving average filter, followed by a moving average filter to reduce electromyogram noise, a complex lead synthesis (built using all leads), a complex lead signal scan, and an adaptive threshold evaluation of each sample. The adaptive threshold(R) is created by linearly combining a beat expectation threshold, an integrating threshold(F), and a steep- slope threshold (M).

ECG segmentation is performed by analysing each QRS complex and clipping the ECG signal 200 ms to the left of the R-peak to 400 ms to the right (values based on the average length of the P-Q and S-T complexes). ECG patterns can thus be extracted from continuous ECG signals. Fig 3 and Fig 4 respectively depict the real ECG signal and a single ECG pattern. The folder contains photos of these portions.

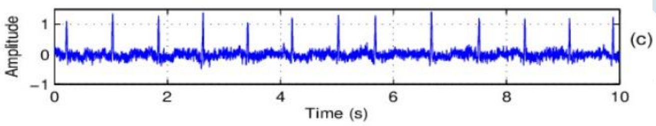

Figure 3. ECG signal before segmentation

B. Siamese Networks

A Siamese neural network, also known as a twin neural network, is a kind of Artificial Neural Network(ANN) that employs the same weights to compute equivalent output vec- tors from two distinct input vectors simultaneously. A pre- computed version of one of the output vectors frequently serves as a benchmark for comparison with the other output vector. While strictly speaking, this is a distance function for locality-sensitive hashing and is comparable to comparing fingerprints.

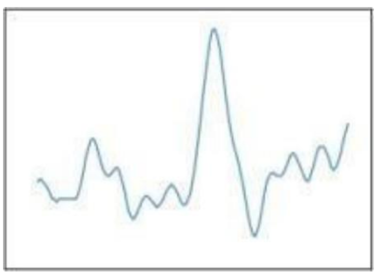

Figure 4. ECG signal after segmentation

One of the simplest and most widely used one-shot learning methods is the siamese network, a special kind of neural net- work. We only learn from one training example per class when using the one-shot learning technique. Therefore, Siamese Networks are frequently utilised in applications where there are few data points available for each class. Twin networks that accept various inputs but are connected by an energy function make up a siamese neural network. Based on a similarity function or energy function, siamese networks are constructed. In terms of design, Fig 5 depicts two parallel neural networks with independent inputs and merged outputs that serve as predictions.

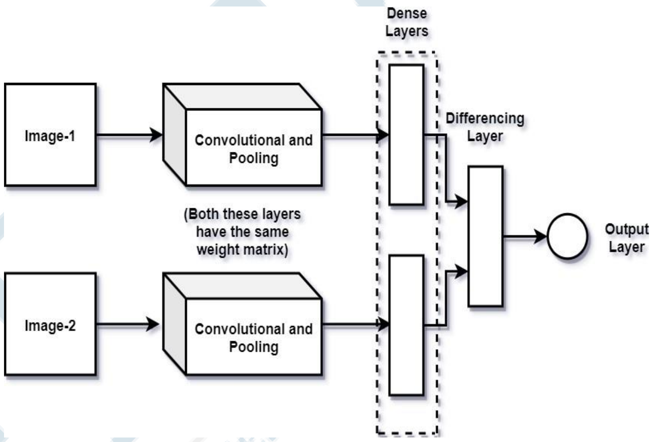

Figure 5. System Design of Siamese Networks

The first part of a Siamese network involves using con- volution neural networks to extract features, and the second phase involves metric learning to calculate the energy function between the images. The ECG segment images are compiled into a batch of pairs before being fed into the Convolution Neural Networks. For example, let’s say Image X and Image y are both pictures of the same person or are comparable pictures in half of the pairings of pictures. And in the remaining half of the image pairs, both of the photographs are different or depict different people. The same convolution neural networks are used to process these pairs of eleven photos (CNN). It indicates that both CNN models are set up with identical parameters and weights. The two sub-networks replicate parameter updating. To ensure that two really similar images could not conceivably be mapped by their separate networks to a variety of locations in the feature space, both CNN models provide this assurance. One of the most popular deep learning techniques for computer vision problems is convolution neural networks, or CNN or ConvNet. A computer basically transforms a picture when it receives it into a matrix of pixel values. The dimensions of this matrix are [image width x image height x number of channels] and the range of pixel values is 0 to 255. Whereas red, green, and blue make up the three channels of coloured images, grey scale images only have one channel (RGB). The matrix size of each image of ECG signals is [334 x 217] which is a 2D matrix.

The following three crucial layers make up CNNs. Convolution, pooling, and fully connected layers are what they are called. The first and central layer of the CNN is the convolutional layer. It is one of the CNN's fundamental components and is employed to extract significant information from images. a convolution procedure that will take the image's most crucial details out. A matrix of pixel values serves as the representation for each input image. The filter matrix is an additional matrix in addition to the input matrix. A kernel or plain old filter is another name for the filter matrix. The filter matrix is moved by one pixel over the input matrix to complete the convolution process, after which the results are added up and producing a single number. The entire matrix is subjected to this process, and the resulting matrix is either an activation map or a feature map.

Features are extracted using the convolution process, and the new matrix, or feature maps, represents the extracted features. Multiple filters can be used for extracting many features from an image rather than just one, creating a variety of feature maps. The quantity of filters will therefore determine the feature map's depth. The depth of the feature map will be seven if seven filters each extract a separate feature from the source image. Back propagation is used to learn the ideal filter matrix values, which are used to extract the most crucial features from the images. The filter matrix is initially started arbitrarily. When using convolution operation, the size of the filter and the number of filters must be given. A stride is the quantity of pixels that we slide over the input matrix by the filter matrix. A more accurate representation of the image can be encoded when the stride is set to a small value as opposed to a high amount. It takes less time to compute a stride with a high value than one with a low one. However, the convolution layer's feature maps have too many dimensions. Pooling operations are used to minimise the dimensionality of feature maps. By decreasing the size of the feature maps and keeping only the information that is necessary, the amount of calculation is decreased. Down sampling and sub-sampling operations are other names for a pooling procedure, and it makes the CNN translation 12 invariant.

Thus, by retaining only the most crucial properties, the pooling layer lowers the size of the spatial domain. The feature maps' depth won't change as a result of the pooling procedure; just their height and breadth will vary. Operations that pool data include max pooling, average pooling, and sum pooling are just a few of the several forms. The filter slides across the input matrix in max pooling and only accepts the highest value available in the filter pane. Simply take the average value of the input matrix contained within the filter window when using average pooling. Summarize all of the input matrix's values within the filter window to perform sum pooling. w. In this project, the convolution operation is carried out using the Rectified linear unit (RELU) as the output feature maps' activation function. A max-pooling layer with a set filter size and specific stride is optionally added after the convolution operation. A standard CNN model is made up of a succession of convolution layers, pooling layers, dense layers or fully linked layers, and softmax layers as the output. The last convolutional layer's units are compressed into a single vector. Using a single sigmoidal output unit, the subsequent layer calculates the induced distance metric between each Siamese twin.. This layer is followed by a fully linked layer.

Energy function is employed in CNN in place of a softmax layer. Metric learning is the next stage in Siamese Networks. Energy function between feature vectors of pictures acquired from parallel CNN layers is computed in metric learning. The metric calculated between two feature vectors is known as the energy function. The metric has two different measurements: a similarity measure and a distance measure. Euclidean distance, computed using equation (1), and Manhattan distance, derived using equation (2), are the two different energy functions based on distance (2). Dot product calculations are used to determine the various energy functions based on similarity metrics and are provided in equation (3). Radial basis function (RBF) calculation as per equation (4) and arc cosine calculation as per equation (5). In this study, metric learning is done using the Manhattan distance, then the sigmoid function. The energy function's output is provided as a parameter for the sigmoid function in equation (6). The chance of resemblance between the photos is determined by the sigmoid function, which has just one node. Hence, the sigmoid function's output spans the range of 0 to 1. If the output of the sigmoid function's is greater than 0.5, the two images in a pair are said to be comparable. Otherwise, there are differences between the two photos of a pair.

Let us assume that there are two points, such as (x1, y1) and (x2, y2) in the two-dimensional(2D) coordinate plane.

Therefore, the Euclidean distance formula is given by: here,

- "d" is the Euclidean distance
- (x1, y1) is the coordinate of the first point
- (x2, y2) is the coordinate of the second point.

$$d = \sqrt{(x2-x1)^2 + (y2-y1)^2} \quad (1)$$

the Manhattan distance between two points (x1, y1) and (x2, y2) is calculable as:

$$distance = |x2 - x1| + |y2 - y1| \quad (2)$$

Dot product(f(x), f(y))

$$Dotproduct(f(x), f(y)) = f(x).f(y) \quad (3)$$

ARC cosine:

$$Cos(x, y) = x.y/\|x\| * \|y\| \quad (4)$$

Radial Function:

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$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$f(x) is$ (5)

Sigmoid Function:

$S(x) = 1/(1 + e^{-}x) = e^{x}/(1 + e^{x})$ (6)

C. Identifying User

The system's architecture transmits a fresh electrocardiogram (ECG) signal. The Siamese network is given the electrocardiogram (ECG) image to identify the appropriate person. The new image is compared to other ECG signal images, and similarity between each pair and the new image is calculated. If the Siamese Networks output is greater than 0.5, then the database contains information on the person associated with that new image of the ECG signal. And the database is used to retrieve that individual's information, such as person id. If the Siamese Networks' output is less than 0.5, the person associated with the provided ECG signal image does not exist in the database.

IV. RESULTS

Images of the ECG are created using the ECG signals. As illustrated in Figure 6, these ECG images are saved in the folder to train the model. The ECG signals are divided before being converted to pictures. This ECG signals are segmented using the Christov segmentation approach. The Python biosppy module includes a method for this strategy.

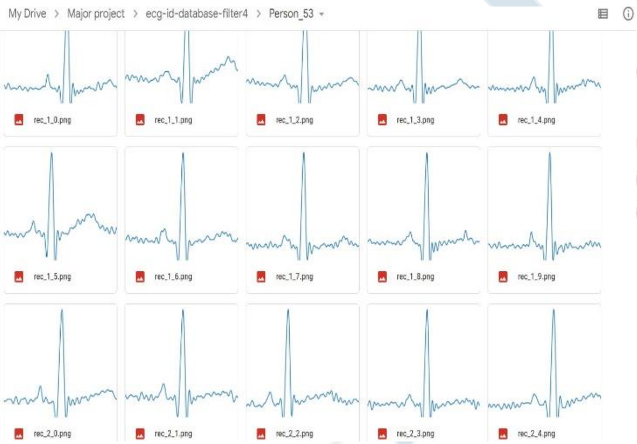
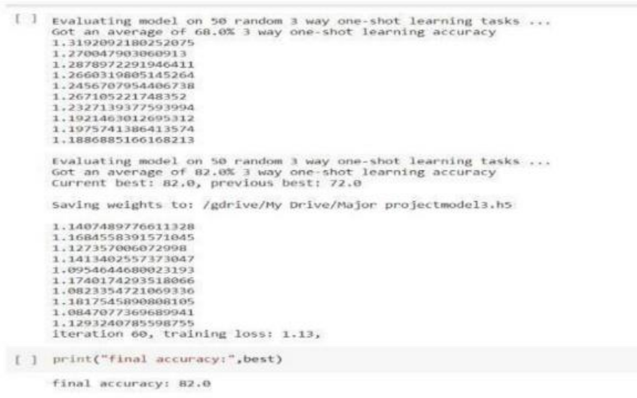


Figure 6. Folder of segmented ECG images

The ECG images are trained using the Siamese Networks model to identify the appropriate user or person. This model produces a similarity value as its output. The specific photographs are deemed to be a perfect match if the similarity value exceeds 0.5. Otherwise, the current database does not contain a match for the specific image. Over a period of 100 iterations, the accuracy is calculated every 20 iterations. Figure 7 illustrates the trained Siamese Networks model's accuracy, which is 82%.



```
[ ] Evaluating model on 50 random 3 way one-shot learning tasks ...
    Got an average of 68.0% 3 way one-shot learning accuracy
    1.3192092180252075
    1.2700479030609 13
    1.2878972291946411
    1.2660319805145264
    1.2456707954406738
    1.267105221748352
    1.2327139377593994
    1.192146301269 5312
    1.1975741386413574
    1.1886885166168213

    Evaluating model on 50 random 3 way one-shot learning tasks ...
    Got an average of 82.0% 3 way one-shot learning accuracy
    Current best: 82.0, previous best: 72.0

    Saving weights to: /gdrive/My Drive/Major projectmodel3.h5

    1.1407489776611328
    1.1684558391571045
    1.127357006072998
    1.1413402557373047
    1.0954644680023193
    1.1740174293518066
    1.0823354721069336
    1.1817545890808105
    1.0847077369689941
    1.129324078559875 5
    iteration 60, training loss: 1.13,

[ ] print("final accuracy:",best)

    final accuracy: 82.0
```

Figure 7. Accuracy of model

An image of an ECG segment from a person in the database is taken into consideration for test scenario 1. Figure 8 displays Person 53's ECG picture, and Figure 9, figure 10 displays the outcome. According to this model, there is an 78% chance that the chosen image of Person 53 matches an ECG image of the same person, Person 53. As a result, it is determined that Person 53 is a real user in the database and gives his address(location) in the database as the output.

Figure 8. Image of ECG signals of Person53

```
[25] import glob
     import numpy as np
     from PIL import Image
     from tensorflow.keras.models import load_model

     model.load_weights('/gdrive/My Drive/Major project/Major projectmodel4.h5')
     records = sorted(glob.glob('/gdrive/My Drive/Major project/ecg-id-database-filter4/Person_*/rec_*.png'))
     w,h=144,224
     subject1=np.array(Image.open('/gdrive/My Drive/Major project/ecg-id-database-filter4/Person_53/rec_1_8.png').resize((h,w)))[:,:,0:1]/255
     max=0.5
     for record in records:
       #if record==records[0]:
         #continue
       subject2=np.array(Image.open(record).resize((h,w)))[:,:,0:1]/255
       prob=model.predict([subject1.reshape((1,w,h,1)),subject2.reshape(1,w,h,1)])
       #pred=(prob>0.5)[0][0]
       #print(record, prob[0][0])
       if(max<prob[0][0]):
         max=prob[0][0]
         id=record
         #print(max,record)
     #i=[]
     #i=id.split('/')
     print(id, max,"matched")

     1/1 [==============================] - 0s 142ms/step
     1/1 [==============================] - 0s 146ms/step
```

Figure 9. Result of Person53 ECG image

An unknown image of an ECG segment that is not present in the database is taken into consideration for test case 2. Figure 11 depicts the ECG image of the unknown person, and Figure 12 displays the outcome after the model prediction.

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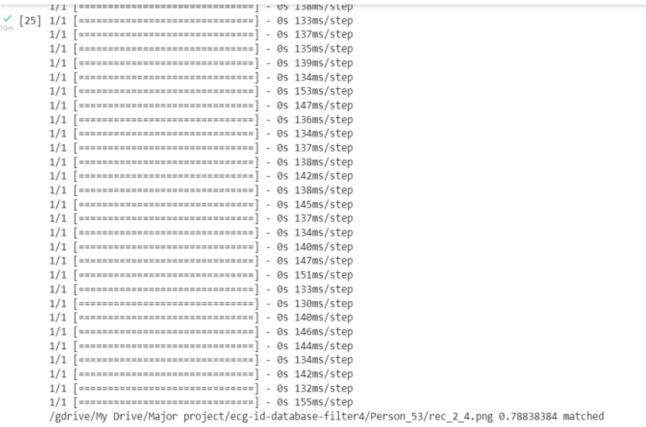

```
1/1 [==============================] - 0s 138ms/step
[25] 1/1 [==============================] - 0s 133ms/step
1/1 [==============================] - 0s 137ms/step
1/1 [==============================] - 0s 135ms/step
1/1 [==============================] - 0s 139ms/step
1/1 [==============================] - 0s 134ms/step
1/1 [==============================] - 0s 153ms/step
1/1 [==============================] - 0s 147ms/step
1/1 [==============================] - 0s 136ms/step
1/1 [==============================] - 0s 134ms/step
1/1 [==============================] - 0s 137ms/step
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1/1 [==============================] - 0s 138ms/step
1/1 [==============================] - 0s 145ms/step
1/1 [==============================] - 0s 137ms/step
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1/1 [==============================] - 0s 140ms/step
1/1 [==============================] - 0s 147ms/step
1/1 [==============================] - 0s 151ms/step
1/1 [==============================] - 0s 133ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 140ms/step
1/1 [==============================] - 0s 146ms/step
1/1 [==============================] - 0s 144ms/step
1/1 [==============================] - 0s 134ms/step
1/1 [==============================] - 0s 142ms/step
1/1 [==============================] - 0s 132ms/step
1/1 [==============================] - 0s 155ms/step
/gdrive/My Drive/Major project/ecg-id-database-filter4/Person_53/rec_2_4.png 0.78838384 matched
```

Figure 10. Result of Person53 ECG image

This model predicted that the chosen unknown image would not match any of the images in the database at hand. As a result, it was determined that the unidentified user did not exist in the training and available database as the similarity measure is less than 0.5.

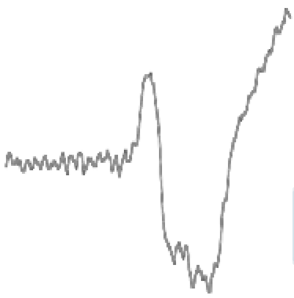

Figure 11. Image of ECG signal of unknown person

```
rec=path+'/images/fig_31200047.png'
s=Image.open(rec).resize((h,w),resample=1)
s=np.array(s)[:,:]/255
k=[]
for i in range(len(s)):
  k.append(np.reshape(s[i][:],[-1,1]))
k=np.array(k)

max=0.5
for record in records:
  #if record==records[0]:
    #continue
  subject2=np.array(Image.open(record).resize((h,w)))[:,:,0:1]/255
  prob=model.predict([k.reshape((1,w,h,1)),subject2.reshape(1,w,h,1)])
  #pred=(prob>0.5)[0][0]
  #print(record, prob[0][0])
  if(max<prob[0][0]):
    max=prob[0][0]
    id1=record
    #print(max,record)
print(id1, max)

no match 0.5
```

Figure 12. Result of unknown ECG image

V. CONCLUSION

This project's goal is to develop a system that can recognise users based on ECG patterns. ECG signals are used as a bio- metric in this system. Segmented ECG signals are recorded as pictures. Convolution neural networks, the initial component of the Siamese Networks model, are used to notice the fiducial features from the image of each segment. To locate matches, the observable features are compared using metric learning. In the Siamese Networks paradigm, the Manhattan distance serves as a metric learning function. The Siamese Networks model's accuracy in this project is about 82%. The current person or user in the database was precisely recognised by this project.

VI. FUTURE SCOPE

To further increase accuracy and decrease time complexity, several Convolution Neural Network architectures might be utilised. ECG records can be gathered to produce a new dataset rather than using an existing one. The ECG signals can be segmented using other segmentation methods, such as the Engelse and Zeelenberg methodology and the P. Hamilton technique, among others.

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