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IDENTIFICATION OF USER USING ECG SIGNALS

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Abstract: Biometric authentication is used in various fields such as to unlock phones, to access bank accounts using voice recognition, to write online exams using face recognition etc. The electrocardiogram (ECG) signals can also be used as biometric to identify the user. Because the ECG signals are unique for individuals and represent the liveliness of a person.This project provides a system to identify the user based on ECG signals. This project involves processing of signals, training with Siamese Networks, and finally identifying people using trained Siamese Networks models. In this project, ECG-ID dataset which is obtained from Physionet website, is used to train the Siamese Networks in order to identify individual users. ECG-ID dataset has raw electrocardiogram signals of 90 persons. The accuracy is calculated for the Siamese Networks model, which is around 80 percent. The results from this work can support the statement that ECG signals can be used as biometric.

***Keywords*– Authentication, Biometric, Electrocardiogram, Signal, Siamese Network.**

I. INTRODUCTION

In today's world, User authentication technology, which proves that an individual's identity, is applied in various fields such as Banking system, information communication, medicine, social welfare, administration, access control, immigration inspection and entertainment. Biometrics technology uses an individual's unique bio-information and signals to enroll and store bio- information in real time and compare the already-stored bio-information to distinguish the target.Bio-information can be acquired outside or on the surface of the body. Bio-information can be obtained based on physical and behavioral features that do not change during the entire lifetime of an individual. Bio-information that can be acquired through physical features include fingerprint, face, iris, retina and vein information. Bio-information that can be acquired through behavioral information includes signature, voice and gait information. Bio-signals that exist inside the body are behavioral features including electrocardiogram signals (ECGs), cardiac sounds, electroencephalograms and Electromyograms. Biometrics, which uses physical-feature based bio-information is continuously exposed to therisk of forgeries and/or alterations such as fake fingerprints, disguised faces, fake irises, and altered voices. Because of the uniqueness and stability of ECG signals to individuals, theElectrocardiogram signals can be used as biometric. The user is identified based on ECG signals using Deep Learning algorithms.

II. LITERATURE SURVEY

[1 ECG Biometric Authentication: A Comparative Analysis, Mohit Ingale, Renato Cordeiro, Siddartha Thentu, Younghee Park, and Nima IMA Karimian, IEEE, 2020.

In this paper, authors contributed to create a new large gallery off-the-person ECG datasets that can provide new opportunities for the ECG biometric research community. They explored the impact of filtering type, segmentation, feature extraction, and health status on ECG biometric by evaluation metrics.

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

In this paper, a person identification system has been simulated using electrocardiogram (ECG) signals as biometric. The authors proposed a two-phase method to conduct human identification using the ECG signal, which are the feature extraction and classification.

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

The ECG lead-I signals measured using ECG acquisition devices consist of 1D data. Therefore,it has limitations with regard to feature extraction and data analysis. This paper proposed a user- recognition 4 system that extracts multi-dimensional features through 2D resizing based on bi- cubic interpolation, which improves the calculation speed and preserves the original data values after converting the measured ECG into a spectrogram

[4] ECG-Based Subject Identification Using Statistical Features and Random Forest, Turky N. Alotaiby, Saud Rashid Alrshoud, Saleh A. Alshebeili and Latifah M. Aljafar, Journal of sensors (Hindawi), 2019.

In this paper, a non-fiducial electrocardiogram (ECG) identification algorithm based on statistical features and random forest classifier is presented.

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

Human authentication based on electrocardiogram (ECG) has been a remarkable issue for the last ten years. This paper proposed an authentication technology with the ECG data recorded after the harsh exercise. 55 subjects voluntarily attended this experiment. Therefore, authors concluded that ECGauthentication techniques will be able to be used after 1 minute of catching breath.

III. System design

The system basically takes the input as ECG signals. Then creates the segments from continuous ECG signals. The images of these segments are given to Siamese networks. Then the features areextracted from ECG segments using Convolution Neural Networks. The feature vectors are given to a metric learning function to find similarity. Finally based on similarity measures obtained identify the user. The approach to this model is shown in Figure 1

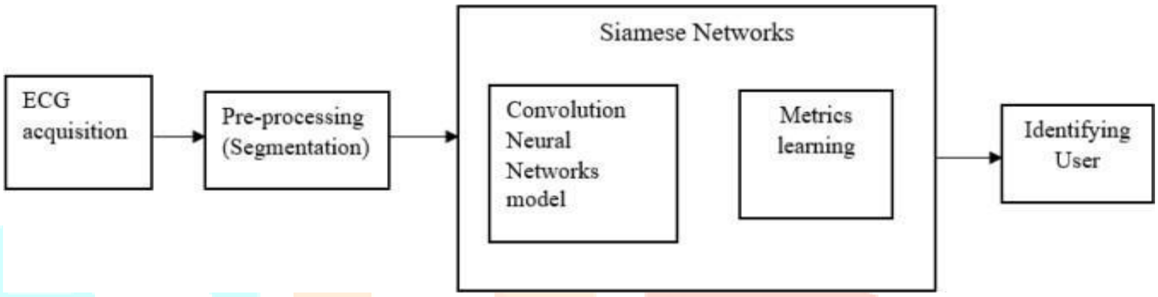

Figure 1: Architecture of the system

As shown above our system architecture is divided into 3 modules

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

Preprocessing

Electrocardiogram (ECG) is a test that detects and records the strength and timing of theelectrical activity in our heart. This information is recorded on a graph that shows each phase of the electrical signal as it travels through our heart. The electrical signal begins in the sinoatrial node which is located in the right atrium and travels to the right and left atria, causing them to contract and pump blood into the ventricles. This electrical signal is recorded as the P wave on the ECG. The PR Interval is the time, in seconds, from the beginning of the P wave to the beginning of the QRS complex. 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 the blood. This slowing signal appears as a flat line 8 on the ECG between the end of the P wave and the beginning of the Q wave. The PR segment represents the electrical conduction through the atria and the delay of the electrical impulse in the atrioventricular node. After the signal leaves the atrioventricular (AV) node it travels along a pathway called the bundle of His and into the right and left bundle branches. The signal travels across the heart's ventricles causing them to contract, pumping blood to the lungs and the body. This signal is recorded as the QRS waves on the ECG. Because these waves occur in rapid succession they are usually considered together as the QRS complex. The ventricles then recoverto their normal electrical state, shown as the T wave. The muscles relax and stop contracting, allowing the atria to fill with blood and the entire process repeats with each heartbeat. The ST segment connects the QRS complex and the T wave and represents the beginning of the electrical recovery of the ventricles. The QT interval represents the time during which the ventricles are stimulated and recover after the stimulation. This interval shortens at a faster heart rate and lengthens at a slower heart rate. The normal features of ECG such as P wave, QRS complex T wave are shown in Figure 2

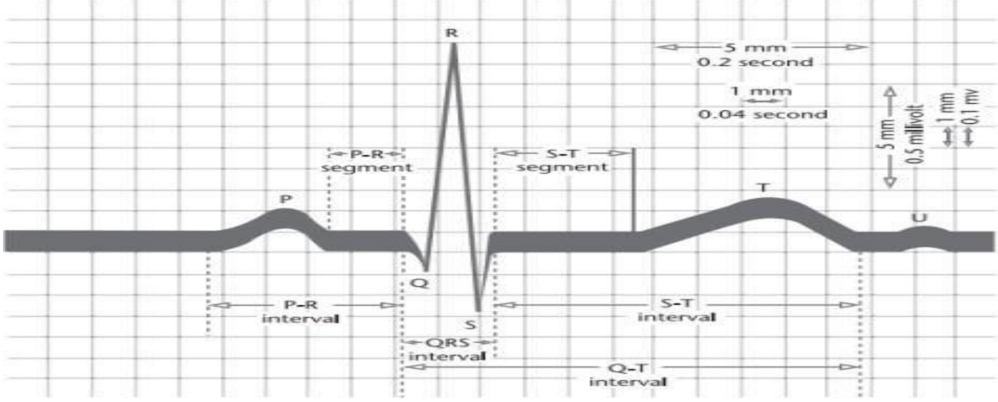

Figure 2:Normal features of electrocardiogram

In this work, ECG-id database from physionet, is used. The database contains 310 ECG recordings, obtained from 90 persons. Each recording contains ECG lead I, recorded for 20 seconds, digitized at 500 Hz with 12-bit resolution over a nominal ±10 mV range; 10 annotated beats (unaudited R- and T- wave peaks annotations from an automated detector); information (in the .hea file for the record) containing 9 age, gender and recording date. These records were obtained from volunteers (44 men and 46 women aged from 13 to 75 years who were students, colleagues, and friends of the author)[1]. The number of records for each person varies from 2 (collected during one day) to 20 (collected periodically over 6 months). The raw ECG signals arerather noisy and contain both high and low frequency noise components. Each record includes both raw and filtered signals. Signal 0 is ECG I raw signal and Signal 1 is ECG I filtered signal. Each record in the ECG-id dataset contains a continuous electrocardiogram (ECG) signal. These continuous signals need to be segmented into a single pattern as shown in Figure 3. Before segmentation of ECG signals, QRS complexes are detected. There are many techniques to detect QRS complex from the electrocardiogram (ECG) signal such as Christov segmentation, Engelse and Zeelenberg (EZEE) segmentation, P. Hamilton (HAM) segmentation, H. Gamboa (GAMBOA) segmentation and ECG Slope Sum Function (ESSF) segmentation. Among these segmentation techniques, Christov segmentation technique is used to detect QRS complexes. Christov proposes a QRS complex detection algorithm which takes the following steps. The first step is power-line interference handling by applying a moving average filter, next movingaverage filter to suppress electromyogram noise, next complex lead synthesis (constructed with all leads), next complex lead signal is scanned and each sample is evaluated with an adaptive threshold. The adaptive threshold is a linear combination of a steep-slope threshold (M), an integrating threshold (F) and a beat expectation threshold (R). ECG segmentation is performed by evaluating each QRS complex and clipping the ECG signal in an interval 200ms to the left of the R-peak to 400ms to the right (values based on the typical duration of the P-Q and S-T complexes) [10]. In this way, ECG patterns are retrieved from continuous ECG signals. The actual ECG signal and single ECG pattern are shown in Figure 3 and Figure 4 respectively. These segments are saved as images in the folder.

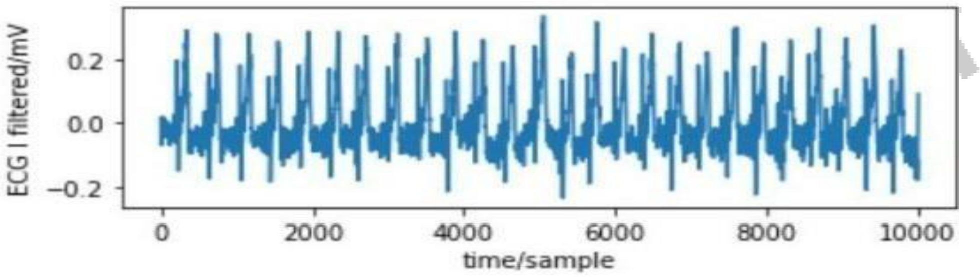

Figure 3:Continuous ECG signal before segmentation

Figure 4:ECG signal pattern after segmentation

SIAMESE NETWORKS

Siamese networks are special types of neural networks and are among the simplest and most popularly used one-shot learning algorithms. The one-shot learning is a technique where we learn from only one training example per class. So, Siamese Networks are predominantly used in applications where we don't have many data points for each of the classes. A Siamese Neural Network consists of twin networks which accept distinct inputs but are joined by an energy function. Siamese networks are based on a similarity function or energy function. In terms of architecture which is shown in Figure 5 there are two parallel neural networks, each taking a different input, and whose outputs are combined to provide a prediction.

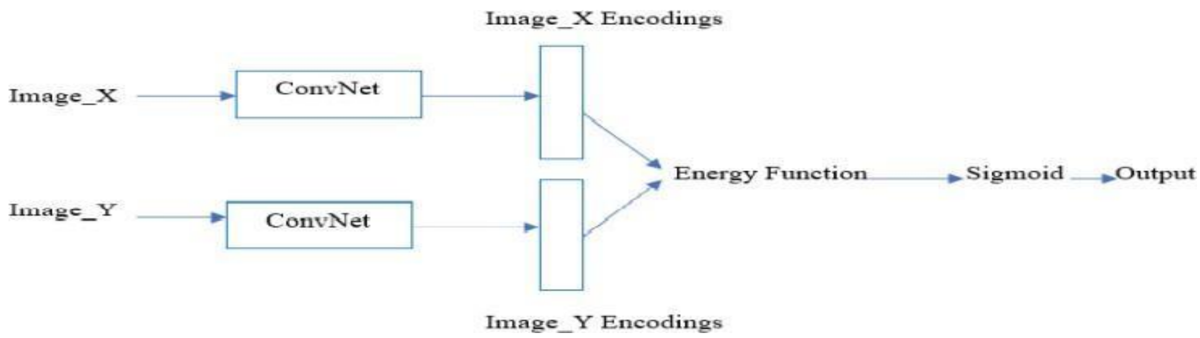

Figure 5:Architecture of Siamese Networks

Siamese Networks has two phases, one is feature extraction with Convolution Neural Networks and another one is metric learning to compute the energy function between the images. Before giving images to the Convolution Neural Networks, the images of ECG segments are grouped as a batch of pairs. In half of the pairs of images, both the images (let's say Image_X and Image_y) are similar images or of the same person. And in the remaining half pairs of images, both the images are dissimilar images or of different persons. These pairs of 11 images are given to the same Convolution Neural Networks (CNN). It means both the CNN model have the same configuration with the same parameters and weights. Parameter updating is mirrored across both subnetworks. So that both CNN models guarantee that two extremely similar images could not possibly be mapped by their respective networks to very different locations in feature space. A Convolution Neural Networks (CNN), also known as a ConvNet, is one of the most widely used deep learning algorithms for computer vision tasks. When the image is fed to a computer, it basically converts it into a matrix of pixel values. The pixel values range from 0 to 255, and the dimensions of this matrix will be of [image width x image height x number of channels]. A grayscale image has onechannel, and coloured images have three channels red, green, and blue (RGB). The matrix size of each image of ECG signals is [334 x 217] (2D matrix).
CNNs consist of the following three important layers. They are Convolution layer, Pooling layer and Fully Connected layer. The convolutional layer is the first and core layer of the CNN. It is one of the building blocks of a CNN and is used for extracting important features from the image. A convolution operation that will extract all the important features from the image. Every input image is represented by a matrix of pixel values. Apart from the input matrix, there is also another matrix called the filter matrix. The filter matrix is also known as a kernel, or simply a filter. The convolution operation is performed by sliding the filter matrix over the input matrixby one pixel, then element-wise multiplication, summing up the results, and producing a single number. This operation is performed on the whole matrix and the resultant matrix is a feature map or activation map.

The convolution operation is used to extract features, and the new matrix, that is, the feature maps, represents the extracted features. Instead of using one filter, multiple filters can be used forextracting different features from the image, and produce multiple feature maps. So, the depth of the feature map will be the number of filters. If seven filters extract different features from the image, then the depth of the feature map will be seven. The filter matrix is initialized randomly, and the optimal values of the filter matrix, with which the important features are extracted from the images, will be learned through backpropagation. The size of the filter and the number of filters need to be specified, when convolution operation is used. The number of pixels we slide over the input matrix by the filter matrix is called a stride. When the stride is set to a small number, a more detailed representation of the image can be encoded than when the stride is set toa large number. A stride with a high value takes less time to compute than one with a low value.But the feature maps obtained from the convolution layer are too large in dimension. In order to reduce the dimensions of feature maps, pooling operations are performed. This reduces the dimensions of the feature maps and keeps only the necessary details so that the amount of computation can be reduced. A pooling operation is also called a Down sampling or Subsampling operation, and it makes the CNN translation 12 invariant. Thus, the pooling layer reduces spatial dimensions by keeping only the important features. The pooling operation willnot change the depth of the feature maps; it will only affect the height and width. There are different types of pooling operations, including max pooling, average pooling, and sum pooling. In max pooling, the filter slides over the input matrix and simply takes the maximum value from the filter window. In average pooling, simply take the average value of the input matrix within the filter window. In sum pooling, sum up all the values of the input matrix within the filter window. In this project, the convolution operation is performed with Rectified linear unit (RELU) as activation function to the output feature maps, optionally followed by a max-pooling layer with specific filter size and specific stride. In the case of a general CNN model, it consists of a series of convolution layer, pooling layer, followed by dense layer or fully connected layer and the output by softmax layer. The units in the final convolutional layer are flattened into a single vector. This convolutional layer is followed by a fully connected layer, and then one more layer computing the induced distance metric between each Siamese twin, which is given to a single sigmoidal output unit. Instead of a softmax layer in CNN, Energy function is used. The next phase in Siamese Networks is Metric learning. In metric learning, energy function is computed between the feature vectors of images obtained from parallel CNN layers. The energy function is defined as the metric calculated between two feature vectors. The metric can be measured in two ways as distance and similarity measure. The different energy functions based on distance are Euclidean distance calculated as given in equation (1) and Manhattan distance calculated as given in equation (2). The different energy functions based on similarity measures are Dot product calculated as given in equation (3). Arc cosine calculated as given in equation(4) and Radial basis function (RBF) calculated as given in equation(5). In this work, Manhattan distance is used for metric learning followed by sigmoid function. The output from the energy function is given as input to the sigmoid function which is given in equation (6). The sigmoid function is a single node defines the probability of similarity between the images. So, the output of the sigmoid function is between 0 and 1. If the output of the sigmoid function is greater than 0.5 then the two images of a pair are similar. Otherwise, the two images of a pair are dissimilar.

$$\textbf{Euclidean distance}(x, y) = \sqrt{(\square 1 - \square 1)^2 + (\square 2 - \square 2)^2} \qquad (1)$$

$$\textbf{Manhattan distance}(x, y) = |(x1 - y1)| + |(x2 - y2)| \qquad (2)$$

$$\textbf{Dot product}(f(x), f(y)) = f(x).\ f(y) \qquad (3)$$

$$\textbf{Arc cosine}(f(x), f(y)) = \frac{\square(\square).\square(\square)}{\|\square(\square)\| \times \|\square(\square)\|} \qquad (4)$$

$$\textbf{Radial basis function}\ (x,y) = \square^{\frac{(-\|\square - \square\|2)}{\square^2}} \qquad (5)$$

$$\textbf{Sigmoid function}\ (\square) = \frac{1}{1+\square^{-\square}} \qquad (6)$$

IDENTIFYING USER

A new electrocardiogram (ECG) signal is passed through the system architecture. The image of electrocardiogram (ECG) is given to the Siamese network to identify the respective person. The new image is compared with other images of ECG signals and similarity is measured between every pair with that new image. The output of Siamese Networks is greater than 0.5 then the person related to that new image of ECG signal, exists in the database. And the details of that person like person id is retrieved from the database. The output of Siamese Networks is less than 0.5 then the person related to the given image of ECG signal, does not exist in the database.

IV. RESULTS

The ECG signals are converted to ECG images. These ECG images are saved in the folder to train the model as shown in Figure 6 Before converting ECG signals to images, the ECG signals are segmented. To convert these ECG signals to segments of ECG, Christov segmentation technique is used. This technique is available as a method in the biospy module in python.

Figure 6: Folder of segmented ECG images

The Siamese Networks model is used to train the ECG images to identify the respective person or user. The output of this model is similarity value. If that similarity value is greater than 0.5, then the particular images are considered as perfect match. Otherwise, there is no match for the particular image in the existing database. The accuracy is calculated for each 20 iterations over 100 iterations. The accuracy of the trained Siamese Networks model is 82% as shown in Figure 7.

```
[ ]  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
     1.270047903060913
     1.2878972291946411
     1.2660319805145264
     1.2456707954406738
     1.267105221748352
     1.2327139377593994
     1.1921463012695312
     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
     1.1293240785598755
     iteration 60, training loss: 1.13,

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

     final accuracy: 82.0
```

Figure 7: Accuracy of model

For the test case 1, an image of ECG segment from one of the persons in the database is considered. The ECG image of Person_14 is shown in Figure 8 and its result is shown in Figure 9. This model predicted that the selected image of Person_14 is matching with an ECG image of the same person i.e., Person_14 with 86% probability. So, it is identified that the user Person_14 exists in the database.

Figure 8: Image of ECG signals of Person_14

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

model.load_weights(path+'/Major projectmodel4.h5')
records = sorted(glob.glob(path+'/ecg-id-database-filter4/Person_*/rec_*.png'))
w,h=144,224
subject1=np.array(Image.open(path+'/ecg-id-database-filter4/Person_14/rec_1_1.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(i[5], max)

Person_14 0.8662194
```

Figure 9: Result of Person_14 ECG image

For the test case 2, an image of ECG segment of unknown which does not exist in the database,is considered. The ECG image of unknown is shown in Figure 10 and its result is shown in Figure 11 This model predicted that the selected image of unknown is not matching with any ofthe images in the existing database. So, it identified that the unknown user did not exist in the available and trained database.

Figure 10: 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 11: Result of unknown ECG image

V. CONCLUSION AND FUTURE ENHANCEMENT

The aim of this project is to generate a system which is able to identify users based on ECG signals. In this system ECG signals are used as biometric. The ECG signals are segmented and saved as images. The fiducial features from image of each segment are observed using convolution neural networks, first part of Siamese Networks model. The observed features are compared using metric learning to find matches. The Manhattan distance is used as a metric learning function in the Siamese Networks model. In this project, the accuracy of the Siamese Networks model is around 82%. This project perfectly identified the existing person or user in the database.

Further different Convolution Neural Networks architecture can be used to improve the accuracy and reduce the time complexity furthermore. A new dataset can be created by collecting ECG records instead of using existing dataset. Some other segmentation techniques like Engelse and Zeelenberg technique, P. Hamilton technique etc. can be used to segment the ECG signals.

REFERENCES

[1] Mohit Ingale, Renato Cordeiro, Siddartha Thentu, Younghee Park, and Nima IMA Karimian, "ECG Biometric Authentication: A Comparative Analysis", IEEE, 2020.
[2] Sihem Hamza and Yassine Ben Ayed, "SVM for human identification using the ECG signal", Elsevier, 2020.
[3] Beom-Hun Kim and Jae-Young Pyun, "ECG Identification For Personal Authentication Using LSTMBased Deep Recurrent Neural Networks", Sensors, 2020.
[4] Gyu-Ho Choi, Eun-Sang Bak , and Sung-Bum Pan, "User Identification System using 2D resized Spectrogram features of ECG signals", IEEE, 2019.
[5] Turky N. Alotaiby, Saud Rashid Alrshoud, Saleh A. Alshebeili and Latifah M. Aljafar, "ECG-Based Subject Identification Using Statistical Features and Random Forest", Journal of sensors (Hindawi), 2019.
[6] Nikita Samarin and Donald Sannella , "A Key to Your Heart: Biometric Authentication Based on ECG Signals", arXiv, 2019.
[7] Di Wang, Yujuan Si, Weiyi Yang, Gong Zhang 1 and Jia Li, "A Novel Electrocardiogram Biometric Identification Method Based on Temporal-Frequency Autoencoding", Electronics, 2019.
[8] George B. Moody, "WFDB Programmer's Guide", Harvard-MIT Division of Health Sciences and Technology, 2019.
[9] Sudharsan Ravichandiran, "Hands-On Deep Learning Algorithms with Python", Packt Publishing Ltd., 2019.
[10] Song-Kyoo Kim, Chan Yeob Yeun, Ernesto Damiani, and Nai-Wei lo, "A Machine Learning Framework for Biometric Authentication Using Electrocardiogram", IEEE, 2019.
[11] Francois Chollet, "Deep Learning with Python", Manning Publications Co., 2018.