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Debbis, The Deep Electrocardiogram Based Biometric Identification System

by

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of the requirements of the Degree of
Bachelor of Science in Computer Science

Project Supervisor


Prof. Liming ZHANG

25 June 2021

DECLARATION

I sincerely declare that:

1. I and my teammates are the sole authors of this report,
2. All the information contained in this report is certain and correct to the best of my knowledge,
3. I declare that the thesis here submitted is original except for the source materials explicitly acknowledged and that this thesis or parts of this thesis have not been previously submitted for the same degree or for a different degree, and
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Date : 25 June 2021

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ABSTRACT

With the rapid growth in authentication, there is an increased demand for individual identification and advanced security. While traditional methods for human identification such as passwords and tokens are easily accessible and implemented, they are prone to theft or loss. The Electrocardiogram (ECG) displays the potential to be used as a physiological signature for biometric systems because of its uniqueness, specificity, and unidimensional nature.

In this literature, I propose Debbis, the Deep Electrocardiogram Based Biometric Identification System. Through this, I demonstrate a novel Siamese neural architecture incorporating the Euclidean distance for biometric verification and deep convolutional neural networks based on multiresolution analysis for closed-set classification, both on time-series signal segments. I evaluated these methods using recordings from two major public databases: MIT-BIH and ECG-ID. Additional data were also recorded from active participants and simultaneously tested using an ECG monitoring device. Debbis achieved a competitive test accuracy score of 99.81% and validation loss of 0.82%. Furthermore, I simulated a biometric system using a web framework for model deployment and access testing and obtained state-of-the-art results with just 5-7 heartbeats as test samples.

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CHAPTER 1. INTRODUCTION

Since every existing authentication technique can be virtually compromised, institutions should not solely rely on any single control to grant access and authenticate individuals. With the advancement of technology and rising security concerns, more and more trustworthy authentication technologies are in demand [1].

1.1 Biometric System

Biometrics are inherent physiological or behavioural characteristics typically used to identify and authenticate an individual digitally and grant them access to systems, devices, or information [2]. Any physiological or behavioural attribute can qualify as a biometric if it satisfies the criterion of being universal, distinctive, permanence, and collectible. Typically, a biometric system requires three modes of operation [3]:

- **Enrolment:** The biometric system collects the physiological or behavioural characteristics, process them through feature extraction, and store the extracted features as a template.
- **Verification mode:** The system verifies if the individual is enrolled by comparing the captured biometric features with the all the corresponding stored templates.
- **Authentication:** After a positive verification, the individual is classified against all enrolled individuals to assess if the verified individual is who they say they are.

While fingerprints and recently, iris and facial recognition are the most widely used biometrics, they are primarily prone to errors due to falsification [4]. This paves the way for the novel authentication approach, the Electrocardiogram (ECG) based biometric system.

1.2 ECG as Biometric

ECG is a representation of the myocardial bioelectrical signal activity, reflected by periodic contractions and relaxation. These contractions and relaxation are caused by a change in voltage across the cell membrane of heart cells, creating a recordable continuous signal pattern [5]. Using external electrodes to record the signal, the ECG is represented by segments, each corresponding to a distinct stage of the cardiac cycle as illustrated in Figure 1. This morphological representation is unique to everyone [6], and it's such specificity among other attributes that make the ECG an appropriate biometric candidate.

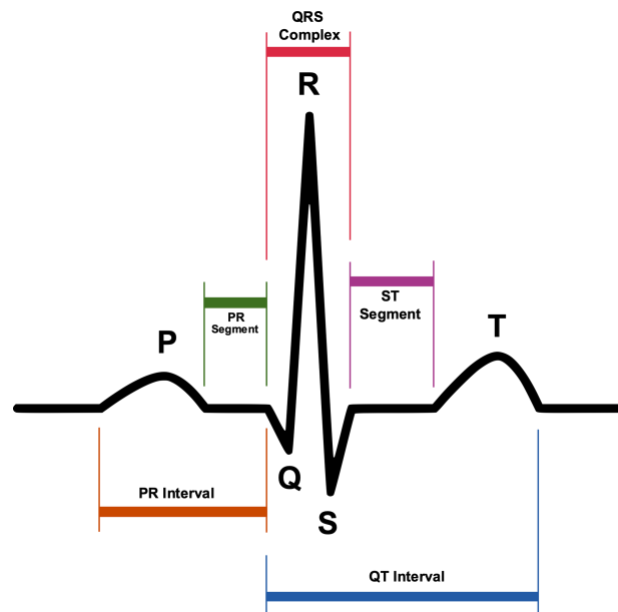


Figure 1: Segment representation of the Electrocardiogram.

1.3 Objectives, Motivation and Challenges

Because of its intrinsic and physiological origin, the ECG signal provides guaranteed uniqueness and permanence resulting in higher inter-individual variability [7]. Besides, it allows robustness against credentials falsification. Due to its general possession and presence in all users, ECG also provides a high degree of universality. ECG also verifies Liveness Detection by guaranteeing the biometric pattern is genuine in presenting individuals based on their inherent liveness property [7], unlike iris or fingerprints which require additional processing to establish the liveness of the reading. Therefore, the recognition systems based on ECG have higher security and reliability.

Despite its robustness, one of the main challenges of using ECG is the risk of abnormalities caused by morphological changes in the heart. Abnormal myocardial changes lead to a higher heart rate variability, reducing the system's recognition rate [8].

1.4 System Development, Environment and Resources

As per the three modes of operations mentioned in [1.1 Biometric System](#), the basic framework of the system begins with the extraction and storage of ECG feature-based templates into a memory-based model. The model is then deployed onto a Web API with an access point for biometric simulation where the user is validated and authenticated upon live ECG sample submitted.

The proposed system is experimented implemented with Python 3 Programming Language and additional Machine Learning toolkits and libraries [9]. Data pre-processing tasks were carried out on a Macintosh 2.4 GHz Quad-Core Intel Core i7 16 GB RAM computer. Sourced from the MIT-BIH and ECG-ID public databases, I carried out the data pre-processing tasks on a Macintosh 2.4 GHz Quad-Core Intel Core i7 16 GB RAM computer. Additional signal recordings of active participants were added and simultaneously tested using an ECG monitoring device. The ECG monitoring device is designed based on a BMD101 sensor chip and contains two dry metal electrodes acting as finger recording access points. I set up and trained both the

Convolutional and Siamese Neural architecture model through the reproducible Google Colab Notebook running on a Tesla P100-PCIE-16GB GPU.

Generally, the proposed task was executed over a period of a year course at the University of Macau, where 10% of the time was allocated to project and concept familiarity, 60% on data engineering and the rest of 30% on model development and deployment.

This work presents Debbis, an ECG-based biometric approach based on deep learning. I propose to use the novel Siamese neural architecture incorporating the Euclidean distance for biometric verification and template matching, and deep Convolutional Neural Networks (CNN) based on multiresolution analysis to extract features that allow performing a closed-set authentication. Furthermore, deploy the system onto a web platform enabling real-time simulation. The remaining of the report is organized in the following works: literature survey and related works, project execution, software design and implementation, testing and evaluation, discussion, ethics, and professional conduct and finally, conclusions.

CHAPTER 2. LITERATURE SURVEY

The ECG-based biometric system's design depends on the variability of several aspects, such as the number of leads analyzed, the type of features exploited, and the type of classifier used [10]. These aspects have a significant influence on the system's performance. Even though higher accuracy is associated with using multiple leads, one-lead ECG configuration is more widely accepted and suitable for biometrics because of its simplicity and speed during the signal acquisition phase [11].

In previous recognition research work [10] [12], the ECG-based biometric methods are divided into fiducial, non-fiducial classes. Fiducial methods use points of interest within the heartbeat wave P, Q, R, S and T illustrated in Figure 1, present in all healthy ECG signals. Non-fiducial techniques target extracting unique information from the ECG waveform without having to localize fiducial points. Some methods combine both fiducial and non-fiducial to form the partially fiducial approach which uses the R peak as a reference for waveforms segmentation, creating segments of QRS complex [12].

ECG recognition methodologies can also be classified based on the type of classifier used: k close neighbours, nearest middle, LDA, neural networks (NNs), generative model classifiers (GMCs), vector machines (SVMs) help, and others. Of these classes, nearest neighbour, nearest centre, and LDA are the most commonly used in ECG recognition literature [10]. A common concept is shared by all classifier-based systems whereby they analyze the ECG signal to extract meaningful features and use them as classifier inputs. For the same level of accuracy, Deep learning methods are more computationally and parametrically efficient. Deep learning methods can create deep data representations and learn new and more abstract representation of the input.

However, more recent work using Deep learning techniques such as Generic and Temporal Convolutional Neural Network (TCNN), Recurrent Neural Network (RNN) and Autoencoders for ECG-biometrics is emerging [13] [14] [15] [16]. Most of the work in the literature obtained promising results. However, they only considered closed-set biometric identification. Most studies did not explicitly illustrate that deep networks trained on samples obtained from a set of classes can be effectively used to confidently reject unknown classes. During realistic circumstances, unknown classes or imposters can emerge unexpectedly, which drastically weakens the robustness of these existing methods [17].

A classification task, rather than a recognition task, is being used in several studies [13] [14] [15] [16] [18]. In classification, we assume that there is a predefined set of classes from which we must discriminate. In terms of recognition, we assume that there are some classes that we can recognize within a much larger space of things we cannot recognize [19]. Verification problems for security-oriented ECG signals limit the target of interest to a single claimed identity while considering the set of all other possible people as potential impostors. There is a finite set of known individuals in a pool of unknown individuals, and labelling something new, novel or unknown should always be a valid outcome. This leads to what is sometimes called "open set" recognition [19].

Few deep learning methodologies have yet ventured into open-set recognition for ECG biometrics applications. There is noteworthy research into open-set recognition which uses one-shot learning [20] [21] [22] [23] [24]. One-shot learning heavily relies on knowledge transfer, using large datasets or learned features from state-of-the-art

general-object detection or classification pre-trained models such as VGG19 [25] and Inceptionv3 (GoogLeNet) [26] for classification using few samples. Recent successful works in biometrics using 1D Electroencephalography (EEG) signals [27] [28], the use of the multimodal Siamese Neural Network (mSNN) have been employed. The novel mSNN model achieved a 98.57% classification accuracy outperforming the current state-of-the-art by 12.86% (in absolute terms)

On the other hand, Debbis attempts to combine Siamese Neural Network (SNN) based on Contrastive Loss for verification and CNNs for closed-set multi-class periodic re-authentication. The use of SNN and CNN individually have demonstrated superior accuracy in this context, thus employing them as combined steps towards accurate ECG individual identification will be vital.

CHAPTER 3. PROJECT EXECUTION SCHEDULE

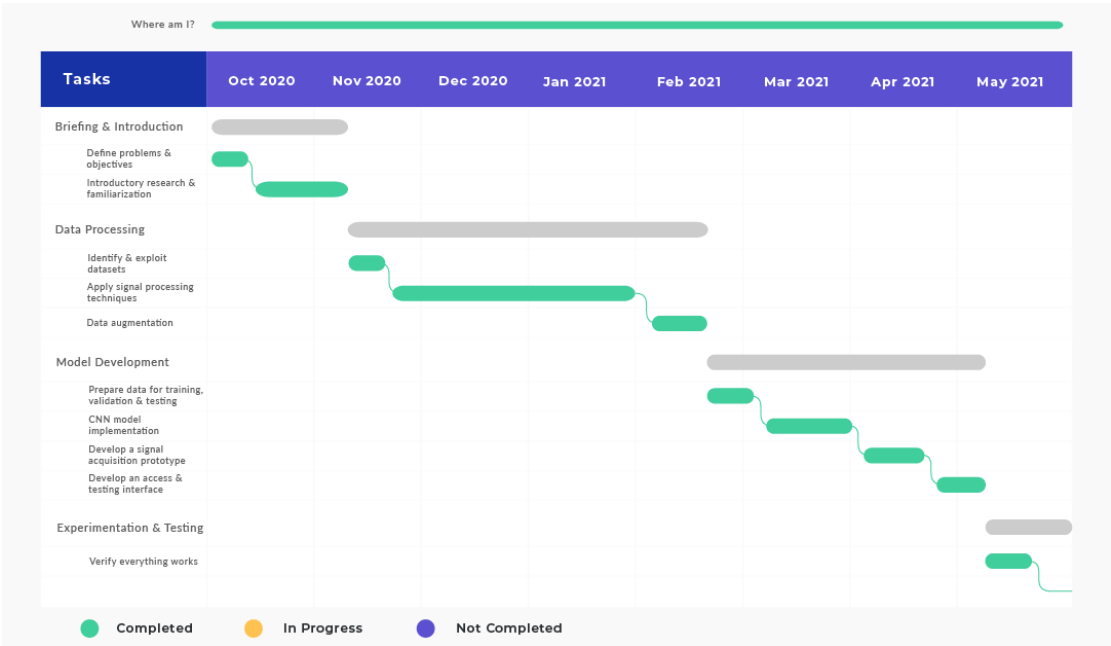


Figure 2: Gantt Chart of the work ditribution against time.

The Gantt chart in Figure 2 illustrates the work distribution against the project’s allocated period.

CHAPTER 4. DESIGN

The development of Debbis consists of two main stages:

- During development, signal acquisition and training of identity verification and authentication models was performed, Figure 3.
- The second stage includes the deployment of the trained models onto a simulated ECG signal secured web framework, Figure 4.

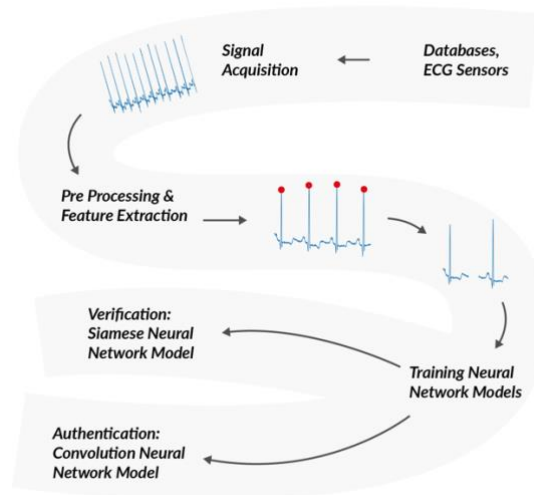


Figure 3 First stage of the Biometric System.

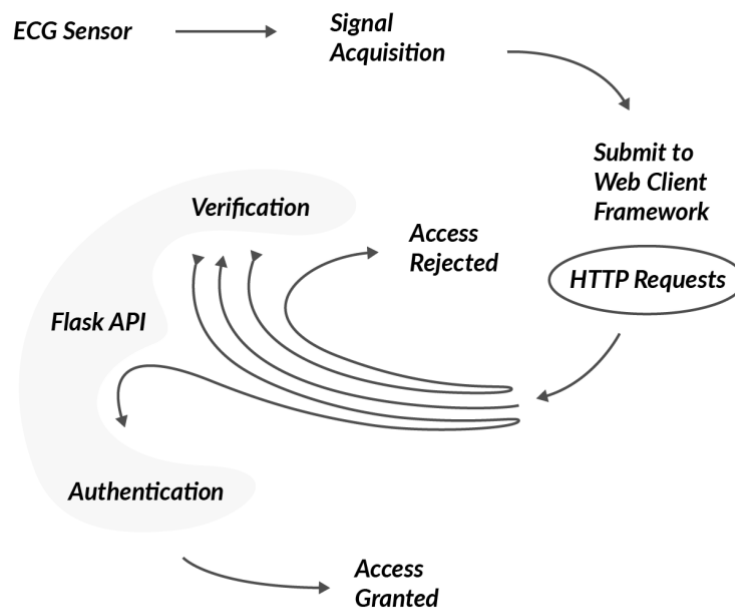


Figure 4 Second stage of the Biometric System

4.1 Goals

In addition to the objectives in Chapter 1, the goals of Debbis also include allowing an efficient and accurate enrolment, verification, and authentication process. Hence, to

achieve these goals, the biometric system should be robust, reliable, and unauthorizedly impenetrable.

4.1.1 Enrolment

This process includes signal acquisition, feature extraction and feature preparation to train the verification and authentication models. One challenging task is identifying an optimal length of signals acquired which should guarantee the following requirements:

- Non-intrusive signal acquisition methods.
- The lowest possible amount of time during signal acquisition.
- Maximum signal length and minimal training time such that trustworthy predictive accuracy scores of the verifying and authenticating models are guaranteed.

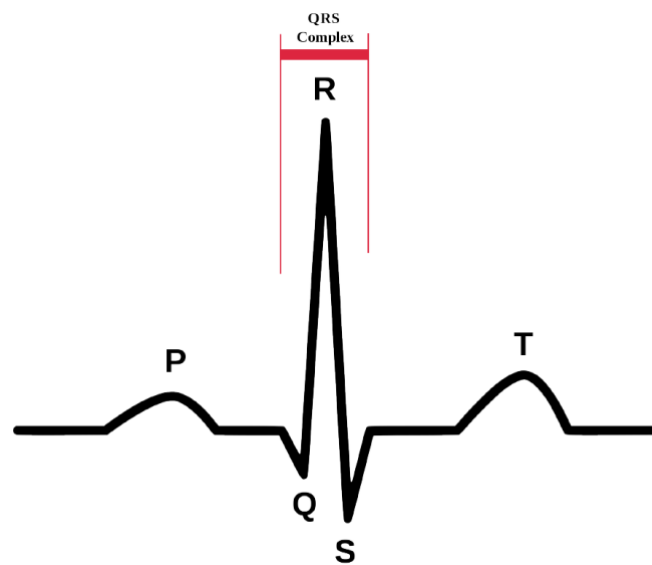


Figure 5: Representation of the QRS complex

During feature extraction, the main point of interest is the QRS complex, Figure 5, due to its central positioning, visual prominence and resistance to change during stress or emotional states [15]

4.1.2 Verification

One major drawback of classification is the limitation to handle Unknown Unknown Classes (UUCs), i.e., classes with unseen features during training. Traditional recognition/classification algorithms have already achieved significant success in a variety of machine learning tasks when training and testing data are drawn from the same label and feature spaces [17].

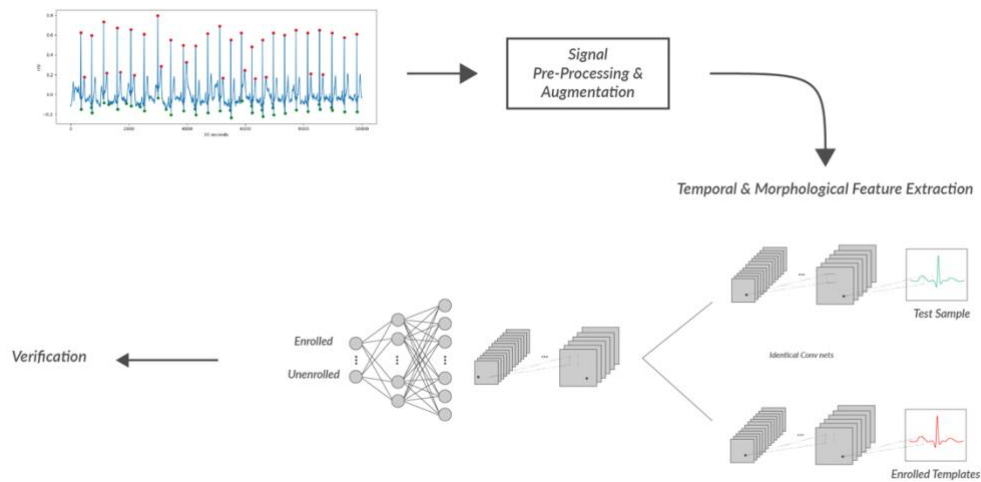


Figure 6 Proposed approach of the Verification task

A more realistic scenario, on the other hand, is usually open and non-stationary recognition/classification, such as in security systems, all non-enrolled individuals should be rejected with high confidence. To meet this challenge, Debbis achieves verification through open-set recognition whereby a Siamese neural network, Figure 6, matches the test signal to all the templates of the enrolled individuals, based on the Euclidean distance, and output the state of enrollment of the test individual on the system. Debbis no longer needs a “catch-all” class when it should reject a non-enrolled individual.

4.1.3 Authentication

After a successful match, the test signal is authenticated through a closed-set multi-classification CNN, Figure 7. For the closed environment among a fixed set of n persons: $P = \{p_1, p_2, p_3 \dots p_n\}$, the task is to develop a model M that can identify person $P(i)$ when given the persons' ECG signal, S_i .

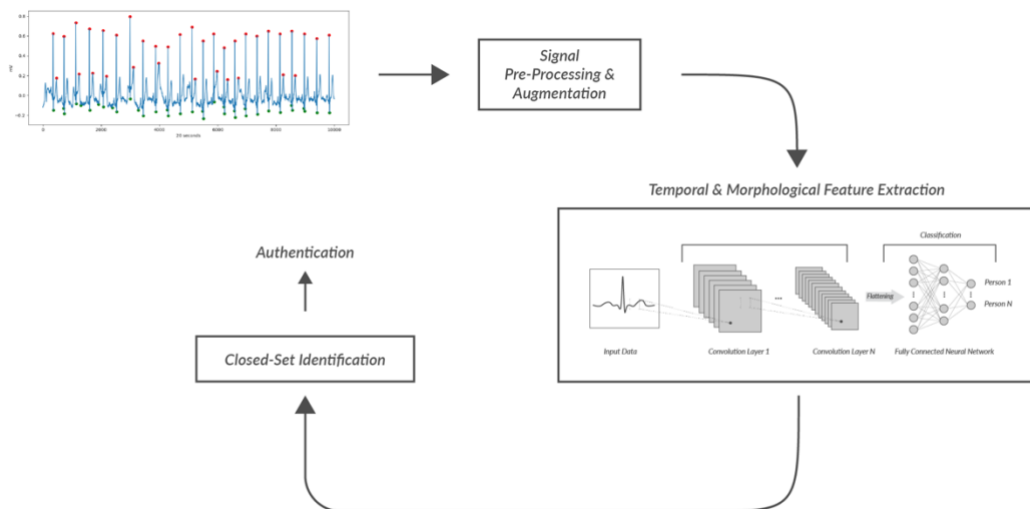


Figure 7 Proposed approach of the Authentication task.

4.2 Datasets

To assess the performance in realistic conditions with a relevant number of users and an optimal record time with continuity, the MIT-BIH [29] and the ECG-ID [30] [31] public datasets from PhysioNet were chosen.

4.2.1 MIT-BIH

Although the MIT-BIH Arrhythmia dataset [29] is focused on arrhythmia detection, it has also been used to benchmark biometric authentication accuracy in several works. This dataset contains ECG signals from 47 people who have arrhythmias of various types. The recordings were digitized at a sampling rate of 360 Hz with an 11-bit resolution over a signal range of 10 mV. Although the ECG signals were recorded in two channels, only the first channel was used in the proposed study.

4.2.2 ECG-ID

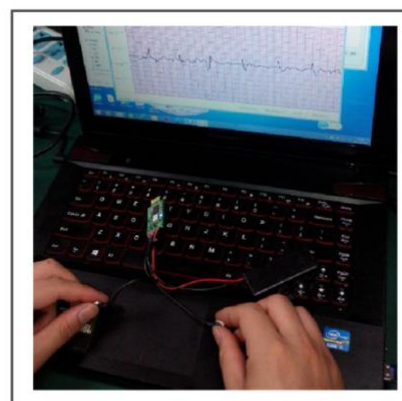
The ECG-ID database [30] [31] is one of the few databases specifically created to investigate ECG-based authentication. As a result, this dataset has become the de facto choice for researchers working with ECG biometrics [Pinto]. In this dataset, 90 people had their ECG signals from lead I recorded for 20 seconds. Over a nominal 10 mV range, the signals were digitized at 500 Hz with a 12-bit resolution. 2 to 20 session data were collected for each subject. Thus, it is common practice among researchers to consider only two sessions for each person to avoid data imbalance [32] [33].

4.2.3 BMD101 Sensor Chip

NeuroSky's BMD101 sensor chip is built with advanced analogue front-end circuitry and a flexible, strong digital signal processing structure. The development board has a Notch Filter and a Low Pass Filter. Typically, the Notch Filter is configured to be a 50Hz, 60Hz, or both notch through arrangement. For both 60Hz and 50Hz, the notch rejection is typically -63dB. The Low Pass Filter has a cut-off frequency of 100Hz. It has a consistent passband to the cut-off frequency and a -40dB passband at the stop frequency.



a) BMD Development ECG Sensor



a) BMD in action

Figure 8 a) Shows the BMD device used to extract signals; b) Demonstrate live signal Acquisition

The device is non-intrusive and only requires the subject to hold the two dry metal electrodes with each of their thumbs, demonstrated in Figure 8.b and the signals are recorded and displayed through the GUI as illustrated in Figure 9. Signals were recorded from two individuals for durations of 20 min each. The device is very susceptible to noise hence it requires a low-noise place with minimal surface vibrations.

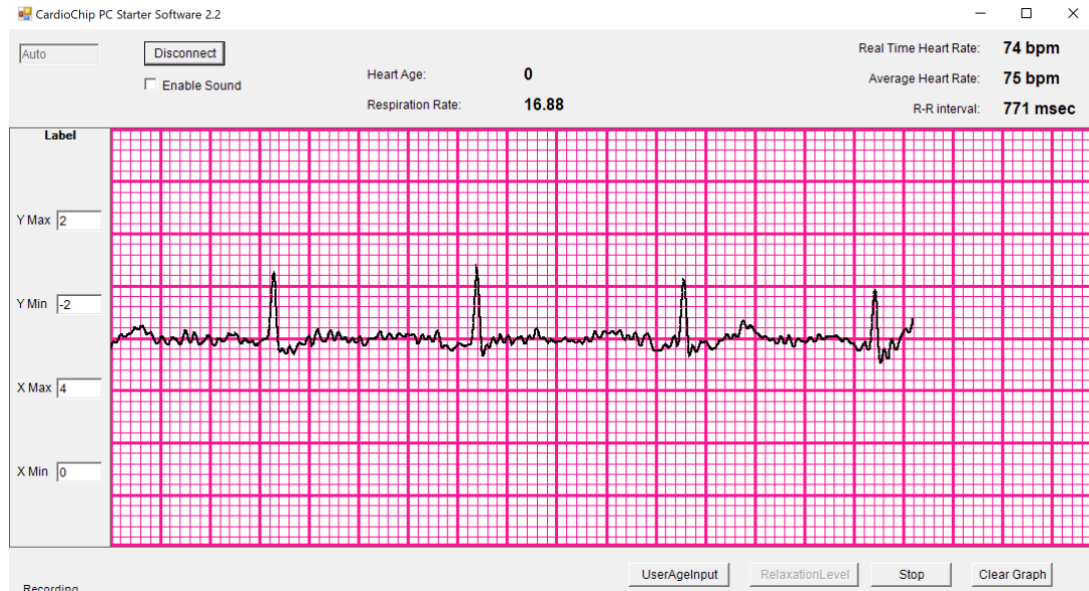


Figure 9 BMD Windows-OS Graphical User Interface

4.3 Neural Network Architectures

Creating a deep learning model for a single heartbeat-based authentication system is challenging because of limited signal duration and the need for large datasets. Short signals provide very little information for sequential input data which translates to the loss of considerable information. Thus, Debbis employed an extensive architecture capable of extracting complex features from each ECG segment. Both the Siamese and Convolutional Neural Networks employed a block structure inherited from VGG19 [25], amended to the needs of ECG features. Both structures contain a learning architecture with 30 layers, whereby between the input and the flatten layer, there exist 5 blocks. Each block contains a 1D Convolution, Batch Normalization, Activation and Max Pooling layer. The block structure allows connecting all the layers with matching feature-map sizes by stacking feature maps formed in earlier layers to feature maps at higher levels. More details on the neural network architectures are discussed in section 5.4.

CHAPTER 5. IMPLEMENTATION

5.1 Signal Acquisition

Both the MIT-BIH and ECG-ID data files are stored in the Waveform Database (WFDB) file format. The *record_name.dat* file formats are binary files containing samples of digitized signals. These files host waveforms, but they cannot be interpreted properly without their corresponding header files. The corresponding *record_name.he*a files are short text files that describe the contents of associated signal files. I used the WFDB software package [34] to read and extract the signals and save them in an easily accessible and universally readable file format, *record_name.csv*.

```
signals, = wfdb.rdsamp(file, sampfrom=0,
                        pn_dir = os.path.join(database, folder))
df = pd.DataFrame(signals)
df.to_csv(os.path.join(dir, folder, file + '.' 'csv'), index=False)
```

The BMD comes with a Windows-OS-compatible Graphical User Interface, Figure 9, to aid in the extraction of signals. A recording individual should be in place to begin, monitor and terminate the signal recording. The optimum signal duration was determined to be 20 minutes. The BMD GUI saves the signals in a *datetime.txt* file format as Figure.

```
# How the datetime.txt file looks like
timestamp:      ADC  HeartRate4sAverage  HeartRate30sAverage
1621355037.727:  2696           95           92
1621355037.727:  1979           95           92
1621355037.727:  1093           95           92
1621355037.727:   812           95           92
1621355037.727:  1304           95           92
1621355037.727:  2055           95           92
1621355037.727:  2492           95           92
1621355037.727:  2575           95           92
1621355037.727:  2607           95           92
1621355037.727:  2682           95           92
1621355037.727:  2608           95           92
1621355037.727:  2241           95           92
1621355037.774:  1845           95           92
1621355037.774:  1744           95           92
1621355037.774:  1902           95           92
1621355037.774:  2008           95           92
1621355037.774:  2017           95           92
1621355037.774:  2174           95           92
1621355037.774:  2628           95           92
1621355037.774:  2978           95           92
1621355037.774:  2650           95           92

# Processing the datetime.txt file
with open('user_id_date.txt', 'r') as f:
    for line in f:
        value = int(line.strip().split()[1])
        array.append(value)

# Normalize array to (-1, +1)
array = np.interp(array, (array.min(), array.max()), (-1, +1))

# Save to csv
df.to_csv('user_id_date.csv', index=False)
```

5.2 Signal Pre-processing

During this stage, the ECG signals are enhanced, and the most discriminating QRS complexes are extracted. No noise filtering was applied because different signal

acquisition methods produced different noise levels and I couldn't access enough individuals to create a model trained purely from the data acquired using the BMD.

5.2.1 Peak Segmentation

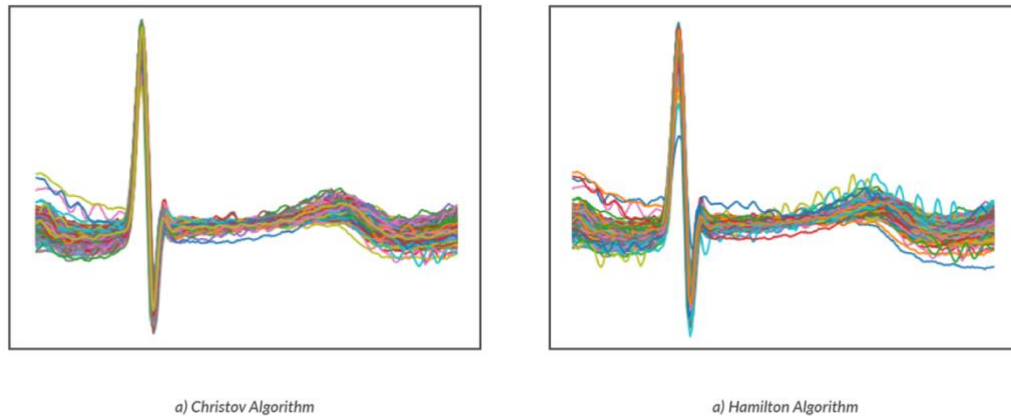


Figure 10 Main contending ECG Segmentation Algorithm

In the second step, I applied the *christov* and *hamilton* QRS segmentation algorithm presented in the literature [35] [36]. A comparison of the two algorithms is presented in figure 5. Among others, the *christov* algorithm demonstrates higher robustness, QRS and beat detection performance [37]. The algorithm filters the ECG through a sequence of moving averages, and a combination of adaptive thresholds is used for QRS detection. For the absence of any power-line interference, the first moving average filter is used. It is implemented as a Finite Impulse Response filter, where the number of coefficients in a 50 Hz duration is equal to the number of samples (20 ms). Similarly, with 28 ms, the second moving average is applied to decrease signal noise. The absolute value of the differential is then taken to illustrate the QRS complexes.

```
def segment(self, array):
    peaks = ecg.christov_segmenter(signal=array, sampling_rate=500)[0]
    for i in (peaks[1:-1]):
        diff1 = abs(peaks[count - 1] - i)
        diff2 = abs(peaks[count + 1] - i)
        x = peaks[count - 1] + diff1 // 2
        y = peaks[count + 1] - diff2 // 2
        peakWave = array[x:y]
```

5.2.2 Data Augmentation

Data augmentation is a technique used to create new training data from the existing one. Typical to popular geometrical augmentation methods typically applied to input data for CNN, such methods are not appropriate for this study. Signal waves have the characteristics of noise, pitch domain and time domain. The signal alterations will revolve around these characteristics in such a way that they only differ by a minimal factor from the original sample.

5.2.2.1 Noise Addition

This process involves the addition of Gaussian noise to the sample because of its normal distribution. Gaussian noises are random samples distributed at regular intervals with a mean of 0 and a standard deviation of 1.

```
factorValue = 0.09
noiseAdding = array + factorValue * np.random.normal(0, 1, len(array))
```

5.2.2.2 Pitch shifting

This process involves shifting the signal in the amplitude domain around *the x-axis* while minimally influencing the time domain.

```
factor = -0.3
pitchShifting = librosa.effects.pitch_shift(array, 500, n_steps=float(factor))
```

5.2.2.3 Time Shifting

This process involves shifting the signal in the time domain around the *y-axis* while minimally influencing the *x-axis*.

```
samplingRate = 500
timeShifting = np.roll(array, int(samplingRate / 150))
```

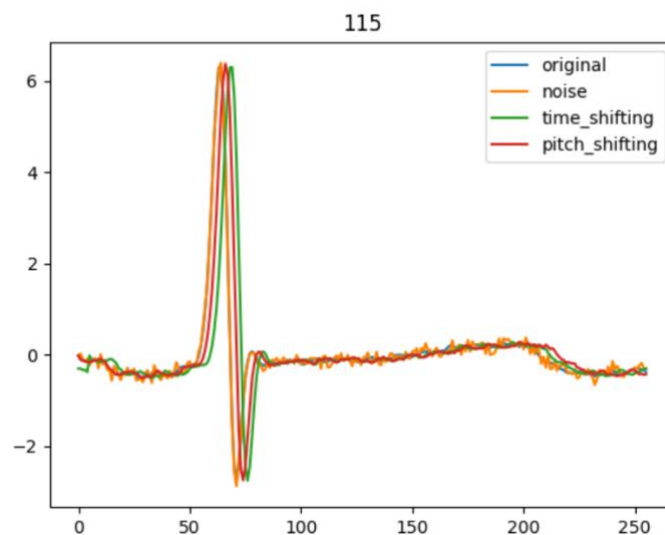


Figure 11 Illustrates the various augmentation methods

The variation outcome of these processes is demonstrated in Figure 11. After a successful pre-processing and augmentation, every individual's signal was saved to a pickle file format. After an assessment, only the MIT-BIH data and two individuals from the BMD were used because the ECG-ID did not have enough data to produce confident results.

5.3 Training Data

5.3.1 SNN Data

The ECG segments were cut to 700 per individual, hence a normal distribution of classes, Figure 12. The pre-processed data is normalized to values between 0-1. Data normalization helps get rid of several anomalies that can complicate the analysis of signals. Afterwards, the data is shuffled and placed into pairs. Each segment pair is either the same (1), meaning they belong to the same class or different (0), meaning they belong to different classes Figure 13. The data is then divided into training, validation and test sets to train and evaluate the performance of the classifier. The Sklearn selection model was used to randomly partition and allocate 60% of the data to

training, 30% for validation and 10% for testing. The training set is used for classifier design, while the test set for performance and accuracy assessment.

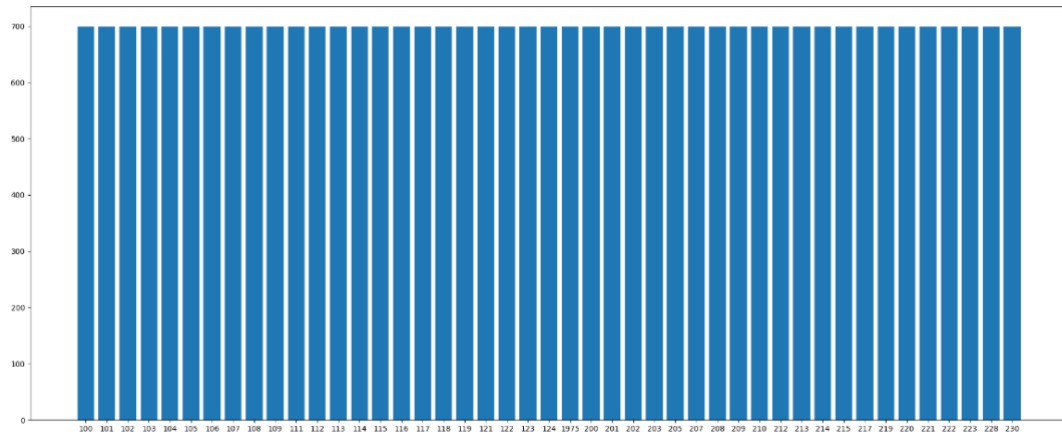


Figure 12 Total training and test data distribution for SNN data

```
# Normalize
x = (x - x.min()) / (x.max() - x.min())
y = np.array(y)

# Shuffle

# Create pairs
p = people
def create_pairs(x, y):
    yy, xx = [], []

    indices = [np.where(y == i)[0] for i in p]
    dic = {p[j]: indices[j] for j in range(len(p))}
    for i in range(len(x)):
        current_image = x[i]
        label = y[i]
        ia = np.random.choice(dic[label], replace=False)
        positive_image = x[ia]
        xx.append([current_image, positive_image])
        yy.append(1)

        choices = np.where(y != label)[0]
        ib = np.random.choice(choices, replace=False)
        negative_image = x[ib]
        xx.append([current_image, negative_image])
        yy.append(0)

    xx = np.array(xx)
    yy = np.array(yy)

    return xx, yy
```

```
x, y = create_pairs(x, y)
```

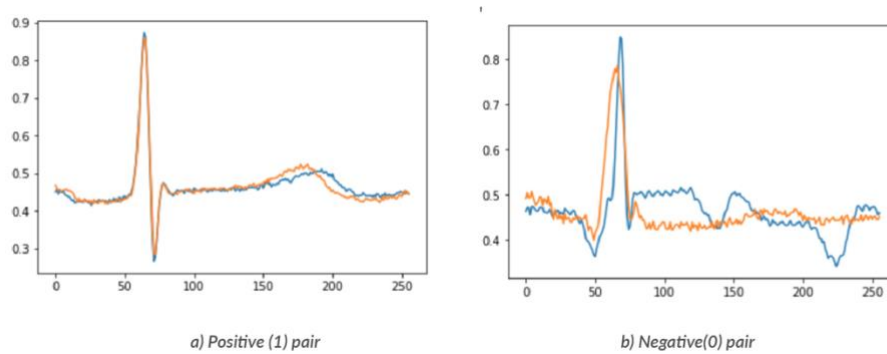


Figure 13 Positive and Negative Pairs

5.3.2 CNN Data

The ECG segments were cut to 10000 per individual, hence a normal distribution of classes, Figure 14. The pre-processed data is normalized to values between 0-1. Data normalization helps get rid of several anomalies that can complicate the analysis of signals. Afterwards, the data is shuffled and divided into training and validation sets to evaluate the performance of the classifier. The Sklearn selection model was used to randomly partition and allocate 60% of the data to training, 30% for validation and 10% for testing. The training set is used for classifier design, while the test set for performance and accuracy assessment.

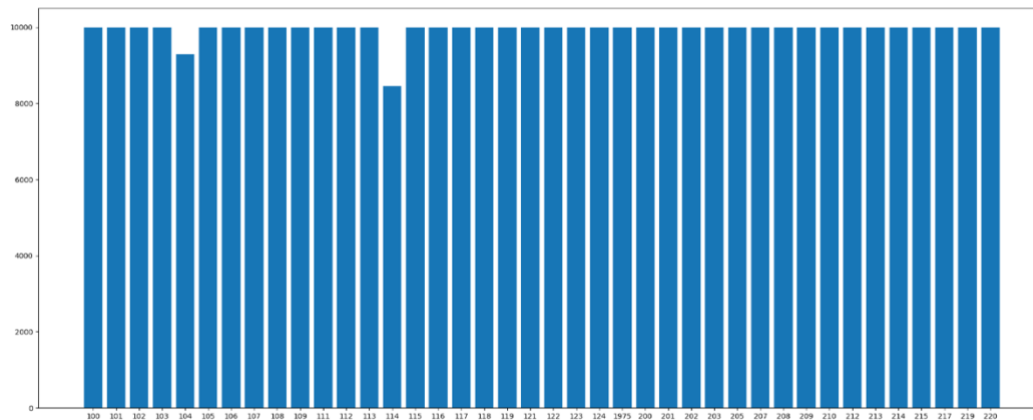


Figure 14 Total training and test data distribution for CNN data

```
# Normalize
x = (x - x.min()) / (x.max() - x.min())
y = np.array(y)

# Shuffle for both SNN and CNN

# Train, Valid and test split
from sklearn.preprocessing import LabelBinarizer

# Determine segment shape (256)
SIG_DIMS = (x.shape[1], 1)

# binarize the labels
lb = LabelBinarizer()
y = lb.fit_transform(y)

# Split
x_train, x_test, y_train, y_test = train_test_split(
    x, y, test_size=0.4, shuffle=True, random_state=42)
x_valid, x_test, y_valid, y_test = train_test_split(
    x_test, y_test, test_size=0.3, shuffle=True,
    random_state=42)

x_train = x_train.reshape(x_train.shape[0], SIG_DIMS[0],
    SIG_DIMS[1])
x_valid = x_valid.reshape(x_valid.shape[0], SIG_DIMS[0],
    SIG_DIMS[1])
x_test = x_test.reshape(x_test.shape[0], SIG_DIMS[0],
    SIG_DIMS[1])
```


5.4 Network Architectures

5.4.1 Siamese Neural Network Structure

The Siamese network contains two input fields for comparing two signal inputs and one output with a state value that corresponds to the similarity of the two signal segments [38]. To extract the features, two different sub-networks based on the structure inherited from the VGG19 [25] block architecture act on each input segment. The distance value is obtained by taking the cosine of the angle between two feature vectors. Figure 15 gives an overview of the proposed framework by applying Siamese network based on contrastive loss to determine if a person is enrolled or not.

5.4.2 Convolutional Neural Network Architecture

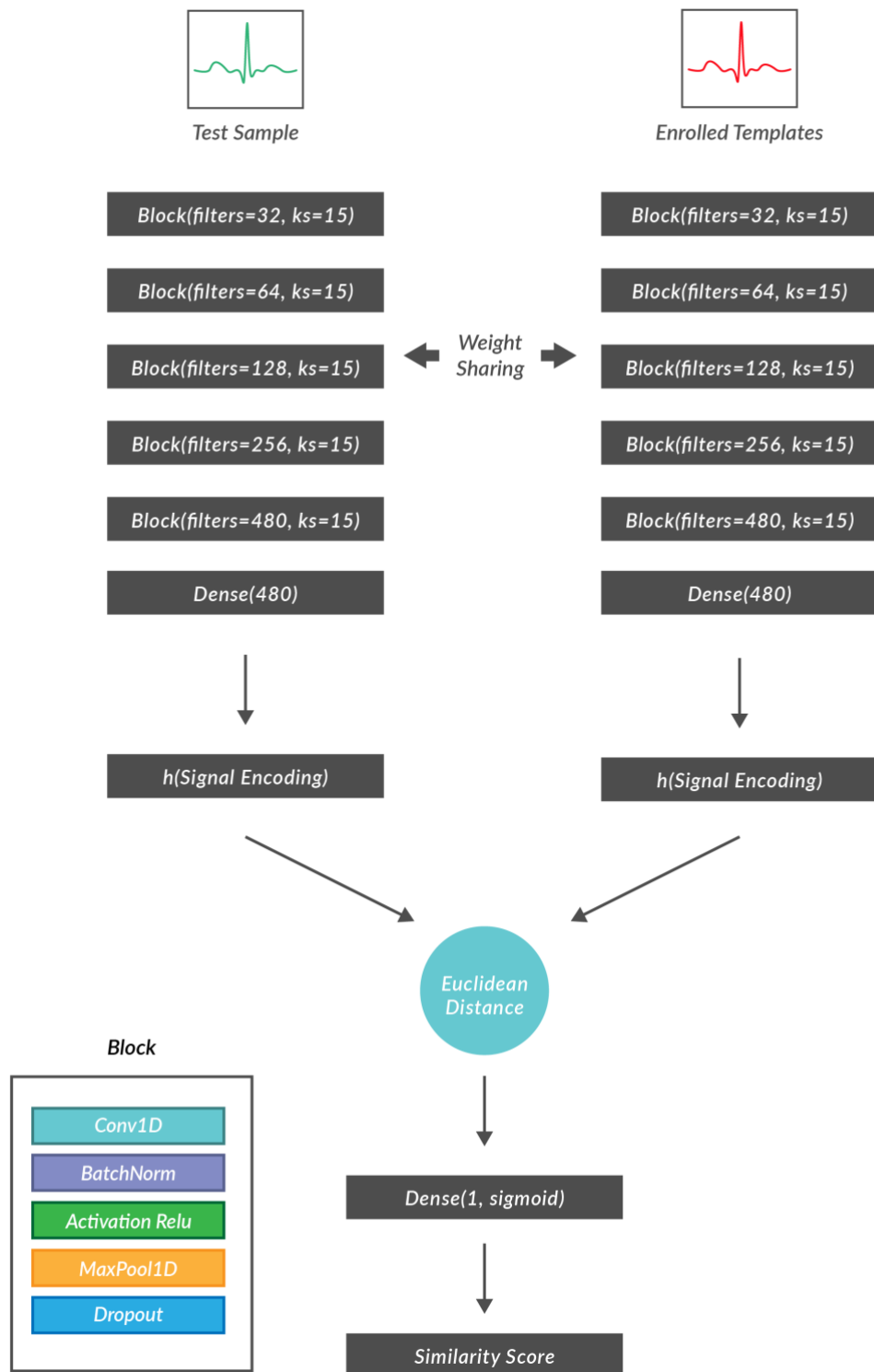


Figure 15 Illustrates the Siamese Neural Network Architecture

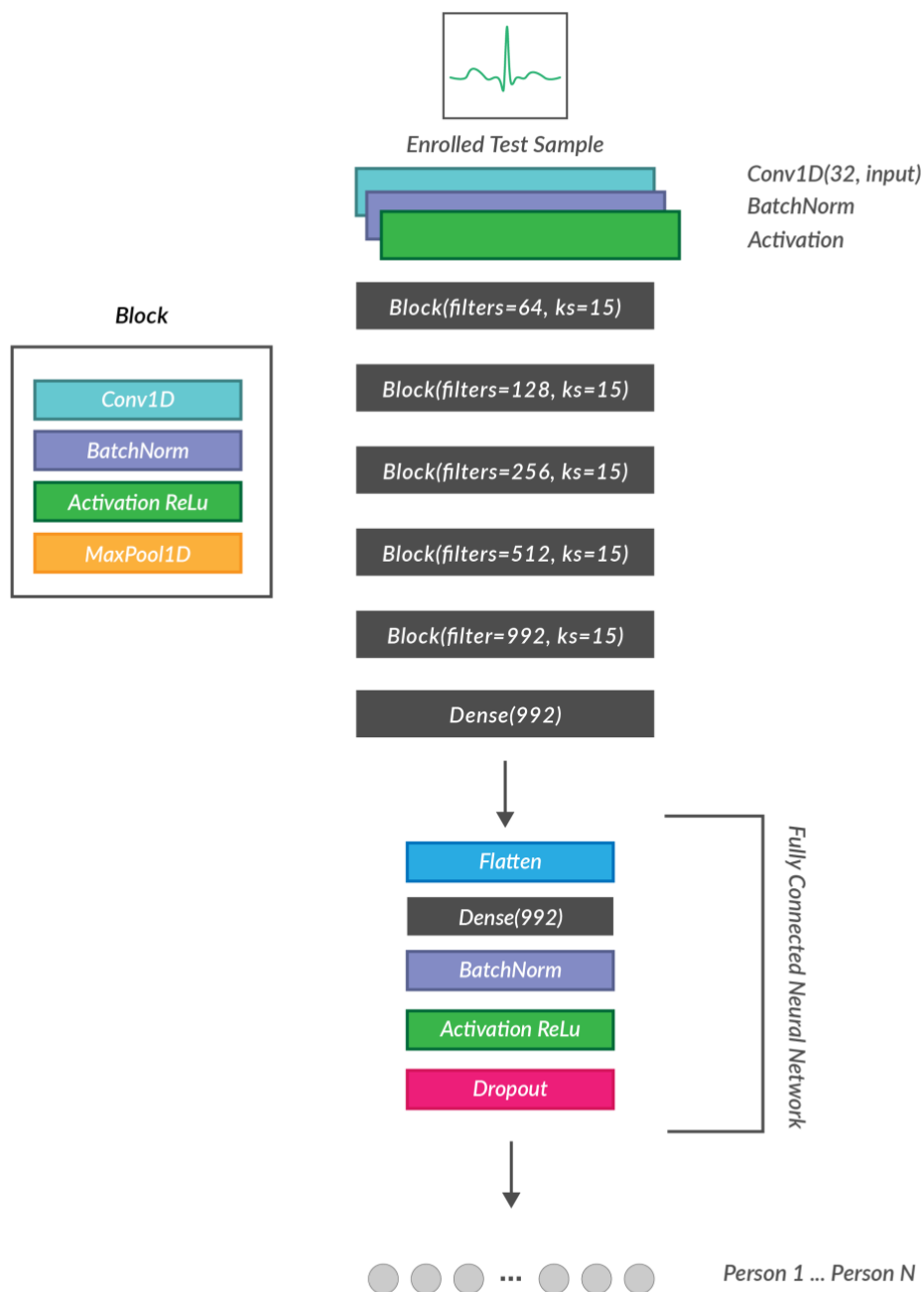


Figure 16 Illustrates the Convolution Neural Network Architecture

CHAPTER 6. TESTING AND EVALUATION

In this experiment, both the SNN and CNN models are fed with 1D time-based ECG signals, each of length 256. Both networks had a Batch Size of 64, and learning rate of 0.00001, and used the Adam optimizer with decay. After numerous experiments, only the data from 39 candidates from MIT-BIH plus 1 candidate from the BMD dataset. Because of the complex network structure used, the data from ECG-ID does not produce substantial results.

6.1 Verification

The SNN was trained on 100 epochs with Model Checkpoint and early stopping in place tracking validation loss. Together with the Euclidean Distance, the SNN uses contrastive loss, which 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 examples.

On average, the training period lasts for a 20 – 25 minutes. The SNN model achieved average results, Figure 17 and Figure 18, whereby the validation loss is 49.69%. After numerous experiments and observations, the decision threshold margin of enrolled against unenrolled test sample is 0.00099999 meaning if the similarity score is above or equal to 0.00099999, then such egg segment resembles one of the enrolled templates hence a successful verification. Test samples are illustrated in Figure 19.

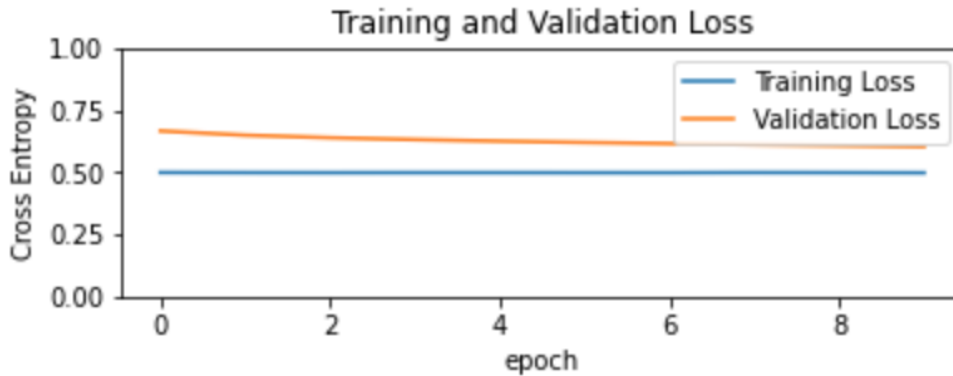


Figure 17 Training and Validation loss for the SNN model

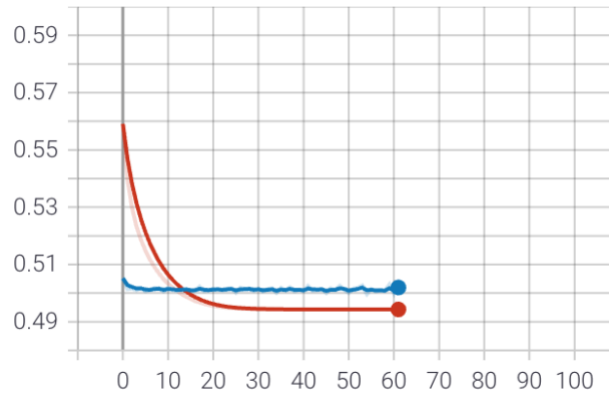


Figure 18 Training results for the SNN. In Blue is the Training loss and Red is Validation Loss

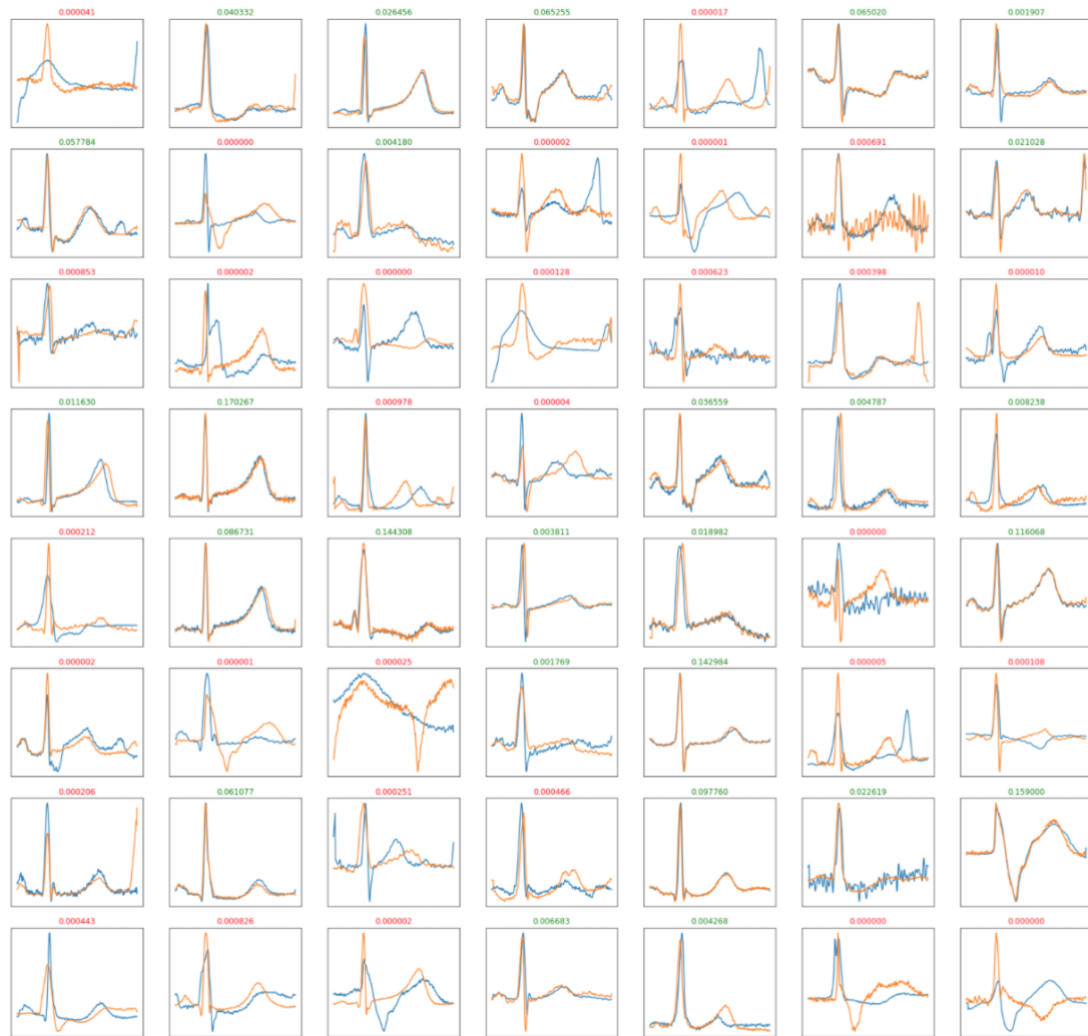


Figure 19 Predicted test samples from the SNN model

6.2 Authentication.

On average, the training period lasts for 1 hour. The CNN model was successfully trained on 100 epochs with early stopping, Model Checkpoint on Validation loss and optimally completed on after an average of 20-25 epochs. The results for the model are substantially excellent given the short duration and complex network structure. The CNN model achieved an accuracy score of 99.93% and validation loss of 0.32% is displayed in Figure 20 and Figure 21. The CNN model has a threshold margin of 99%, meaning for the test data selected of size 47729, 47459 segments are correctly classified with an accuracy of $\geq 99\%$, and 270 segments have an accuracy score $\leq 99\%$.

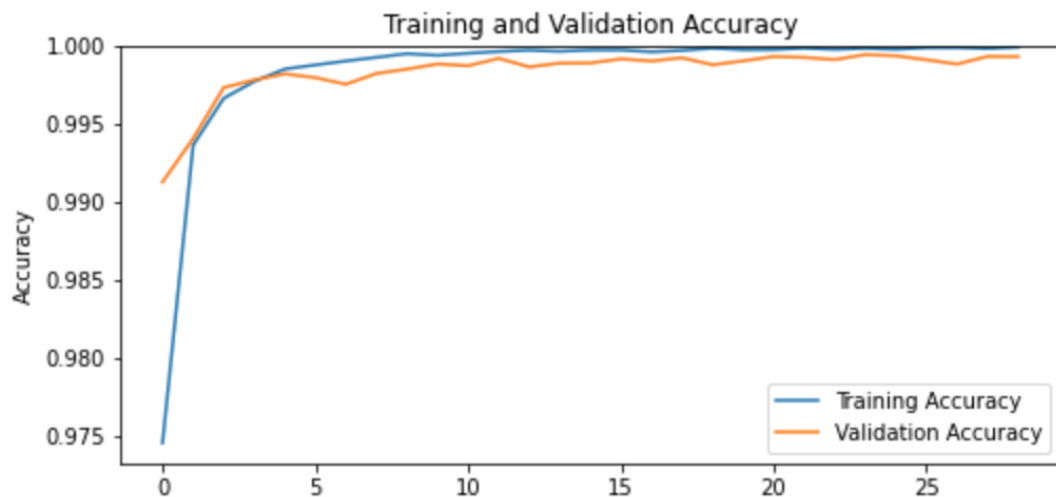


Figure 20 Training and Validation Accuracy scores

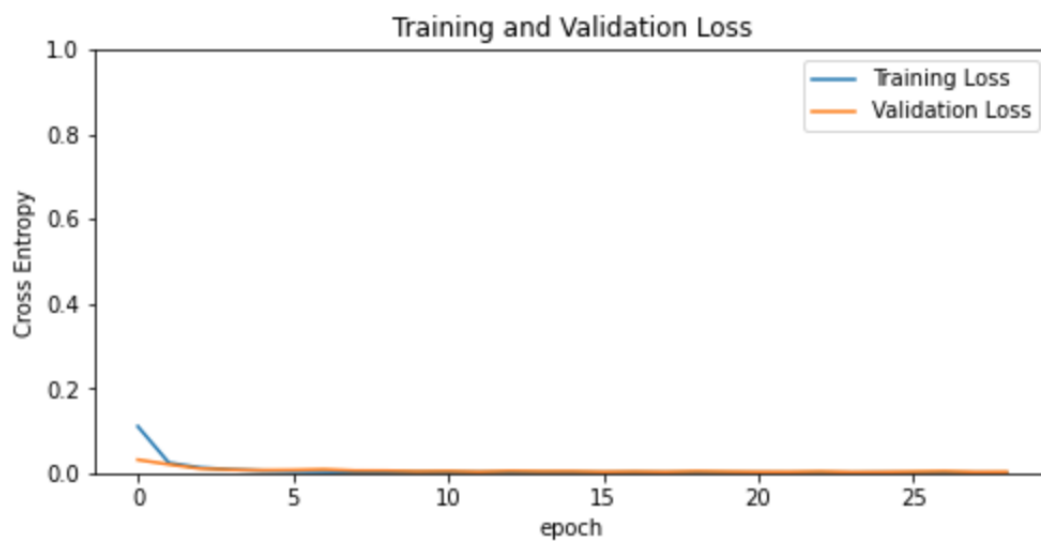


Figure 21 Training and Validation Loss scores

The confusion matrix is displayed in Figure 22, which corresponds to the precision, recall and f1-score all at 100%. Figure 23 displays several predicted samples.

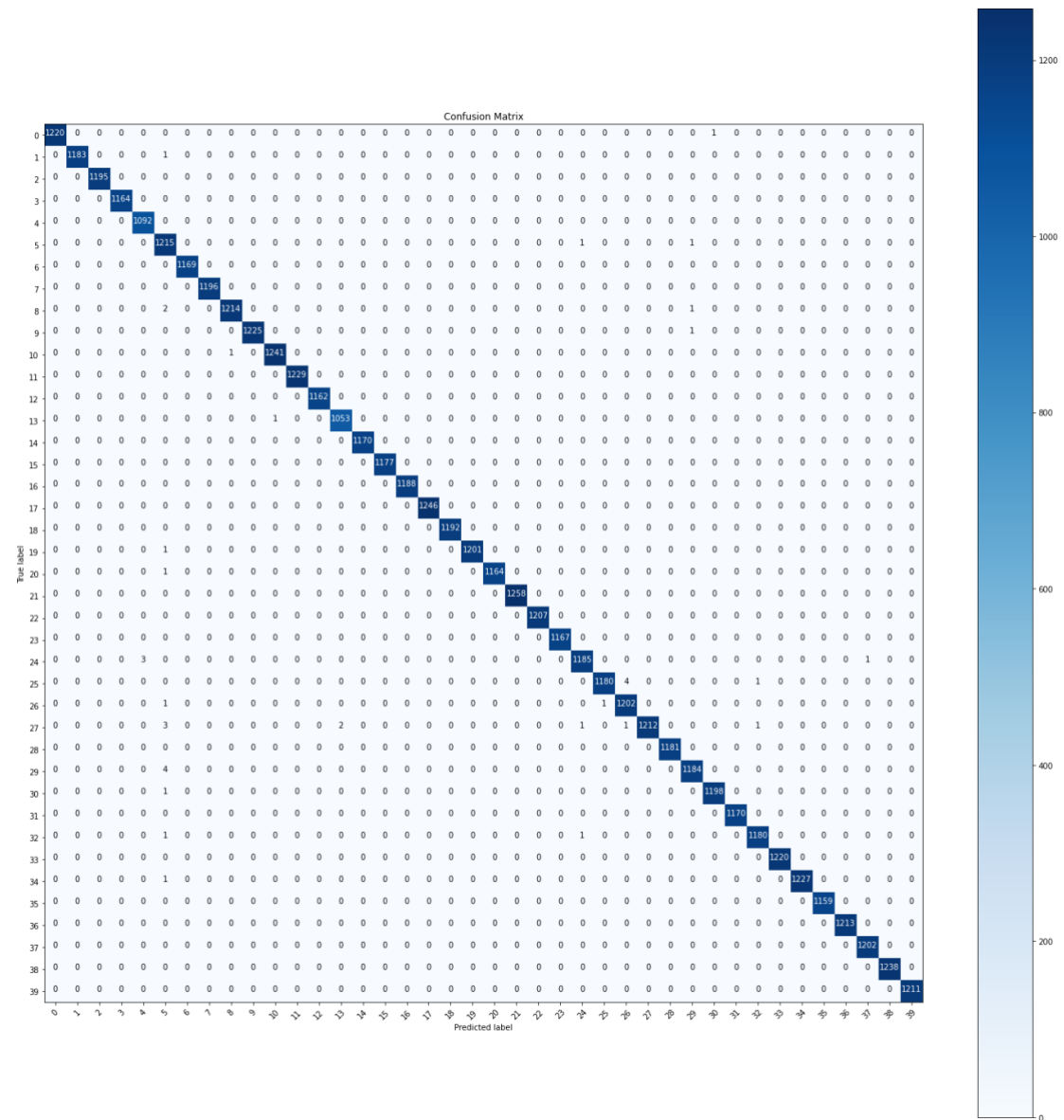


Figure 22 Confusion Matrix of the CNN model

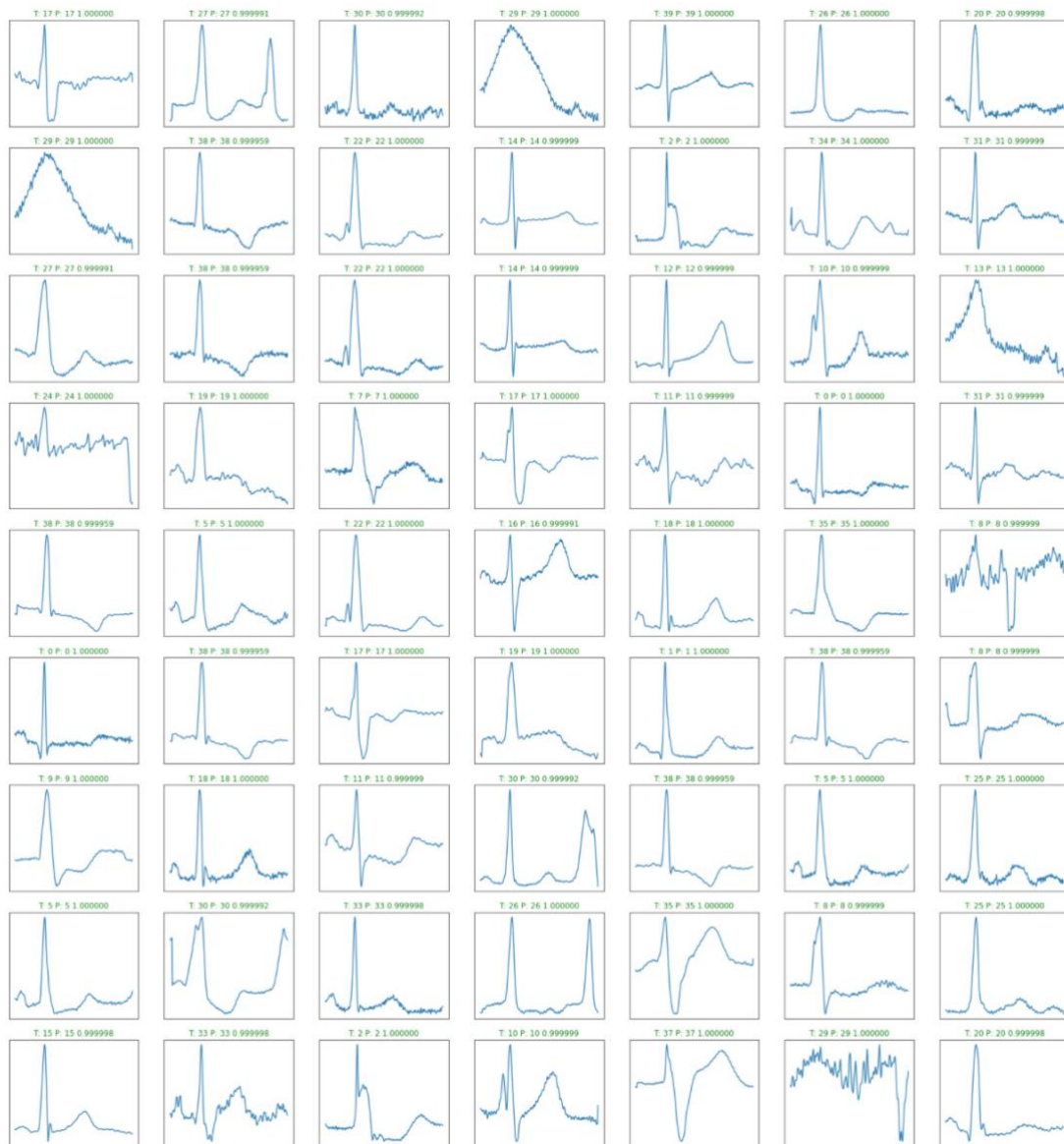


Figure 23 Predicted test samples from the CNN model

CHAPTER 7. DISCUSSION

The performed approach aims to employ Deep Learning as a robust candidate for an ECG Biometric System. The goal is to design an effective enrolment, verification, and authentication strategies for continuous authentication systems. There's an increase in the development of Deep Learning ECG-Based Biometrics [13] [14] [38] [16], which shows promising results. However, most studies only focused on closed-set classification. Though Debbis achieved average results with the Siamese Neural Network model, the implementation of the authentication using the Convolutional Neural Network provides another layer of security to the system.

Despite significant research progress, the ECG-ID dataset in use contains a low number of classes to produce a robust and industry dependable Deep Learning model hence only the MIT-BIH and the BMD dataset were utilized. Also, few industry-level datasets dedicated to user identification and authentication exist [11], and a large section of them are not publicly available or may require special access based on research merit. Subjectively on progress, the study development could be faster to enable enough time for testing and evaluation. Areas I could improve is sufficient time allocation for the project.

CHAPTER 8. ETHICS and PROFESSIONAL CONDUCT

The major ethical implications in the field of Biometrics, particularly ECGs, are privacy and confidentiality. If privacy implies having power over how and when we are portrayed to others, then biometrics that identifies us uniquely may easily violate our fundamental privacy. This is particularly true when you realise that users do not monitor the selection, storage, or use of these identities. One of the main benefits of a biometric signature is that it is unique to each person and does not change over time. Ironically, invariability is perhaps one of the vulnerabilities of biometric systems. Your identity and security are compromised forever if the system is breached. We can't change our physical features, like changing a password.

CHAPTER 9. CONCLUSIONS

The report presents the Debbis, an ECG-based biometric approach based on deep learning. Through the use of Siamese and Convolutional Neural Networks to extract features that allow performing a closed-set identification, identity verification and periodic re-authentication. To evaluate the performance of the study, the model will be tested on test samples obtained from the ECG-ID database for closed-set identification, identity verification and authentication. Future work beyond this study should regard the development of comprehensive ECG datasets to allow advanced exploration into secure biometric systems. Despite both fields being under development and novice, biometric systems will significantly benefit from neural network incremental learning.

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