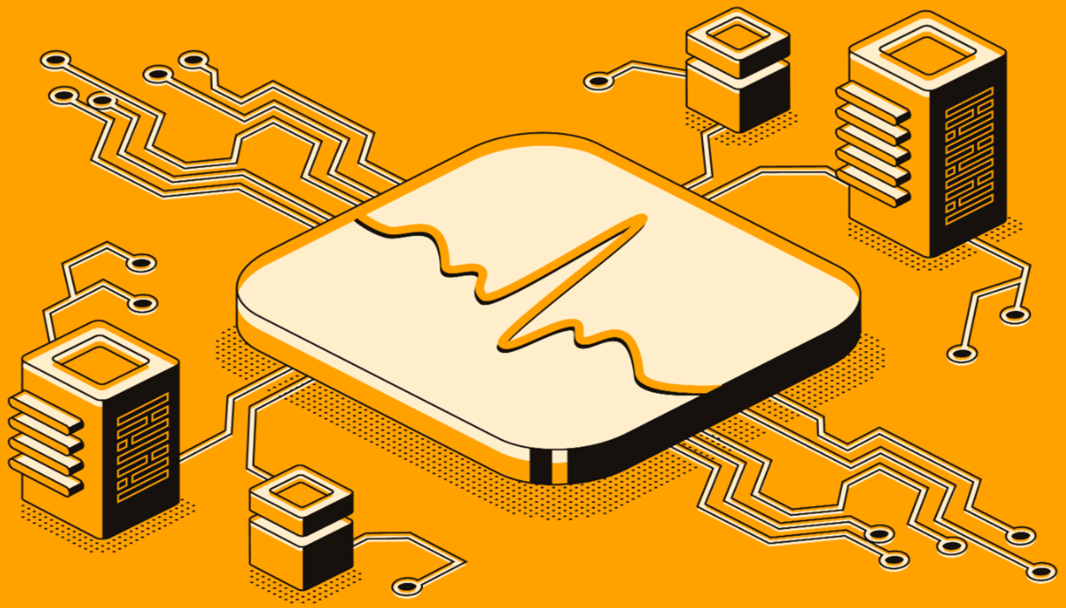

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Deep Electrocardiogram Based Biometric Identification System

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2021 FYP, Computer Science, Faculty of Science and Technology

Overview

- Objectives
- Background
- System Structure
- Data Processing
- Neural Network Architectures
- Results
- Challenges
- Conclusions

Objectives

- Explore ECG biometrics using Deep Learning: CNN and Siamese NN.

Why ECGs?

- Universal, unique and guarantees liveness detection
- Harder to replicate*
- Passwords, pins etc. can get lost, stolen or can be guessed
- Fingerprints [1], iris [2] and facial features [3] can be falsified or reverse engineered from templates

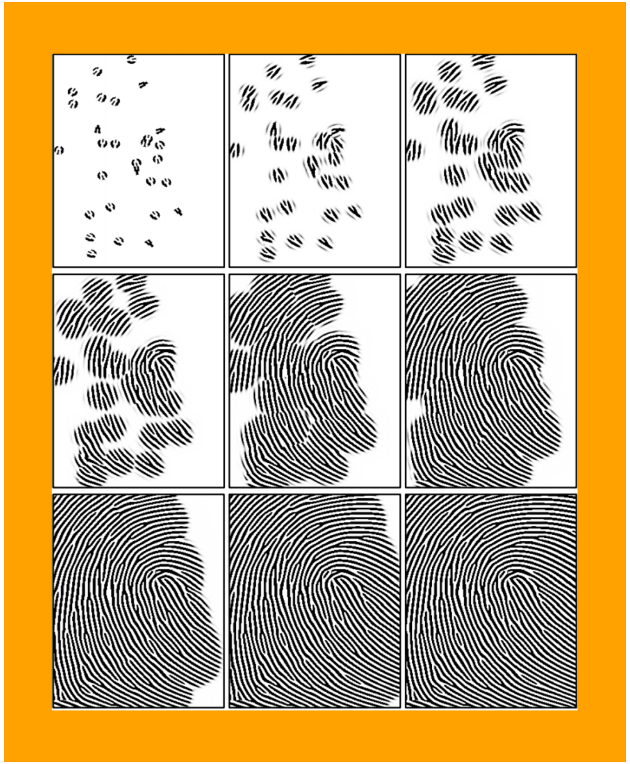


Figure 1: Steps during fingerprint reverse engineering from ISO templates. Source [1]

Background

What is Biometric Recognition (BR)?

- Establishing an identity based on physiological or physical data.
- Current works use [4]:
  - Fiducial method i.e P, Q, R, S and T
  - Non-fiducial methods
  - Partially fiducial methods i.e R-peak detection
- Existing Deep Learning implementations [5]
  - Generic and Temporal CNN
  - RNN
  - Autoencoders

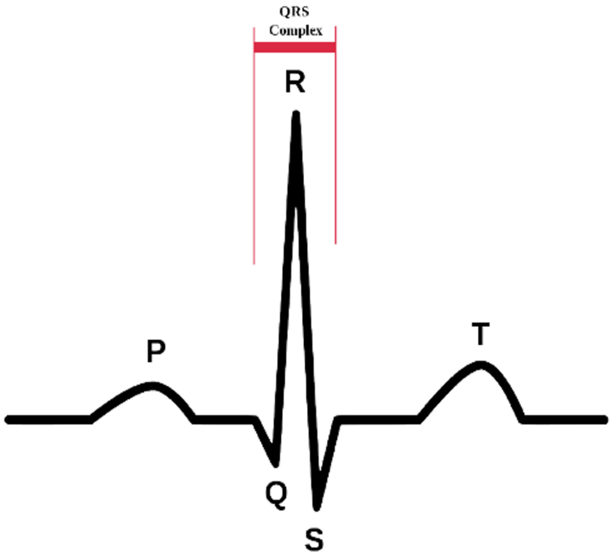


Figure 2: Representation of the QRS complex [Wikipedia]

System Structure

Stages of Biometric System

- Enrolment
  - Saving user details on database
  - Creating templates
- Recognition
  - Verification and or Authentication
  - Compare test samples to templates and output a match

System Structure

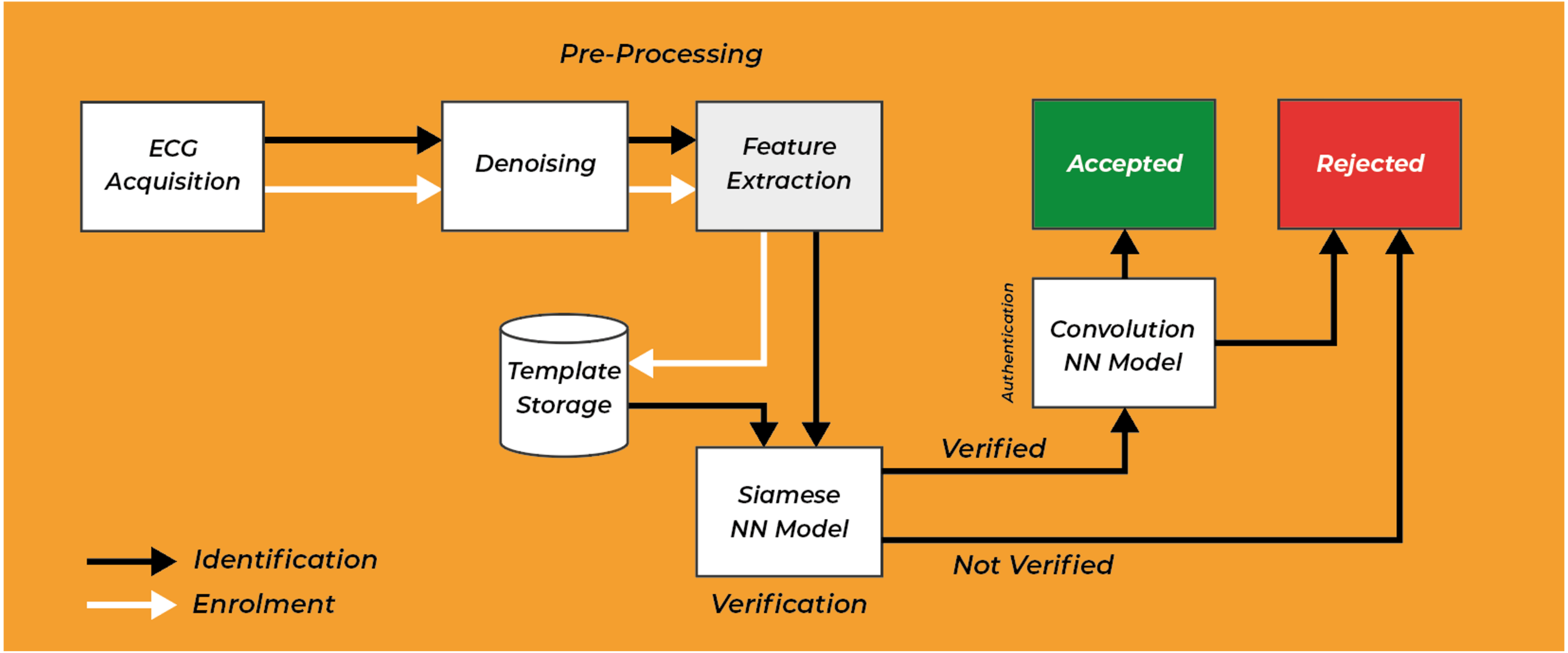


Figure 3: a) System flow structure with verification and authentication

System Structure

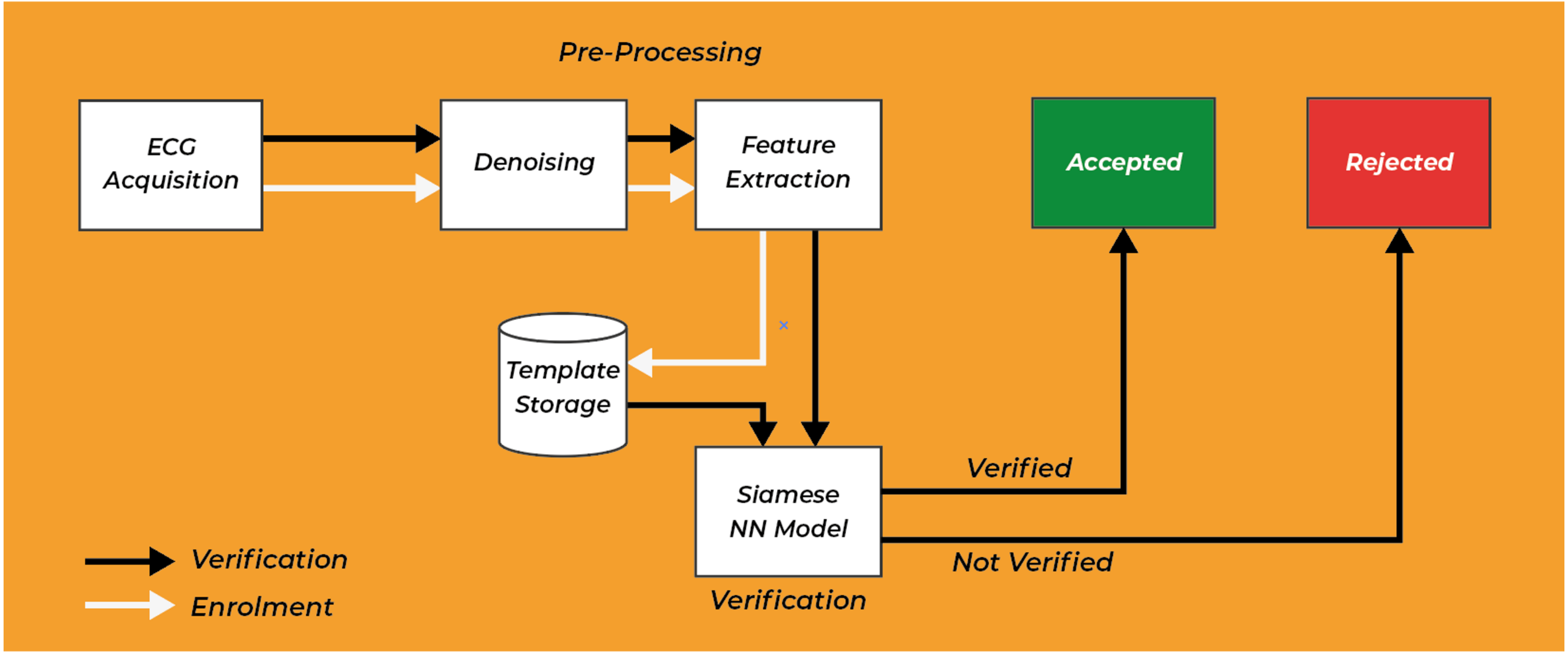
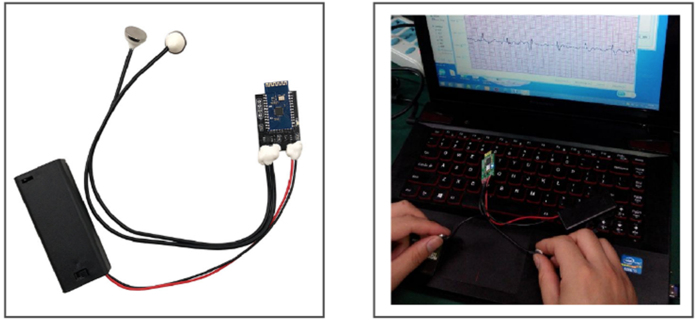


Figure 3: b) System flow structure with verification

Data processing

Data Sources

- MIT-BIH Physionet
- ECG-ID Physionet
- BMD101 Sensor Chip
  - Non-intrusive
  - Subject to hold the two dry metal electrodes with each thumb



a) BMD Development ECG Sensor *a) BMD in action*

Figure 4: a) Shows the BMD device used to extract signals; b) Demonstrate live signal Acquisition

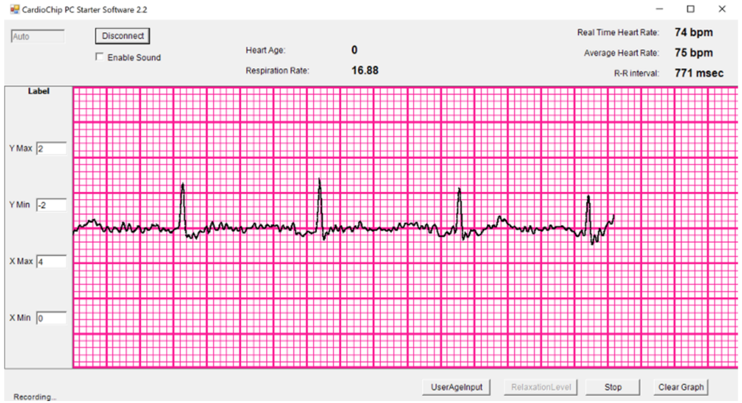


Figure 5: BMD Windows-OS Graphical User Interface

Data processing

ECG Segmentation

- No filters applied
- R-peak segmentation using Christov algorithm [6]
- Resampled to 256

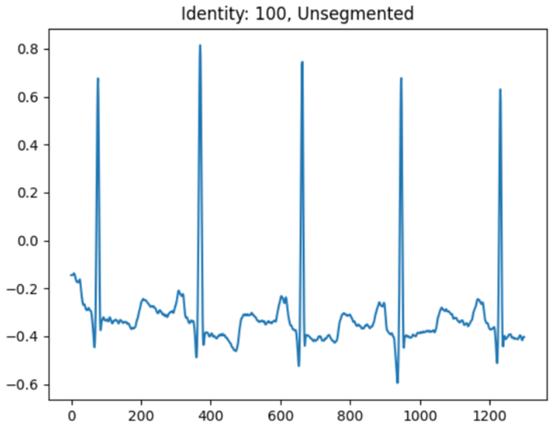


Figure 6: Unsegmented ECG wave section

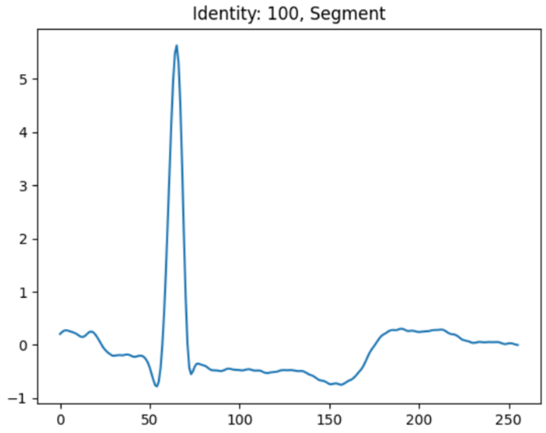


Figure 7: One ECG segment of size 256

Data processing

Data Augmentation

- Gaussian Noise
- Time Shifting
- Pitch Shifting

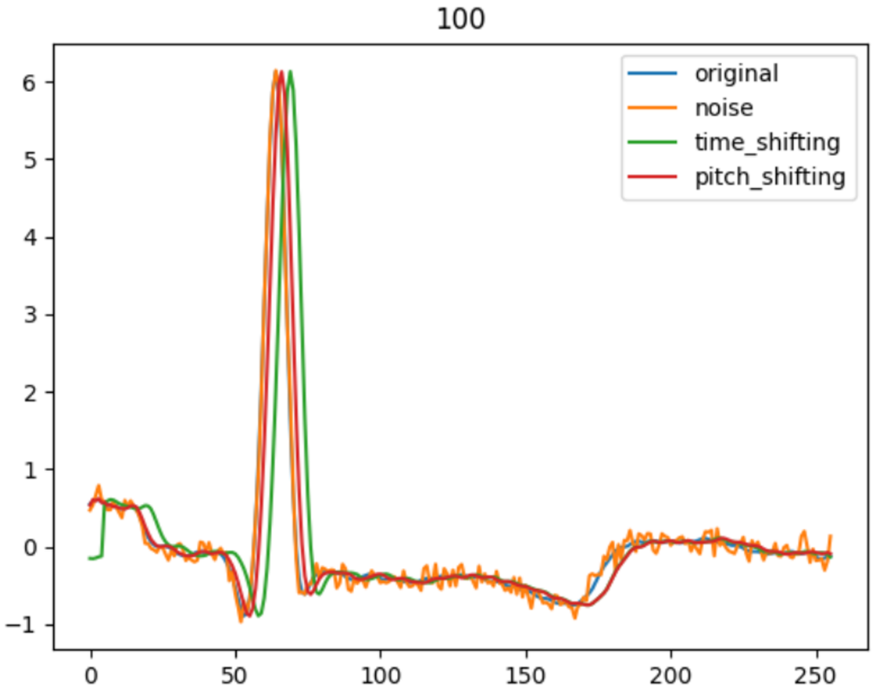


Figure 8: One ECG segment of size 256

Neural Network Architectures

Convolution Neural Network

- 4 block structure inherited from VGG19 [7] architecture
- 256-size 1D signal input

Block

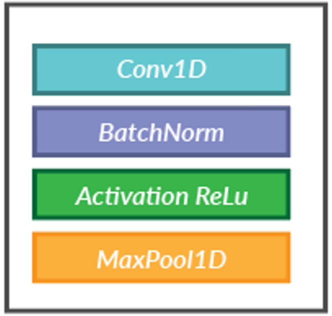


Figure 9: Block structure used in the CNN

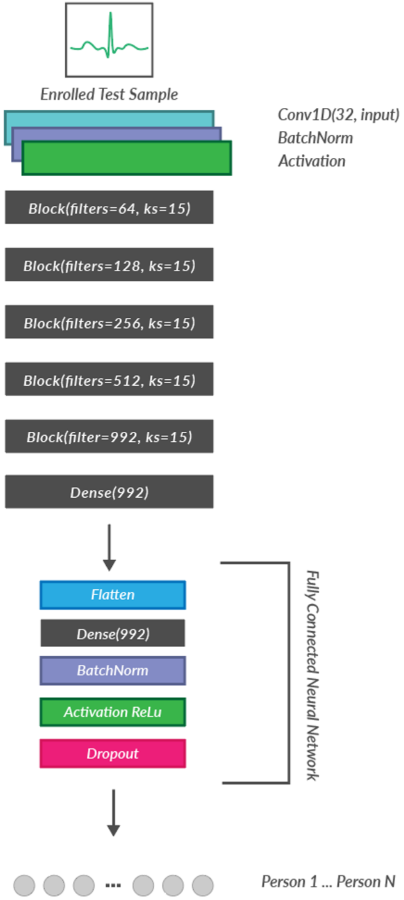


Figure 10: Convolution Neural Network Architecture

Neural Network Architectures

Siamese Neural Network

- 5 block structure also inherited from VGG19 [7] architecture
- 256-size 1D signal pair input
  - Positive and Negative pairs
- Uses Euclidean Distance for similarity score

Block

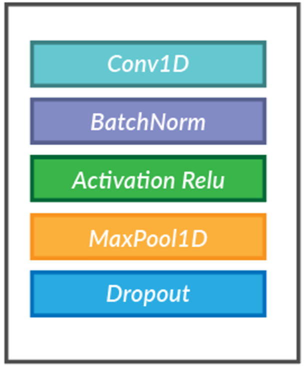


Figure 11: Block structure used in SNN

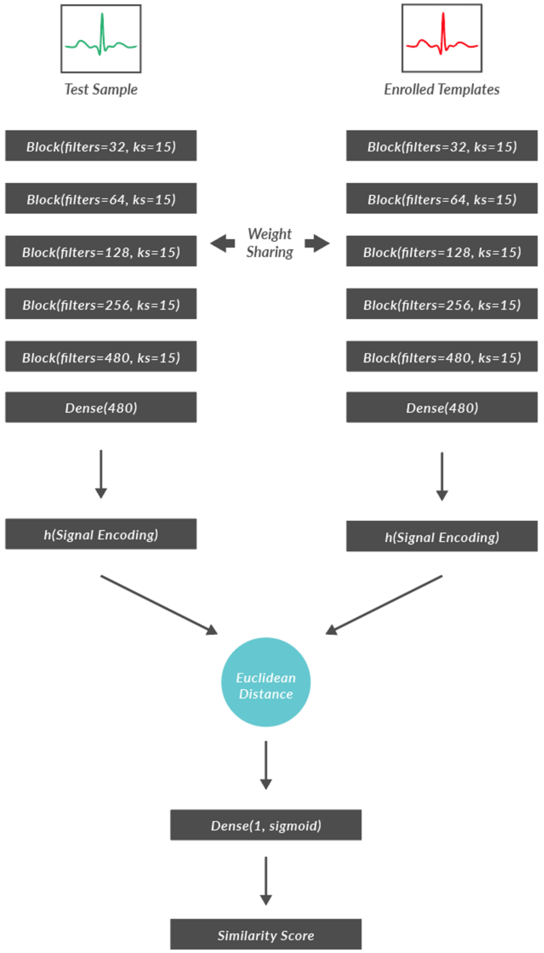


Figure 12: Siamese Neural Network Architecture

Results

- **Data from MIT-BIH and two classes from BMD101 Sensor**
- **ECG-ID dataset failed to produce materialistic results due to limited data.**

	SNN	CNN
Input Type	Segment Pair	1 Segment
Sample size	400 000	397 740
Training time	13 min	54 min
Valid Acc	-	0.9993
Valid Loss	0.4969	0.0029
Threshold, Decision Margin	0.000999	0.99

Figure 10: Convolution Neural Network Architecture

Results

- SNN Training

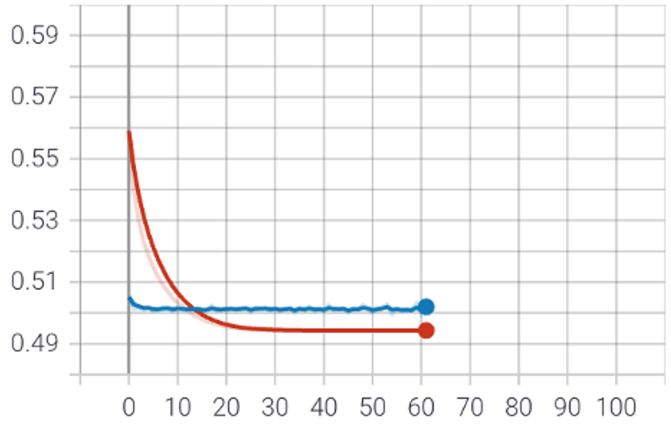


Figure 13: a) Training results for the SNN. In Blue is the Training loss and Red is Validation Loss:

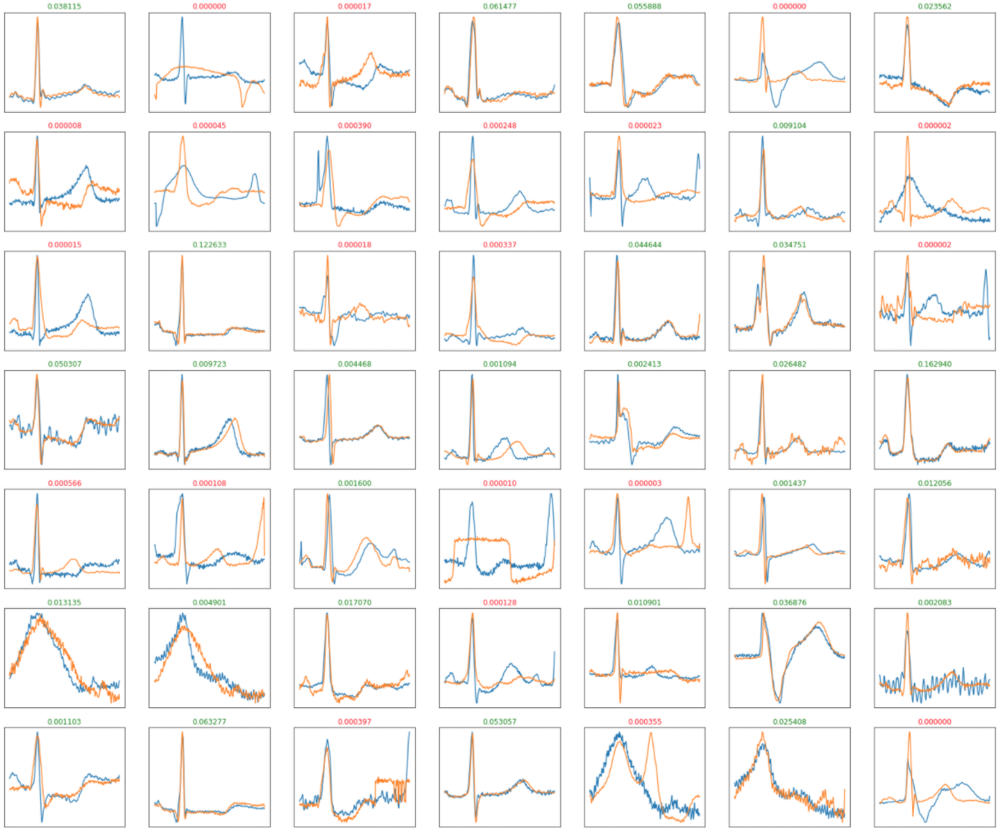


Figure 13: b) Predicted test samples from the SNN model

Results

- CNN Training

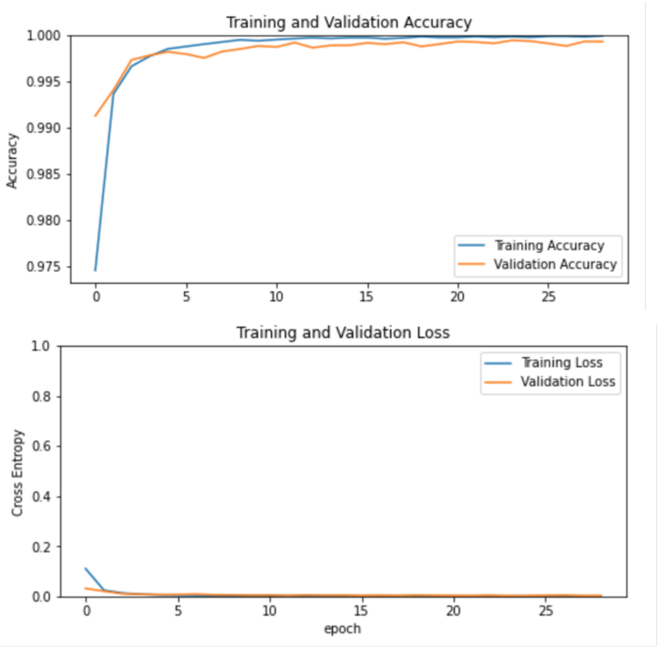


Figure 14: a) Training results for the CNN. In Blue is the Training loss and Red is Validation Loss:

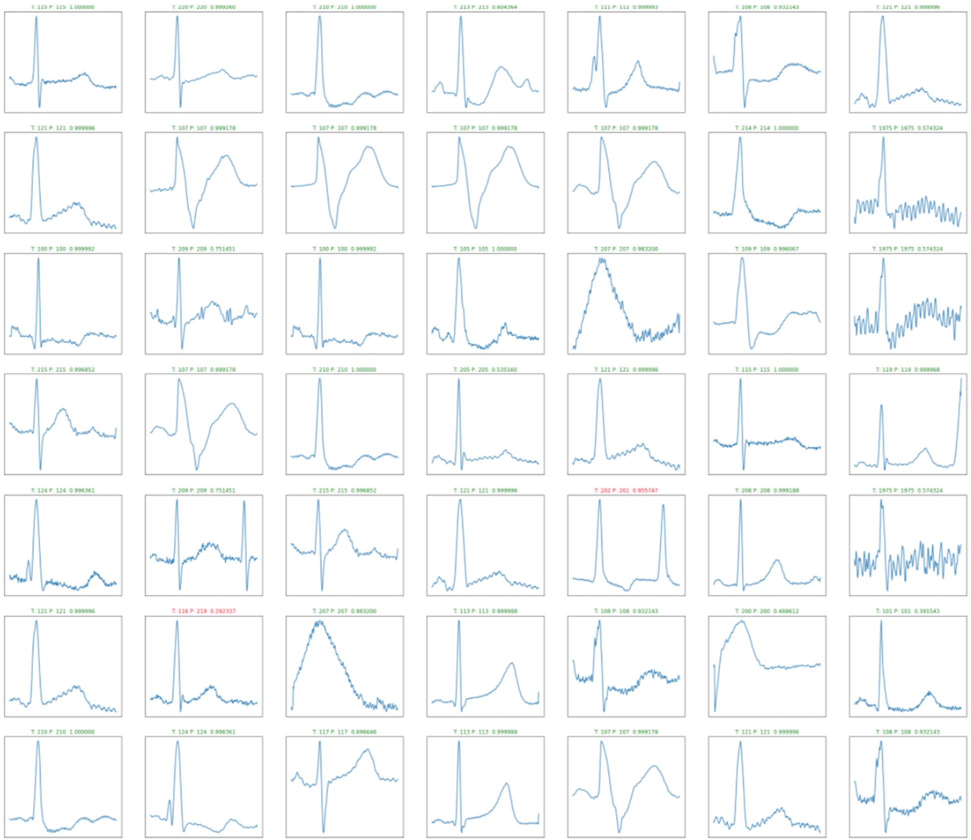


Figure 14: b) Predicted test samples from the CNN model

Challenges

- Closed-set vs Open-set classification
- Binary Classification vs Multi-class classification
- Subjects with cardiac diseases have non-uniform ECGs
- ECGs are susceptible to noise

Conclusions

- Increased efforts for better authentication system and overcoming their limitations.
- 3D face recognition used to counteract 2D limitations, but 3D models are also vulnerable to attacks [8].

References

[1] Cappelli et al (2006, December). Can Fingerprints be reconstructed from ISO Templates?.

[2] Venugopalan et al (2013). Iris spoofing: Reverse engineering the daugman feature encoding scheme.

[3] Mai et al. (2018). On the reconstruction of face images from deep face templates.

[4] Hassan et al. Review of Fiducial and Non-Fiducial Techniques of Feature Extraction in ECG based Biometric Systems

[5] Eduardo et al. ECG-based biometrics using a deep autoencoder for feature learning-an empirical study on transferability.

[6] Christov, I. I. (2004). Real time electrocardiogram QRS detection using combined adaptive threshold.

[7] Simonyan et al (2014). Very deep convolutional networks for large-scale image recognition.

[8] Jia et al (2019). A database for face presentation attack using wax figure faces.

The End

Q & As