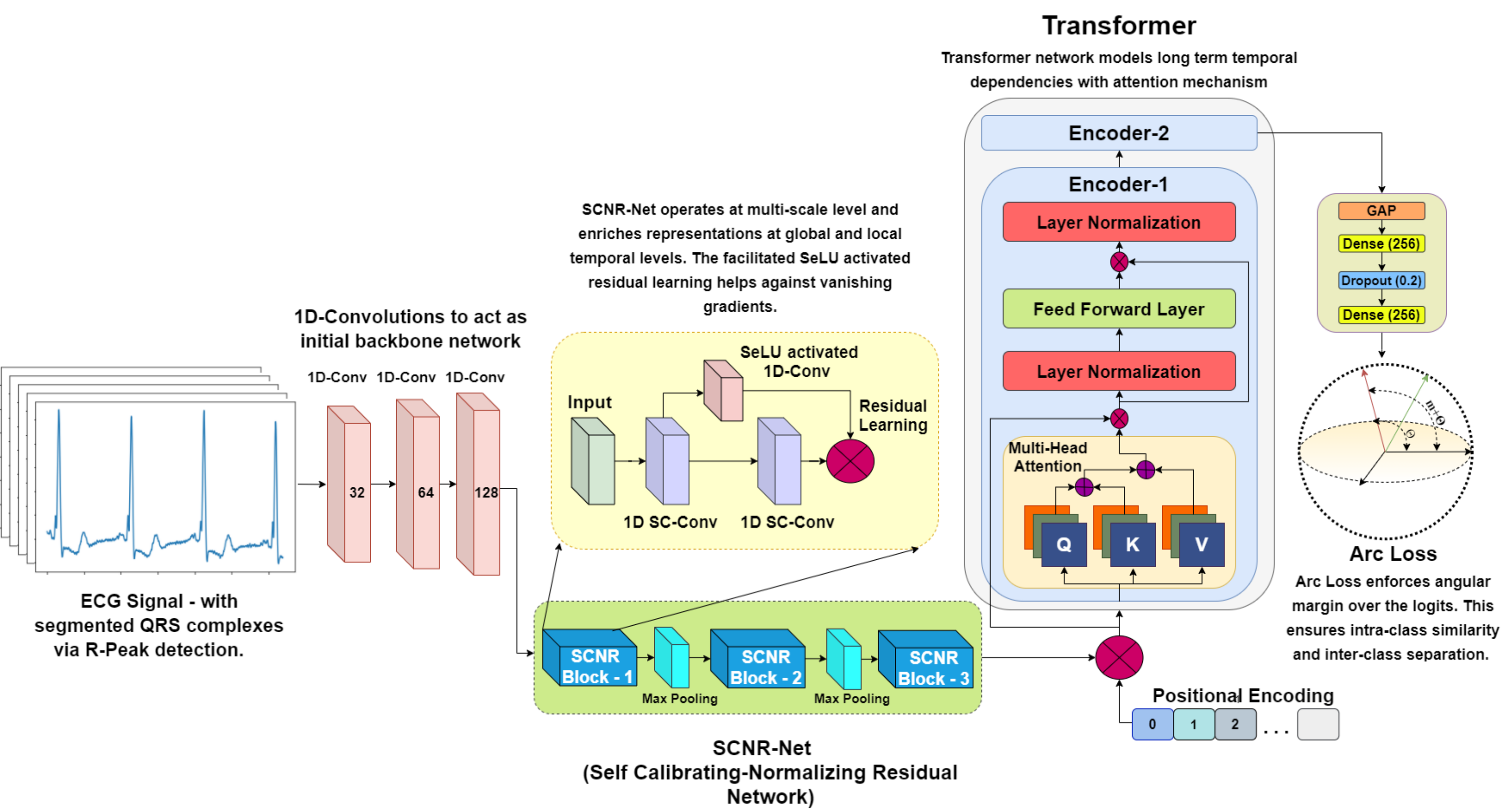
## Datasets

Following are the datasets and their specifications:-

| Sno. | Dataset | Number of Subjects | Health Conditions | Activity | Position | Sampling Frequency | Recording Length |
|---|---|---|---|---|---|---|---|
| 1 | MIT-BIH | 48 | Arrhythmia | Ambulatory Recording | Chest | 360 Hz | 30 Min |
| 2 | PTB | 290 | Mixed | At rest | Chest and Limbs | 200 Hz | 2 Min |
| 3 | ECG-1D | 90 | Healthy | Sitting | Wrist | 500 Hz | 20 Seconds |

## N/W Architecture:



# Experimentation Table - ECG Healthcare Biometrics

## 1. Closed-Set Matching

| Dataset | Model | CRR (%) | EER (%) | FAR (%) | FRR (%) | DI |
|---|---|---|---|---|---|---|
| **State-of-the-art Matching Protocols** | | | | | | |
| ECG-1D | Proposed (SCNET + Transformer) | 95.04 | 1.97 | 1.97 | 1.97 | |
| | [1] | 95.11 | 2.56 | - | - | |
| | [8] | 94.4 | - | - | - | |
| | [6] | 94.4 | - | - | - | |
| MIT-BIH (70-3) | Proposed (SCNET + Transformer) | 99.29 | 0.46 | 0.46 | 0.46 | |
| | [2] | 96.7 | - | - | - | - |
| | [1] | 99.08 | 1.37 | - | - | - |
| PTB-100 - RANDOM + Avg. | Proposed (SCNET + Transformer) | 99.82 | 0.03 | 0.03 | 0.03 | |
| | [3] | 99.49 | - | - | - | |
| | [5] | 99.40 | - | - | - | |
| PTB-290 | Proposed (SCNET + Transformer) | 99.72 | 0.05 | 0.05 | 0.05 | |
| | [4] | 99.66 | | | | |
| | [7] | 95.1 | | | | |
| **Hard Matching Protocols (Baseline) - Transfer Learning (MIT 5050)** | | | | | | |
| ECG-1D | Proposed (SCNET + Transformer + Incremental Learning) | 96.75 | 1.00 | 0.9978 | 1.002 | |
| MIT-BIH (50-50) | Yet | | | | | |
| PTB-(113 Multi-Session ) | Proposed (SCNET + Transformer) [Inter-Session] | 81.15 | 6.33 | 6.31 | 6.34 | -0.07 |

## 2. Ablation Study for Different Modules in the Proposed Network

### a. Vs

| Model | CRR (%) | EER (%) | FAR (%) | FRR (%) | DI |
|---|---|---|---|---|---|
| CONVNET + Bi-LSTM | 92.88 | 3.28 | 3.286 | 3.286 | |
| CONVNET + Transformer | 92.25 | 2.322 | 2.317 | 2.317 | |
| SCNET + Bi-LSTM | 94.59 | 2.42 | 2.416 | 2.424 | |
| Proposed (SCNET + Transformer) | 95.04 | 1.97 | 1.97 | 1.97 | |

### b. Without

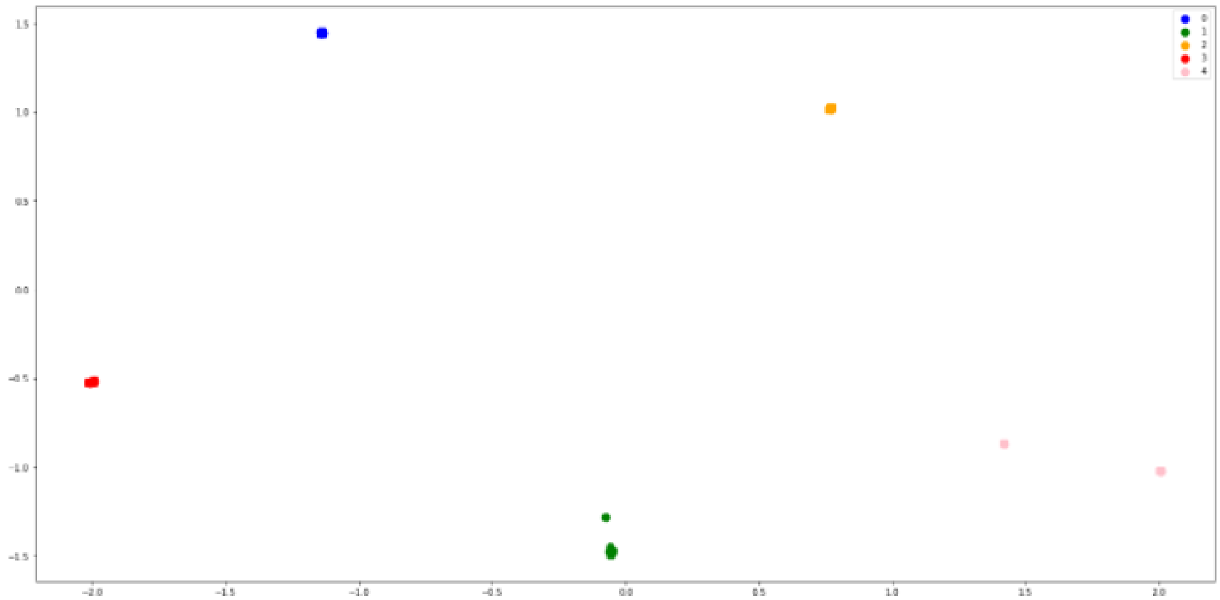
| Model | CRR (%) | EER (%) | FAR (%) | FRR (%) | DI |
|---|---|---|---|---|---|
| w/o Transformer | 93.96 | 2.42 | 2.42 | 2.42 | -1.45 |
| w/o SCNet | 85.49 | 7.18 | 7.18 | 7.18 | -0.95 |

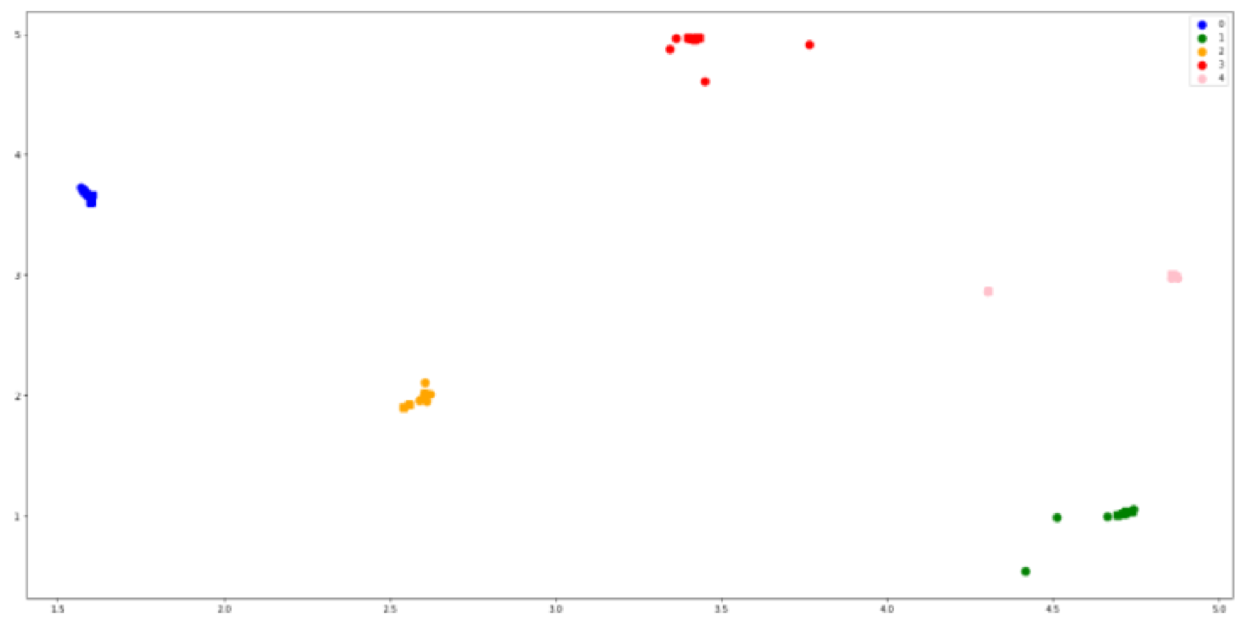
## 3. Open Set Matching

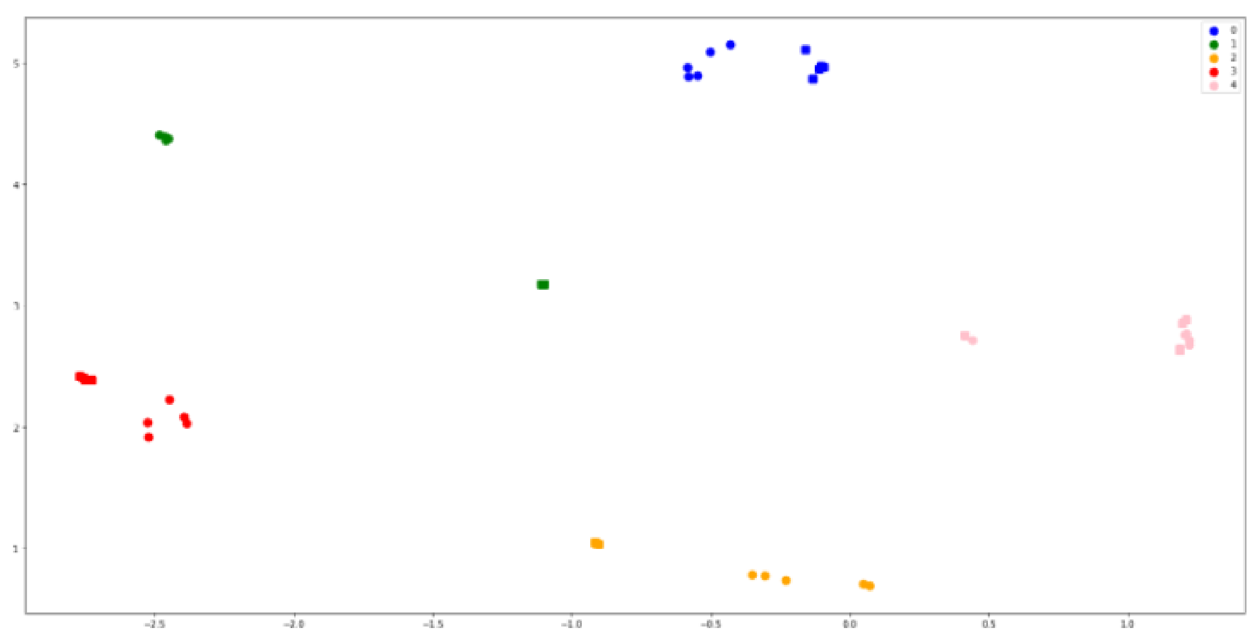
| Dataset | Model | CRR (%) | EER (%) | FAR (%) | FRR (%) | DI |
|---|---|---|---|---|---|---|
| ECG-1D | Proposed (SCNET + Transformer) | 94.59 | 14.08 | 14.08 | 14.08 | -1.17 |
| | Proposed (SCNET + Transformer + Incremental Learning) | 96.39 | 9.77 | 9.75 | 9.77 | -1.50 |
| MIT-BIH | Proposed (SCNET + Transformer) | 94 | 12 | 12 | 12 | |
| MIT-BIH (50-50) | Proposed (SCNET + Transformer) | | | | | |
| PTB-290 | Proposed (SCNET + Transformer) | 89 | | | | |

## 4. Baseline - Cross Database

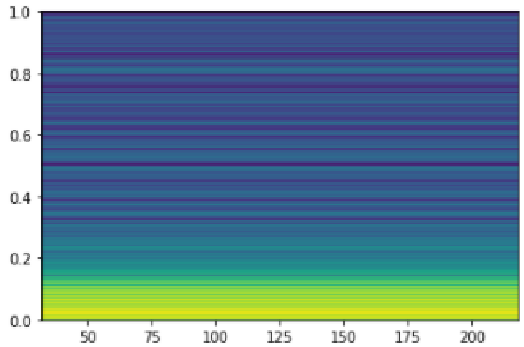
| Training Datasets | Testing Dataset | Model | CRR (%) | EER (%) | FAR (%) | FRR (%) | DI |
|---|---|---|---|---|---|---|---|
| MIT- BIH + PTB-290 | ECG-1D | Proposed (SCNET + Transformer) | 89.68 | 7.02 | 7.02 | 7.12 | -2.05 |
| PTB-290 + ECG-1D (Server Down) | MIT-BIH | Proposed (SCNET + Transformer) | 95 | | | | |
| ECG-1D + MIT-BIH (Server Down) | PTB-113 | Proposed (SCNET + Transformer) | 47 | | | | |


0
1
2
3
4
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0

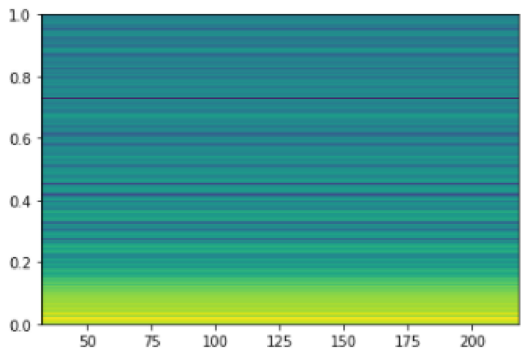

0
1
2
3
4
5
4
3
2
1
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0


0
1
2
3
4
5
4
3
2
1
−2.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0

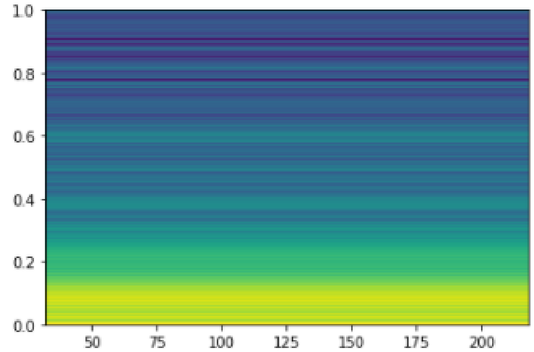
Training Set



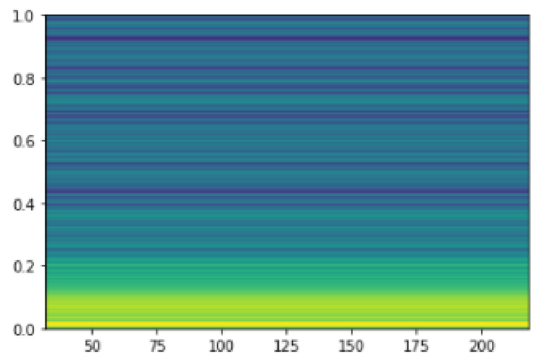

Testing Set

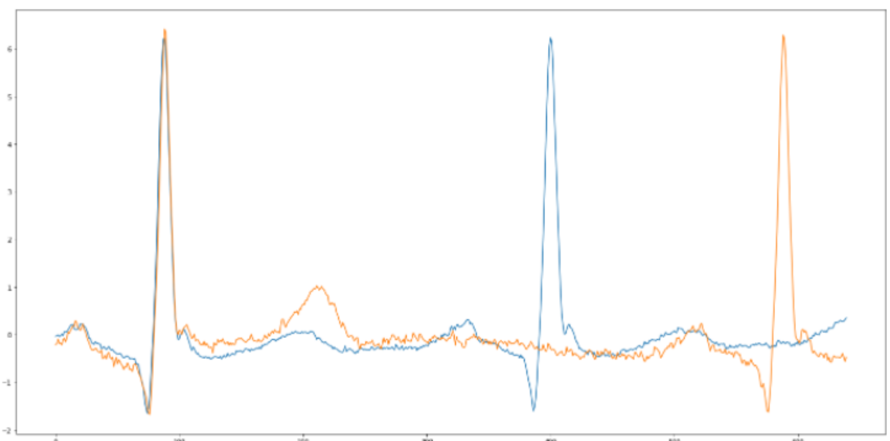


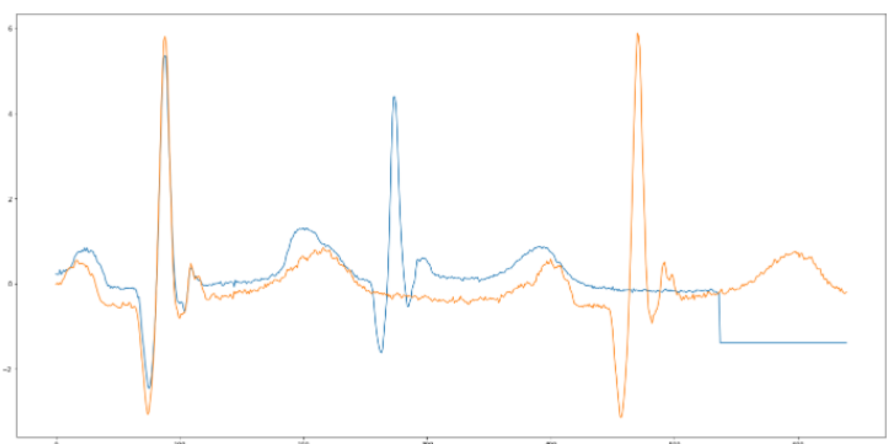

Training Set

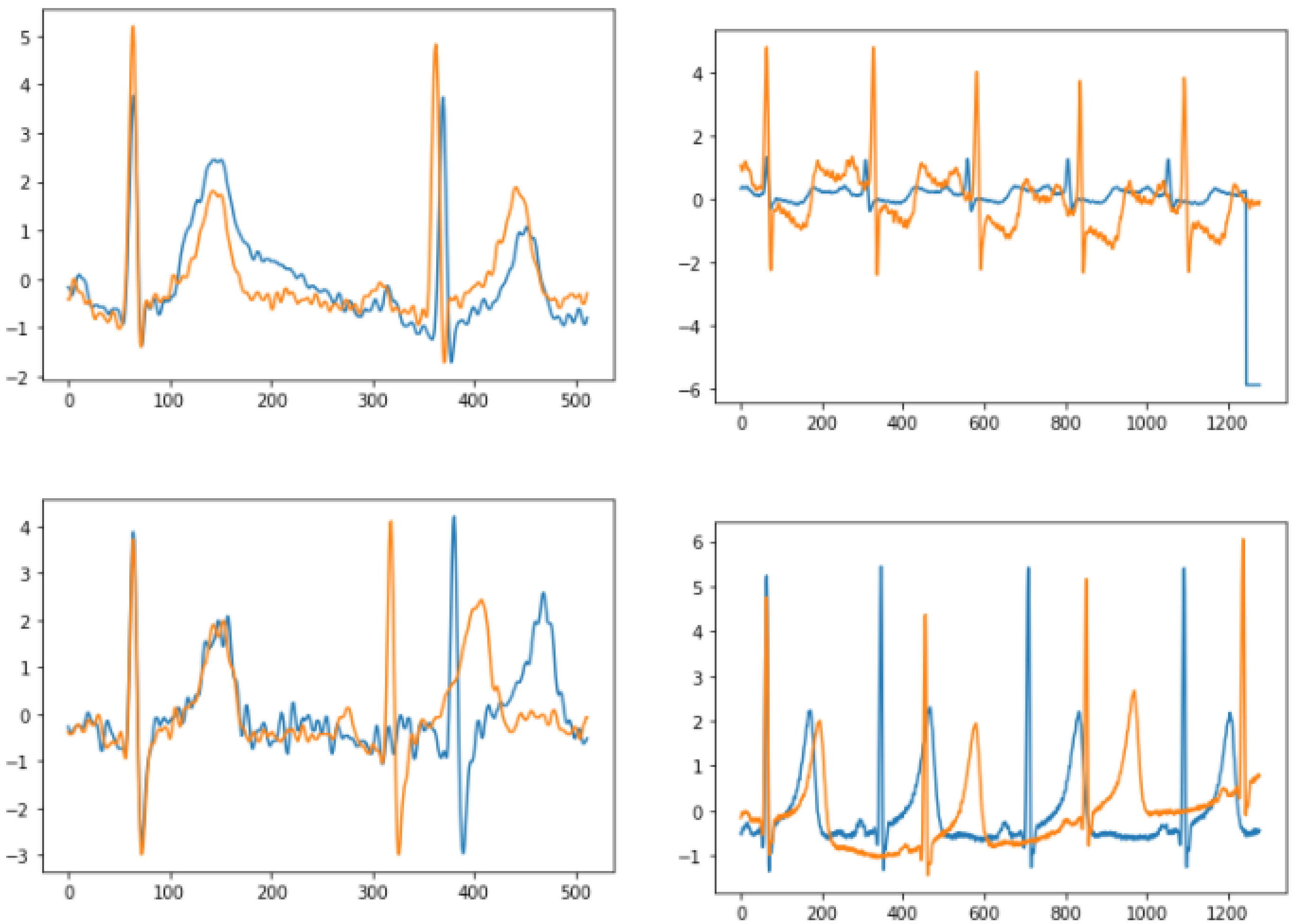


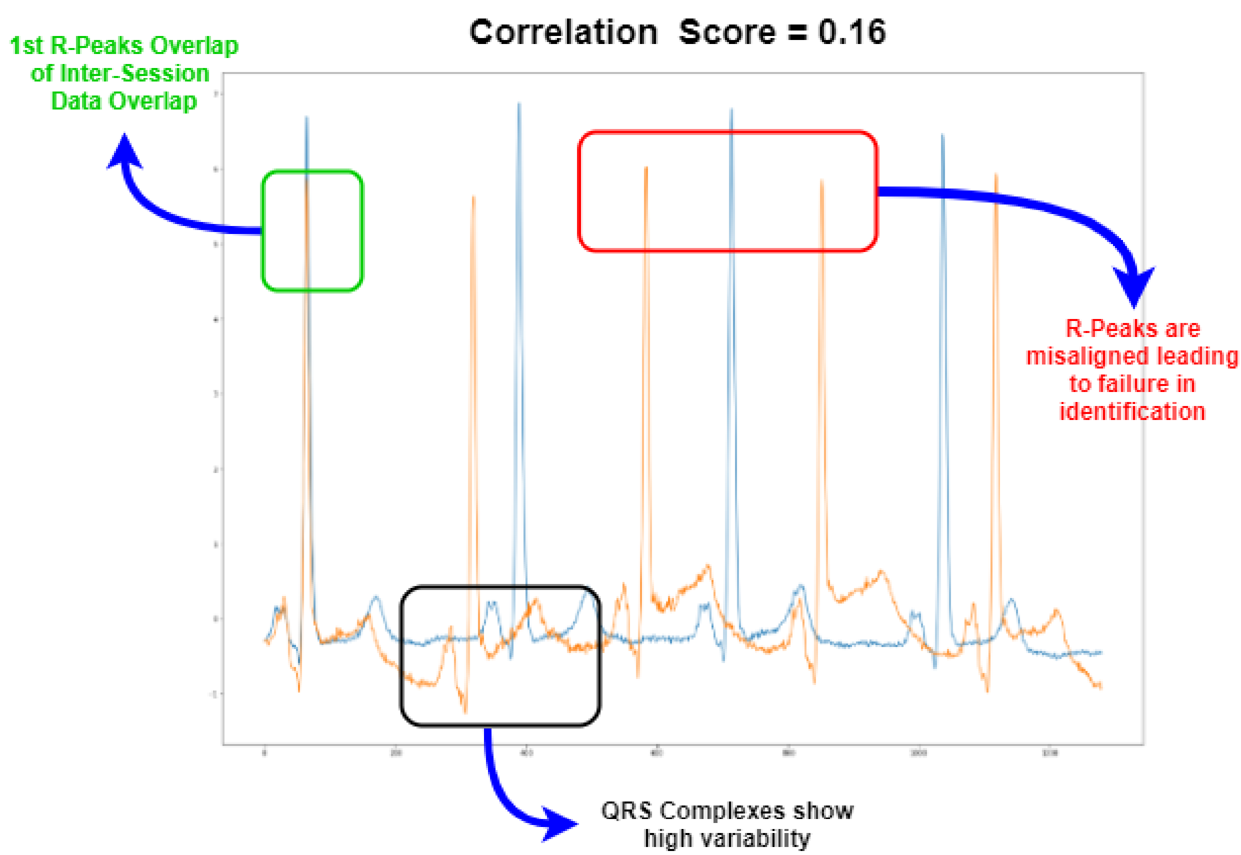

Testing Set

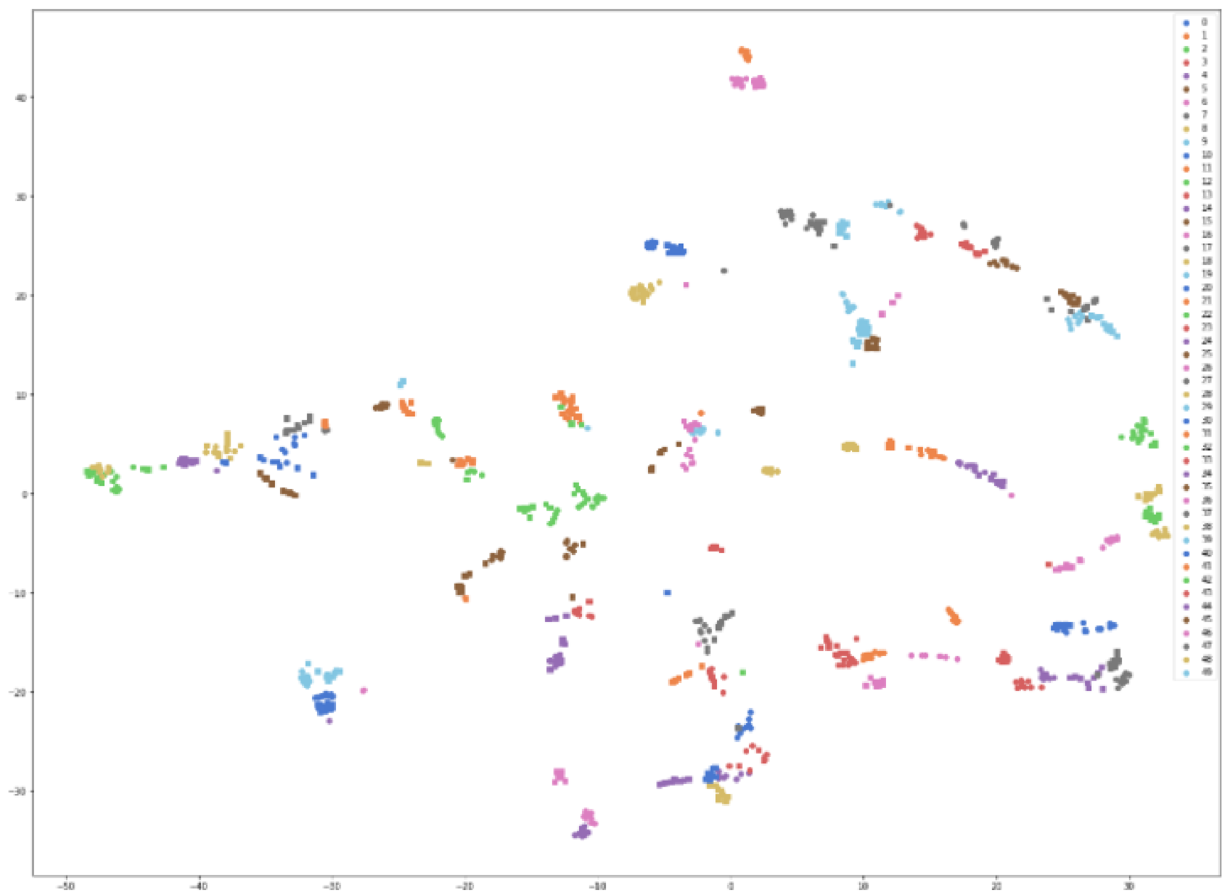


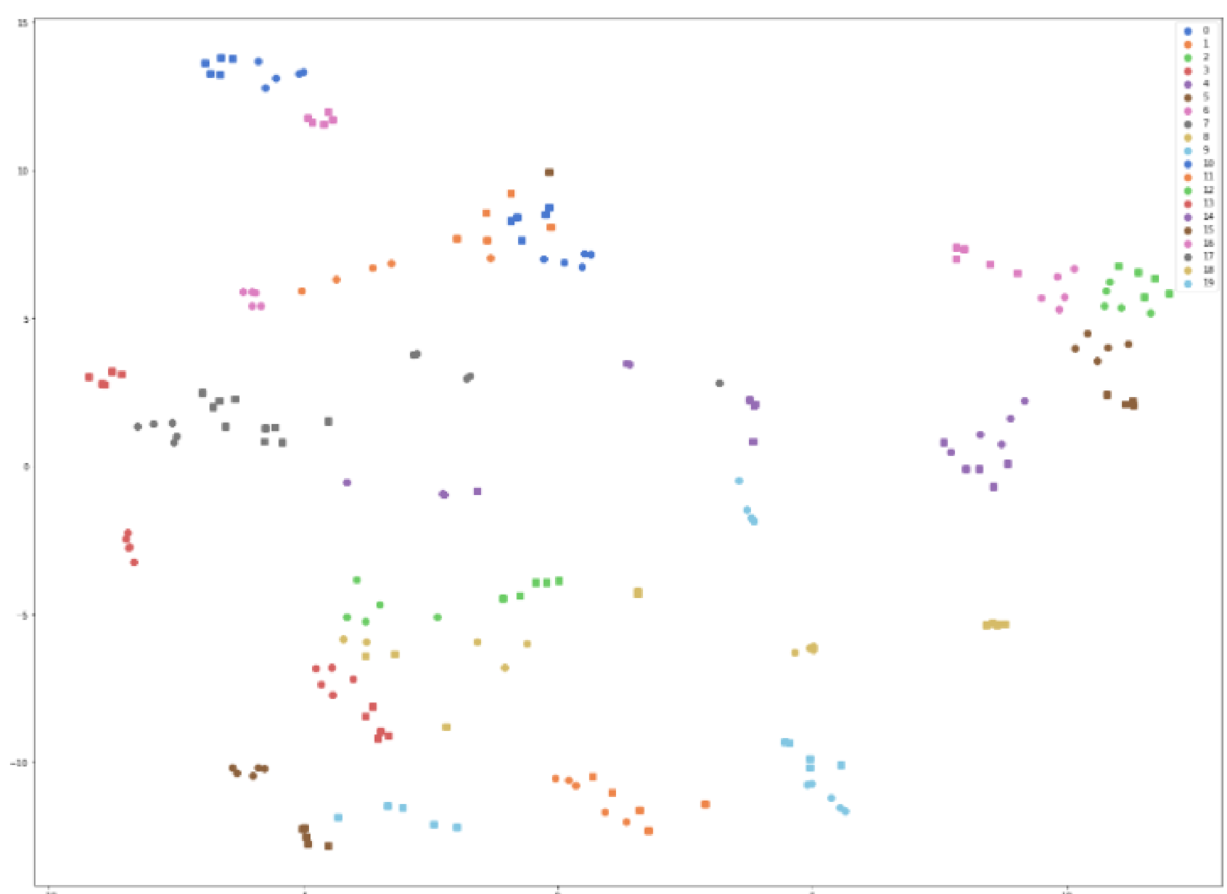




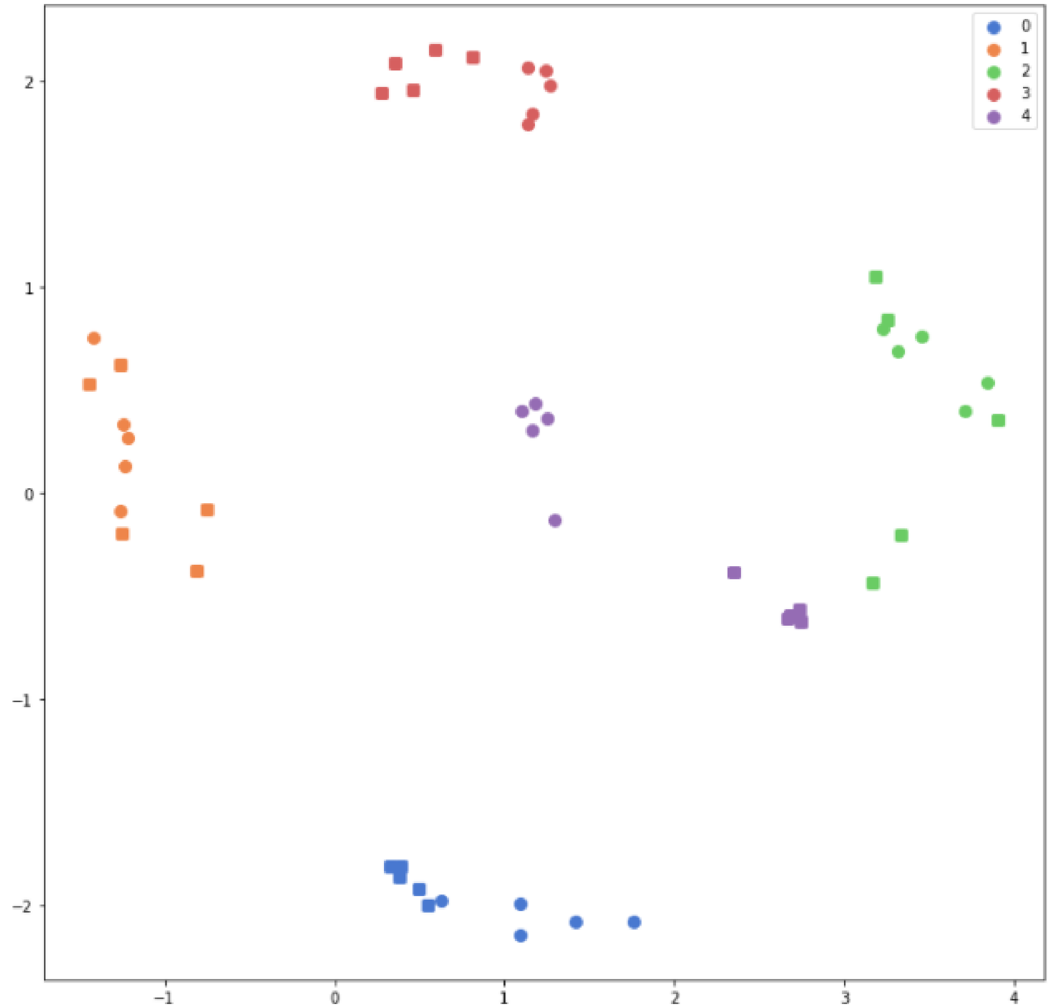

Correlation Score = 0.16
1st R-Peaks Overlap
of Inter-Session
Data Overlap
R-Peaks are
misaligned leading
to failure in
identification
QRS Complexes show
high variability



40
30
20
10
0
−10
−20
−30
−50
−40
−30
−20
−10
0
10
20
30

0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
15
10
5
0
−5
−10
−10
−5
0
5
10




**Plots**

1. ROC Plot for State-of-the-art testing protocols used in MIT(2), PTB(3), ECG-1D(2) ROC curves of the Hard strategies. (Dataset wise Plots)
2. ROC Plot for Ablation Study - vs. (6 Curves in 1)
3. ROC Plot for Open Set Matching (3 Plots each with 2 Curves - Dataset wise plotting).

**References:**

[1] Salloum, R., & Kuo, C. C. J. (2017, March). ECG-based biometrics using recurrent neural networks. In *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 2062-2066). IEEE.

[2] K. A. Sidek, I. Khalil, and H. F. Jelinek, "Ecg biometric with abnormal cardiac conditions in remote monitoring system," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 44, no. 11, pp. 1498–1509,2014.

[3] Labati, R. D., Muñoz, E., Piuri, V., Sassi, R., & Scotti, F. (2019). Deep-ECG: Convolutional neural networks for ECG biometric recognition. *Pattern Recognition Letters*, *126*, 78-85.

[4] J. Wang , M. She , S. Nahavandi , A. Kouzani , Human identification from ECG sig- nals via sparse representation of local segments, IEEE Signal Process. Lett. 20 (2013) 937–940 .

[5] W.-H. Jung , S.-G. Lee , Ecg identification based on non-fiducial feature extrac- tion using window removal method, Appl. Sci. 7 (11) (2017) 1205 .

[6] Di Wang, Yujuan Si, Weiyi Yang, Gong Zhang, and Tong Liu. A novel heart rate robust method for short-term electrocardiogram biometric identification. Applied Sciences, 9(1):201, 2019. 6

[7] Abdeldayem, S. S., & Bourlai, T. (2019). A novel approach for ecg-based human identification using spectral correlation and deep learning. *IEEE Transactions on Biometrics, Behavior, and Identity Science*, *2*(1), 1-14.

[8] Hsu, P. Y., Hsu, P. H., & Liu, H. L. (2020). Fold electrocardiogram into a fingerprint. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops* (pp. 828-829).