TKM College of Engineering, Kollam, Kerala

Efficient Siamese Network Based Approach for Multi-Class ECG Classification in Arrhythmia Detection

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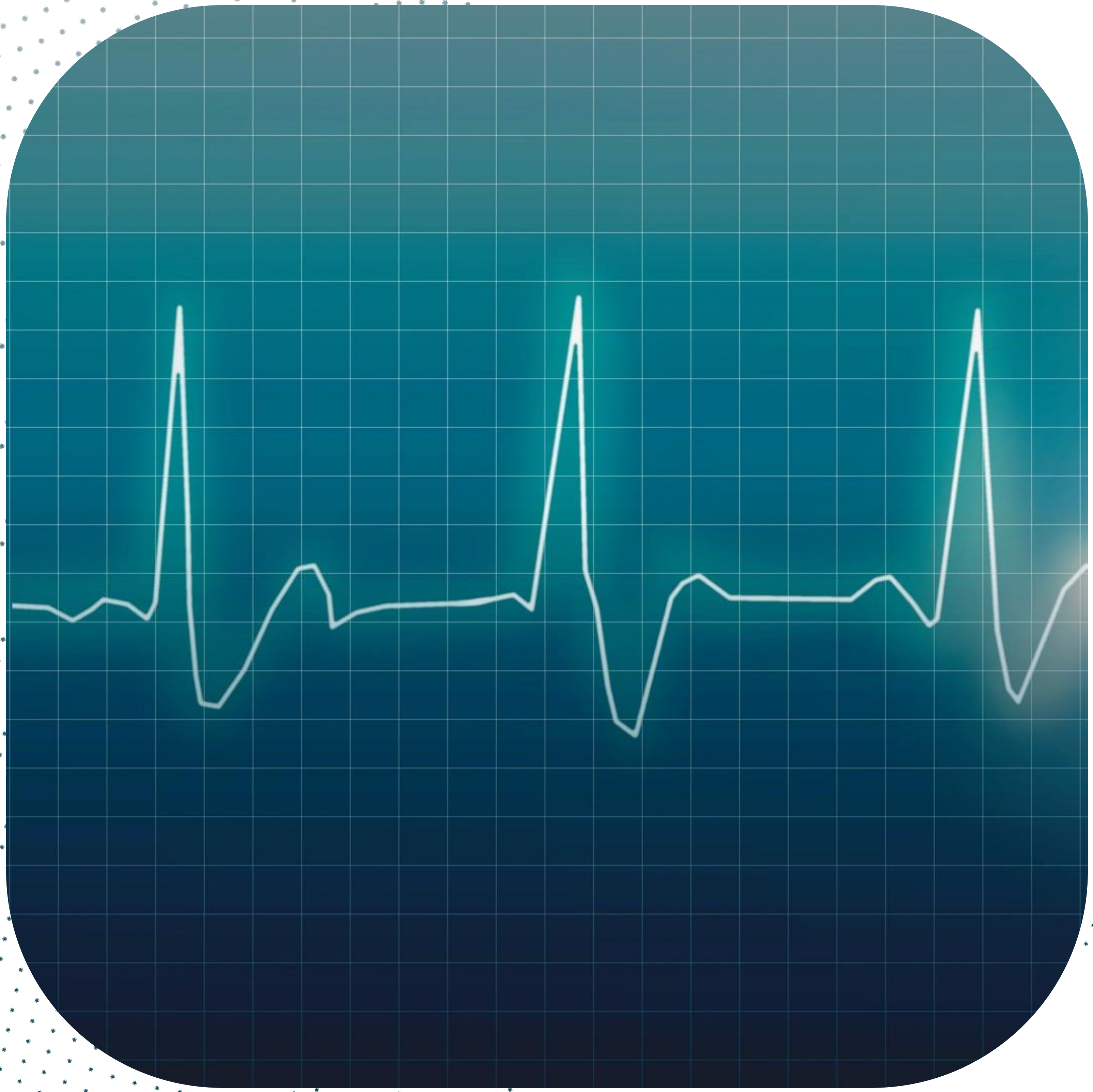
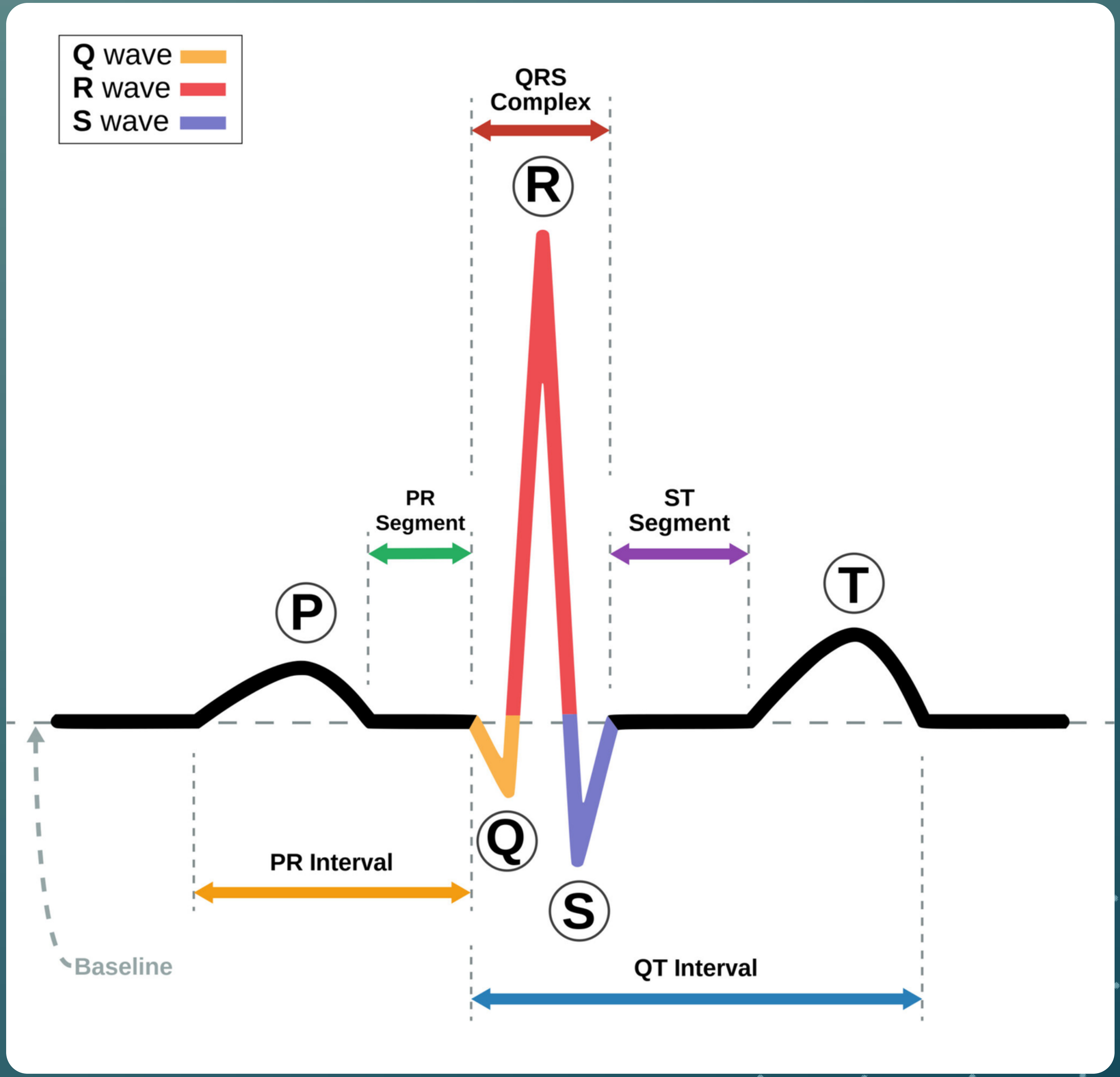


Introduction

- Importance of ECG in diagnosing heart conditions.
- Challenges in traditional ECG classification (e.g., limited data, imbalanced datasets).
- Motivation for exploring Siamese Networks.

Understanding an ECG signal

- **P waves:**
  - It represents atrial depolarisation.
- **PR interval:**
  - It represents the time for electrical activity to move between the atria and the ventricles.
- **QRS complex:**
  - It represents the depolarisation of the ventricles.
- **ST segment:**
  - It represents the time between depolarisation and repolarisation of the ventricles (ventricular contraction).
- **T wave:**
  - It represents ventricular repolarisation.
- **RR interval:**
  - It represents the time between two QRS complexes.
- **QT interval:**
  - It represents the time taken for the ventricles to depolarise and then repolarise.

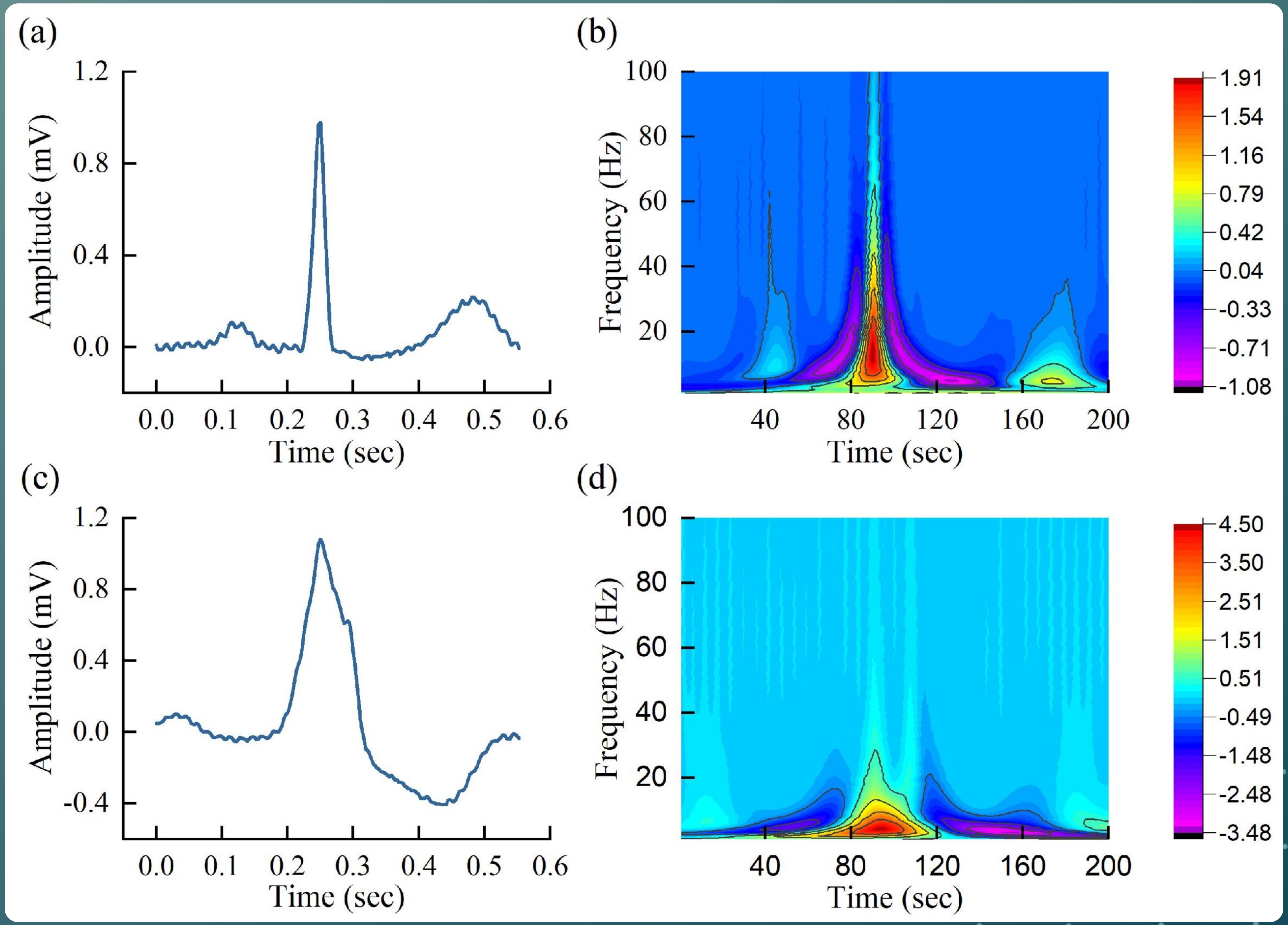


Parts of the Electrocardiogram

Wavelet Transform

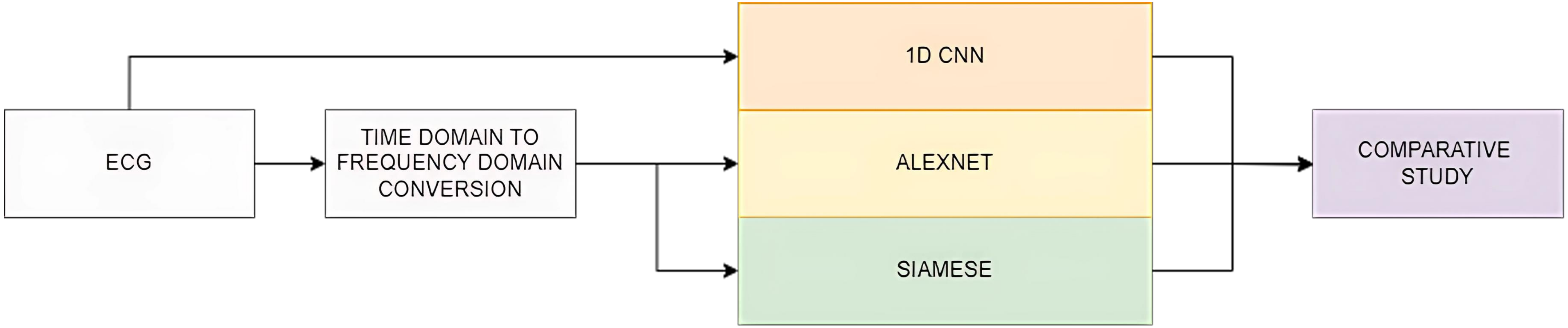
- Wavelet Transform (WT) is a powerful tool for converting ECG signals into the frequency domain
- Advantages of scalogram over spectrogram:
  - Scalograms capture both high-frequency details (sharp peaks) and low-frequency trends (baseline shifts) in the signal.
  - They highlight important features for arrhythmia detection that might be missed in spectrograms.
  - Scalograms are better at handling noise compared to spectrograms.
- Continuous Wavelet Transform (CWT) equation:

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\varphi * \frac{(t-b)}{a}\, dt$$



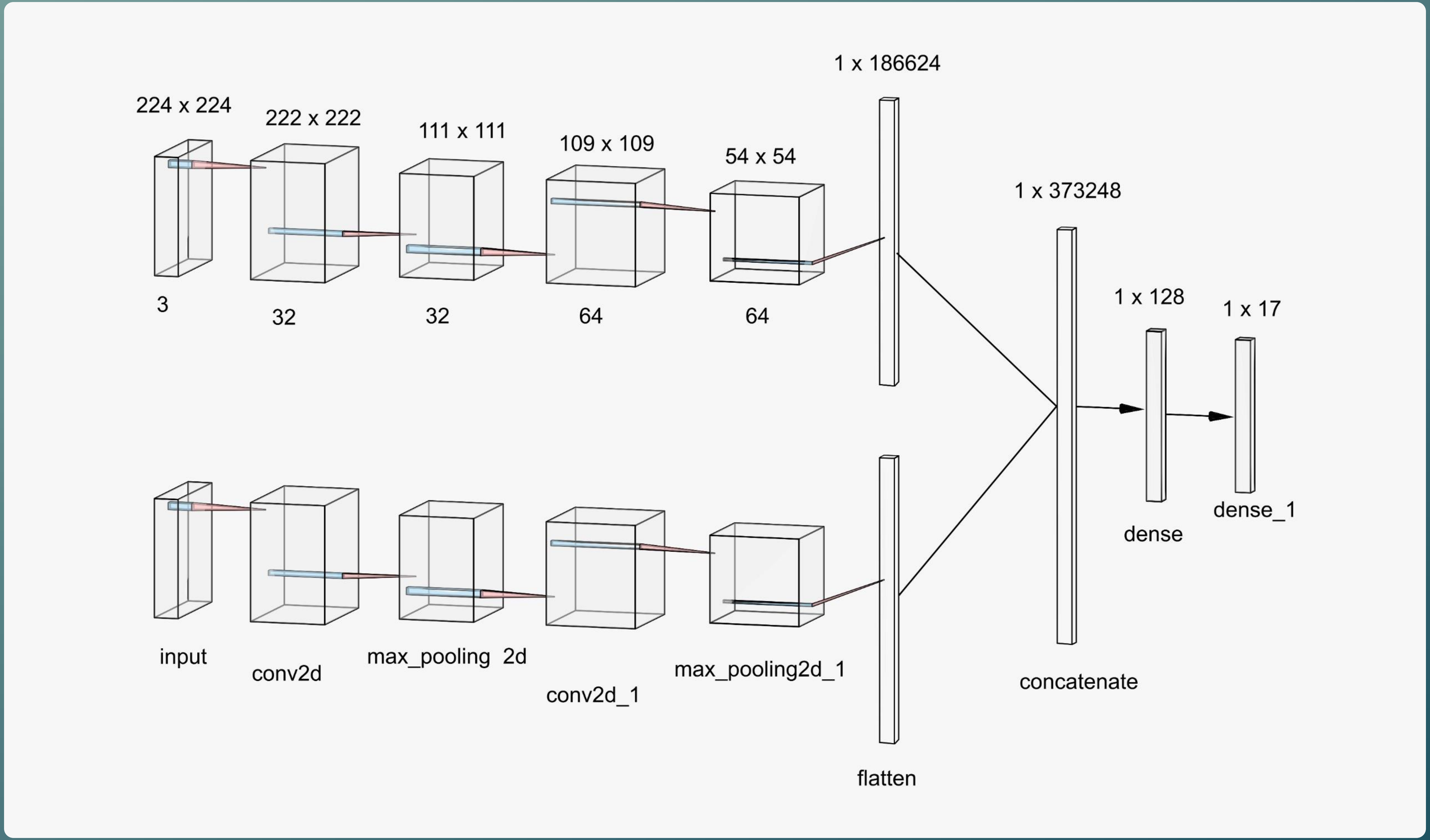
ECG Signal and corresponding Wavelet

Methodology



- **Data Augmentation:** Gaussian noise addition, time scaling, amplitude scaling, time warping, and signal cleaning.
- **Preprocessing:** Wavelet transform to remove noise.
- **Siamese Network:** Twin network structure for feature similarity.

Proposed Architecture

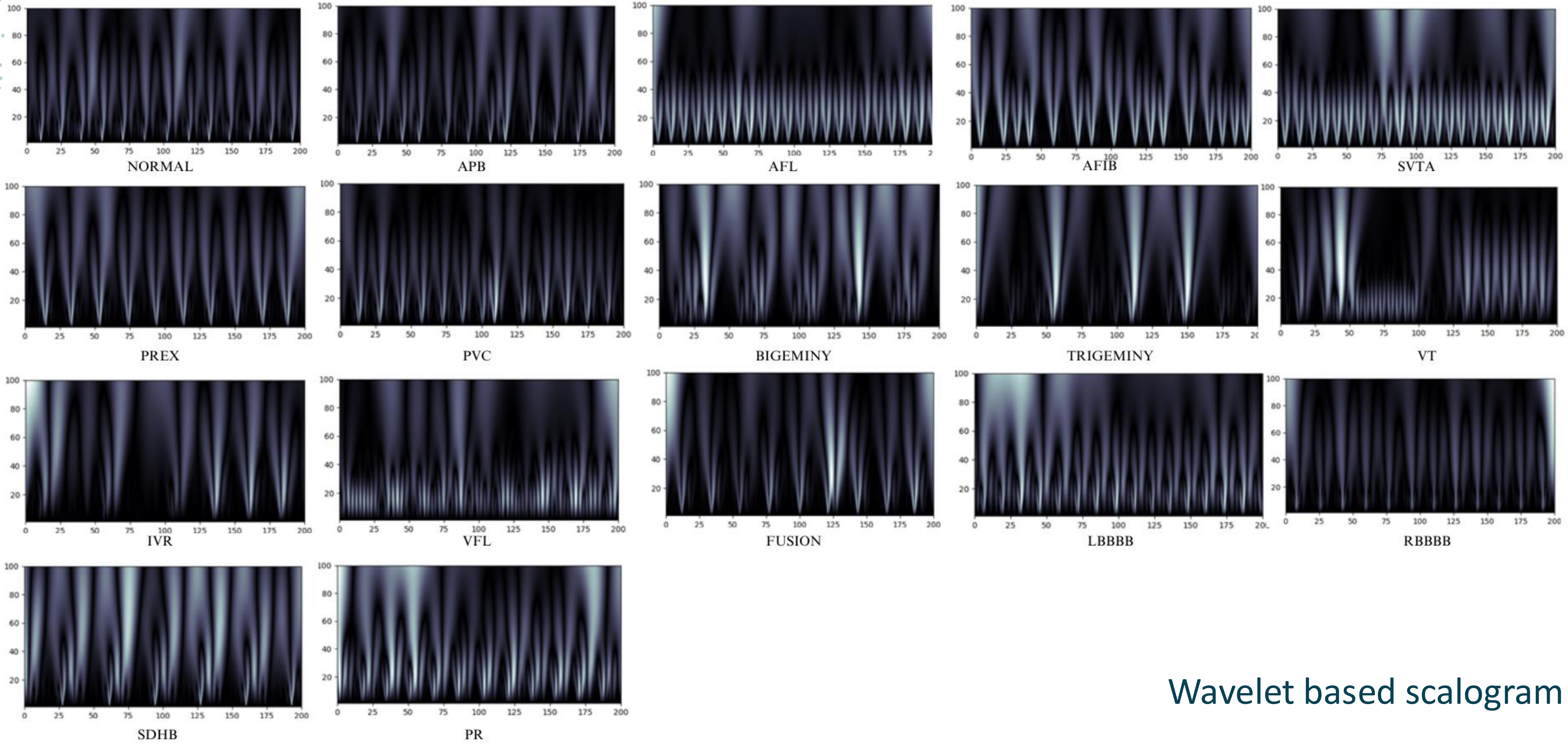


Proposed Siamese Convolutional Neural Network Architecture

Dataset

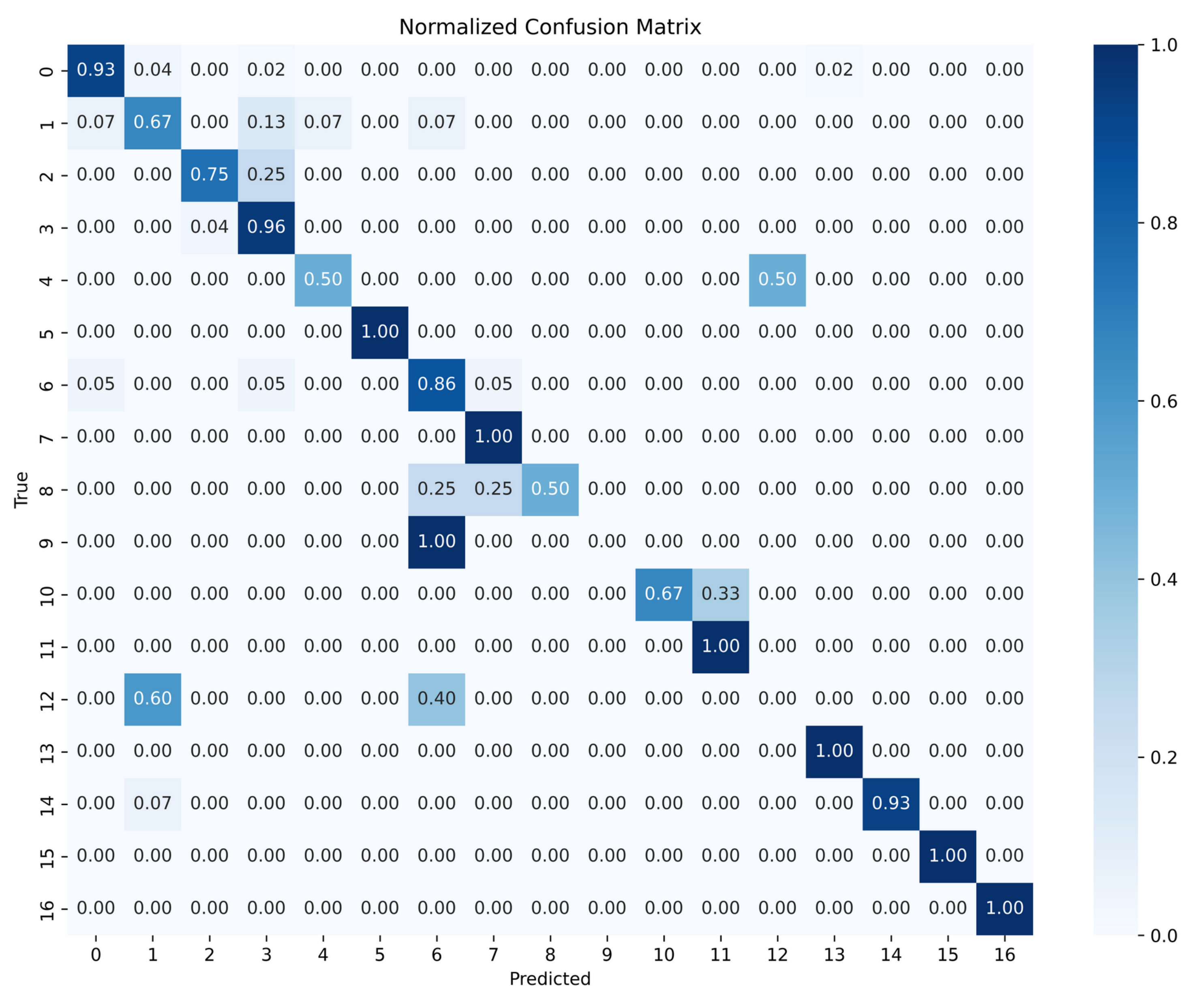
- **Dataset Used:** MIT-BIH Arrhythmia Dataset from the PhysioNet database.
- **Dataset Composition:** Data collected from 47 subjects; MLII signals from 45 patients were used in this study.
- **Classes:** Signals were stratified into 17 classes, including 15 heart disorders, pacemaker rhythm, and normal sinus rhythm.

Arrhythmia Types		Count
Normal sinus rhythm	NSR	283
Atrial bigeminy	APB	66
Atrial flutter	AFL	20
Atrial fibrillation	AFIB	135
Supraventricular tachyarrhythmia	SVTA	13
Pre-excitation	PREX	21
Ventricular bigeminy	PVC	133
Ventricular trigeminy	BIGEMINY	55
Ventricular trigeminy	TRIGEMINY	13
Ventricular tachycardia	VT	10
Idioventricular rhythm	IVR	10
Ventricular flutter	VFL	10
Nodal[A-V junctional] Rhythm	FUSION	11
Left bundle branch block	LBBBB	103
Right bundle branch block	RBBBB	62
Secondary heart block	SDHB	10
Paced rhythm	PR	45

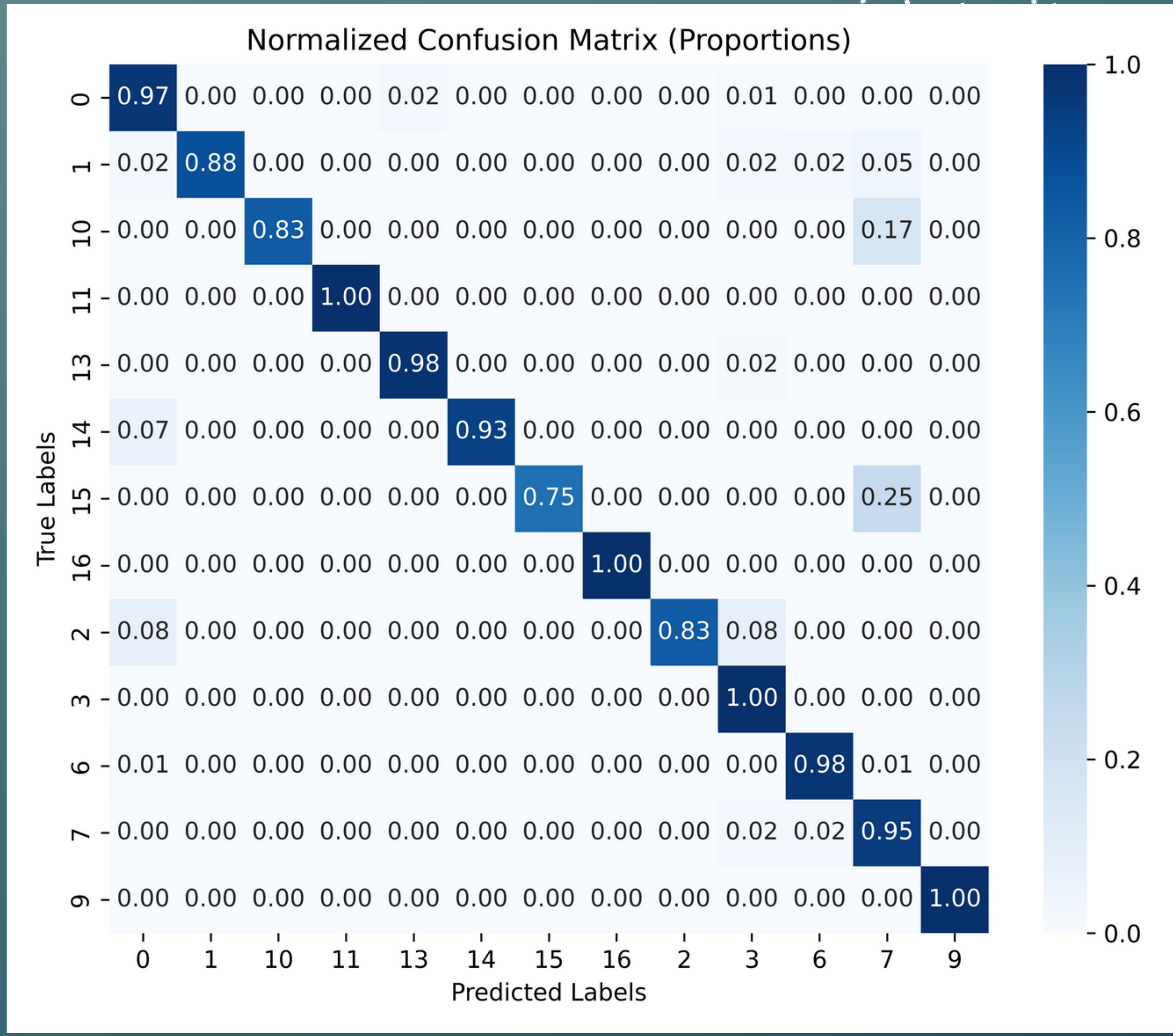


Wavelet based scalogram

Performance Evaluation of Existing Models:

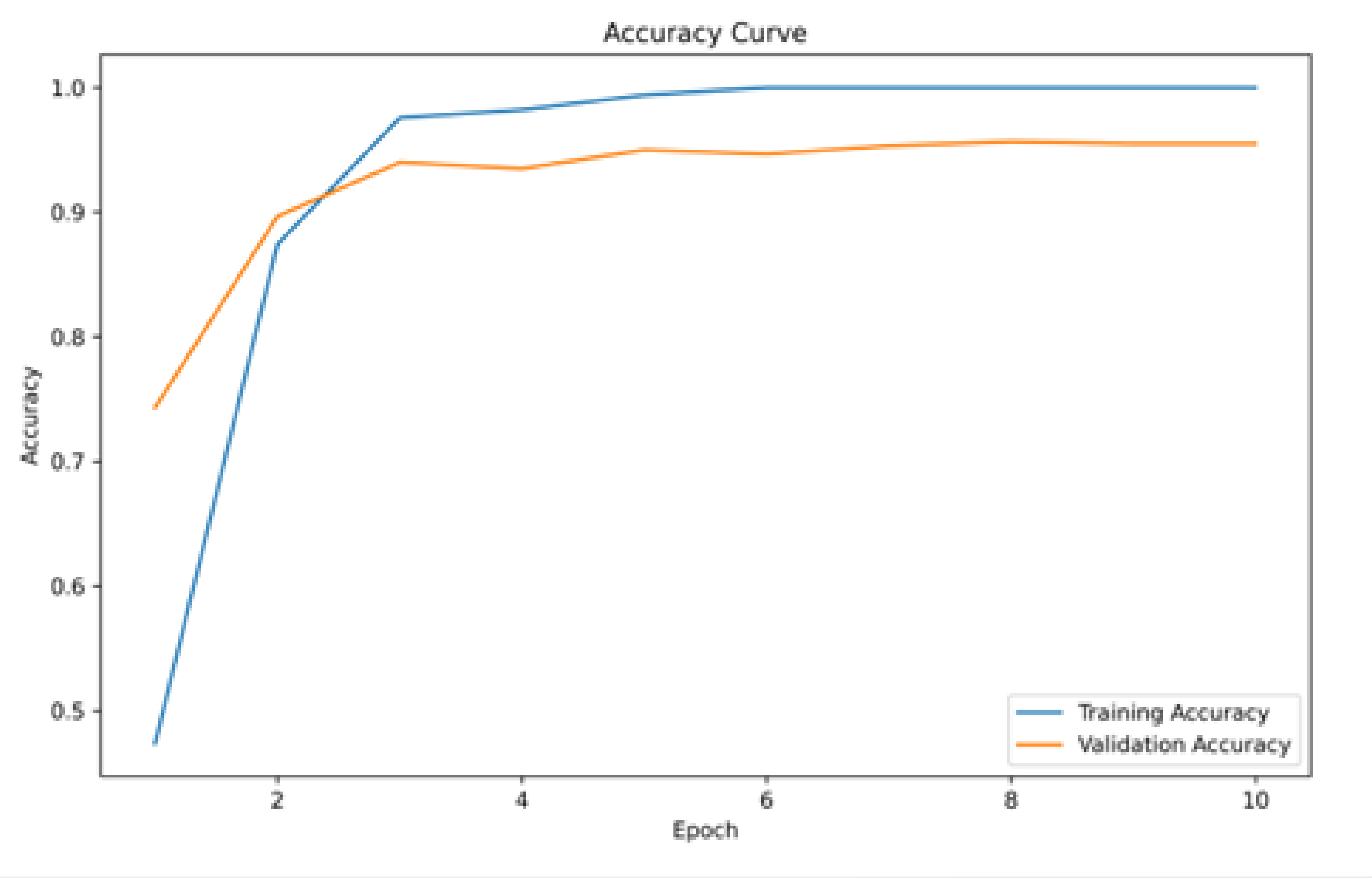


Normalized Confusion Matrix
of **1D CNN Model**

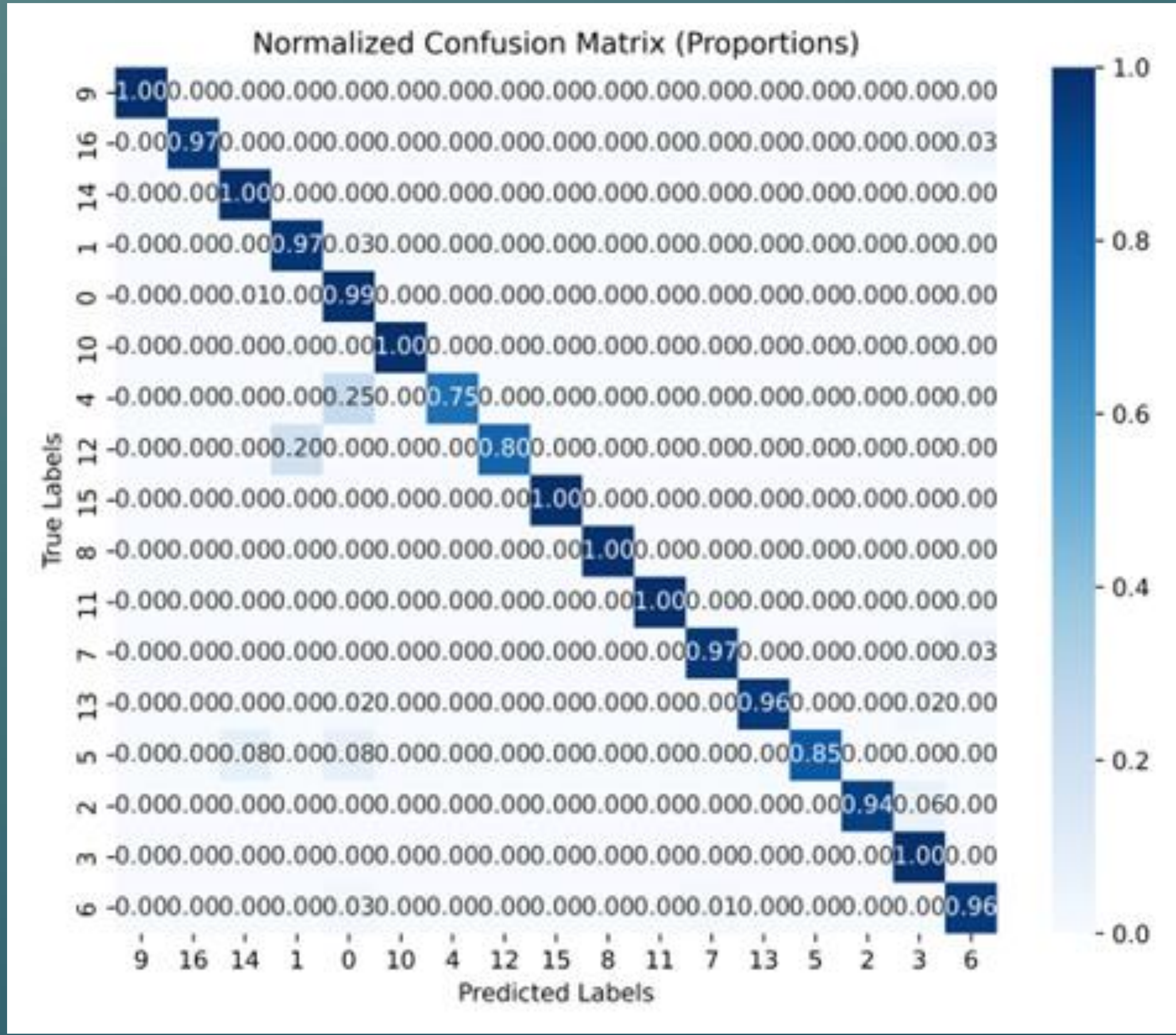


Normalized Confusion Matrix
of **AlexNet Model**

Results

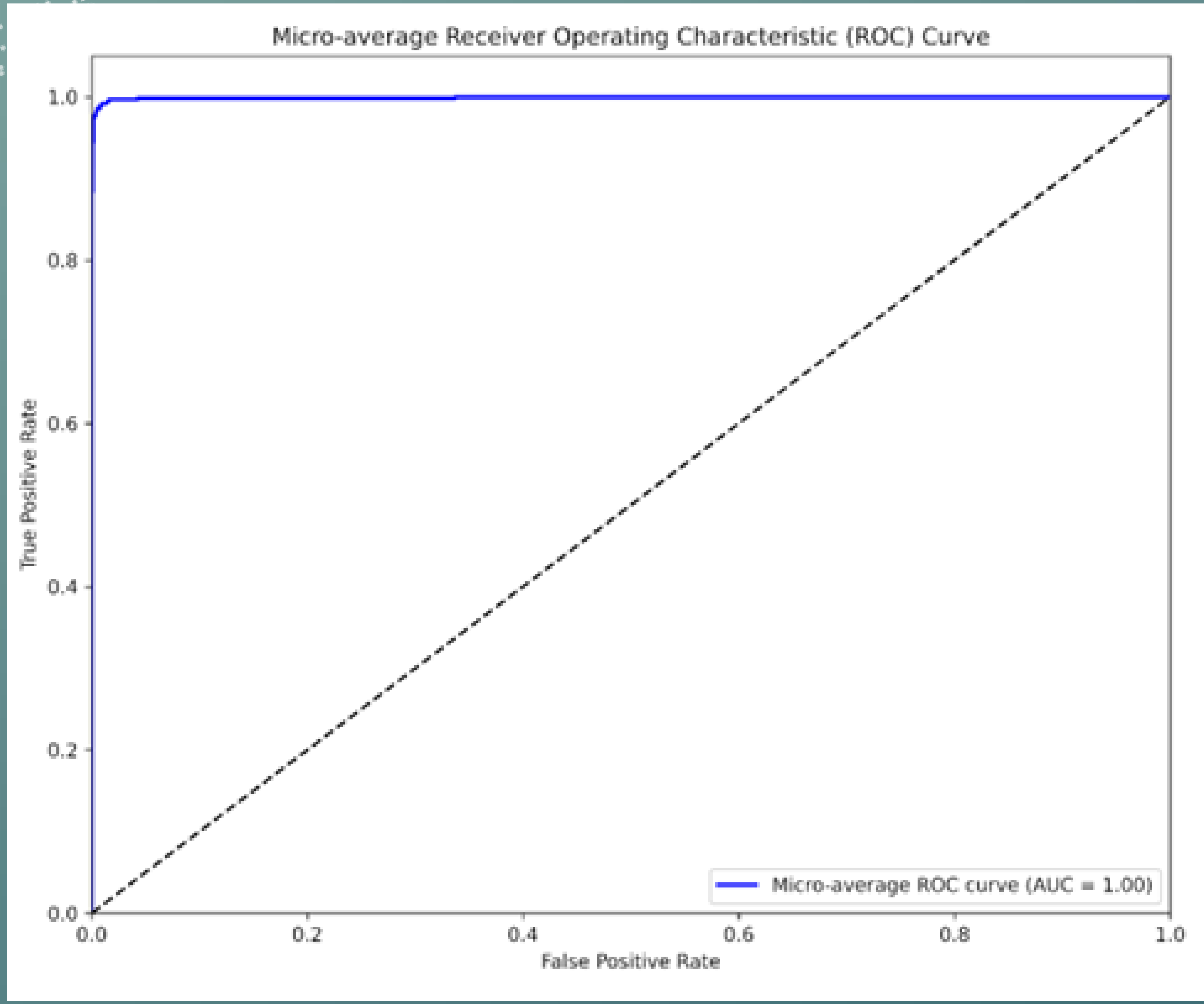


Accuracy Curve
of Proposed Siamese Based
Model

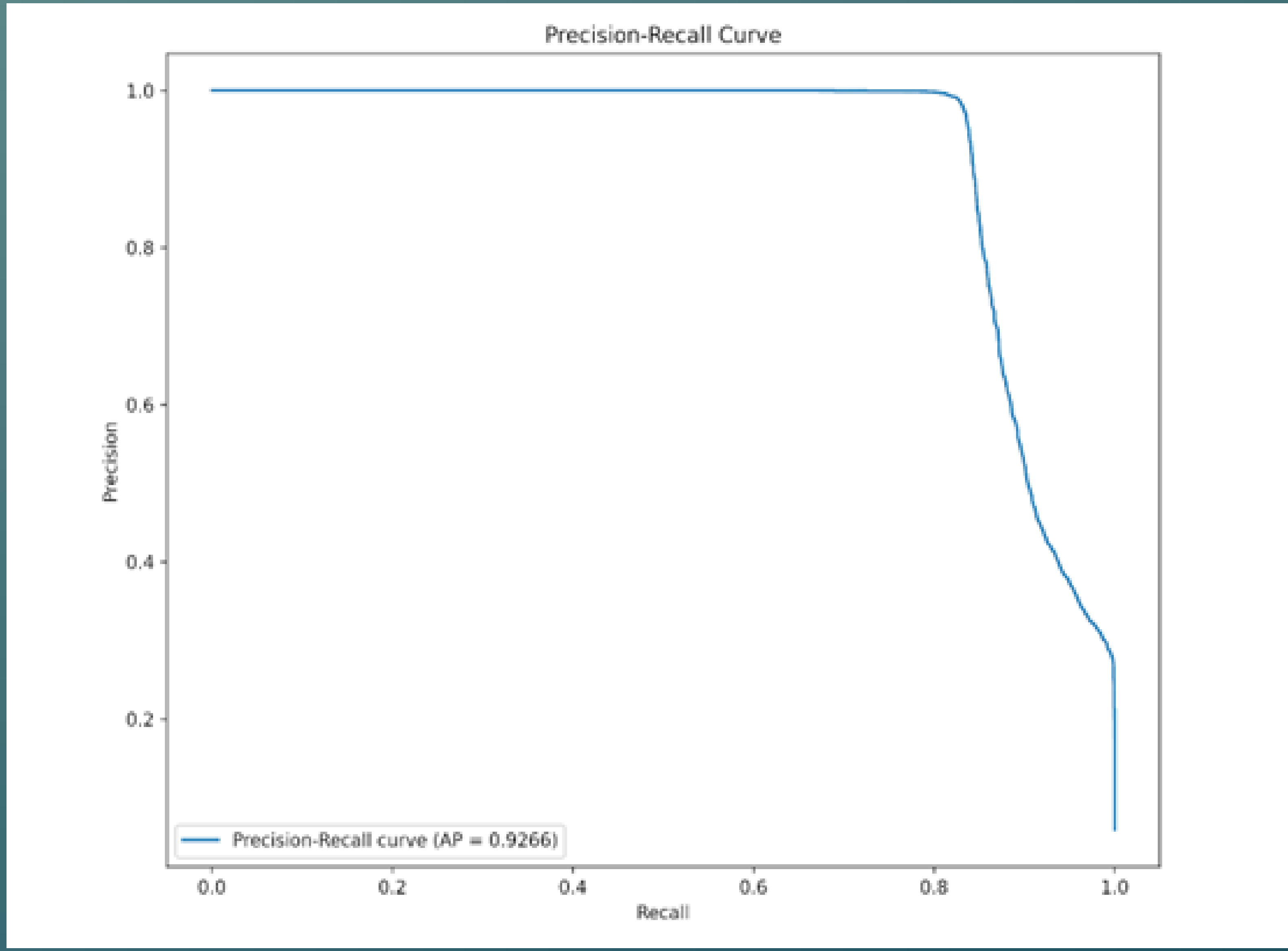


Confusion Matrix
of Proposed Siamese Based Model

Results



ROC Curve
of Proposed Siamese Based
Model



Precision-Recall Curve
of Proposed Siamese Based Model

Results

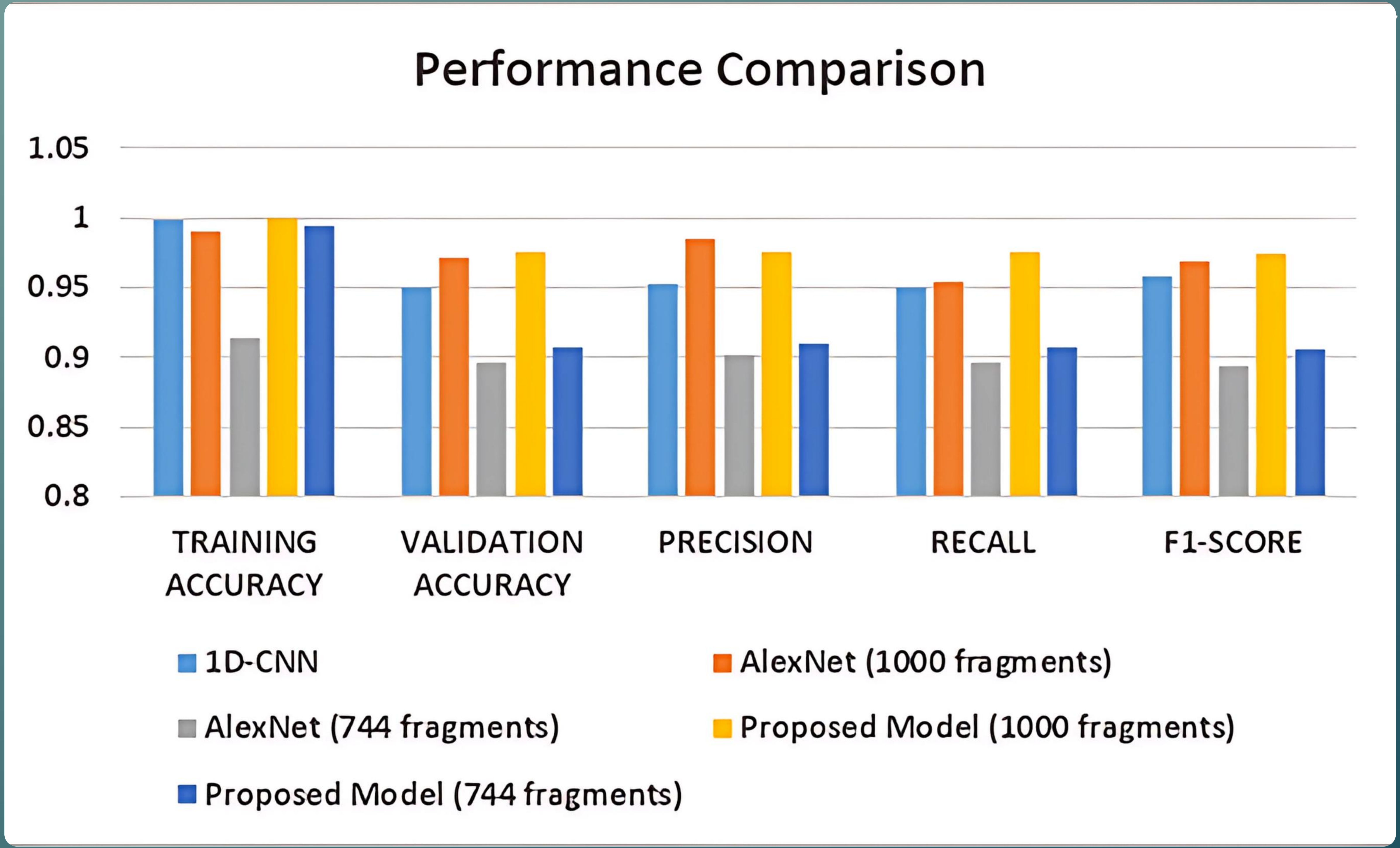
Proposed Siamese Based Model (1000 fragments ECG)

99.99%	Training Accuracy
97.50%	Validation Accuracy
97.56%	Precision
97.50%	Recall
97.46%	F1 Score

Comparison with other models

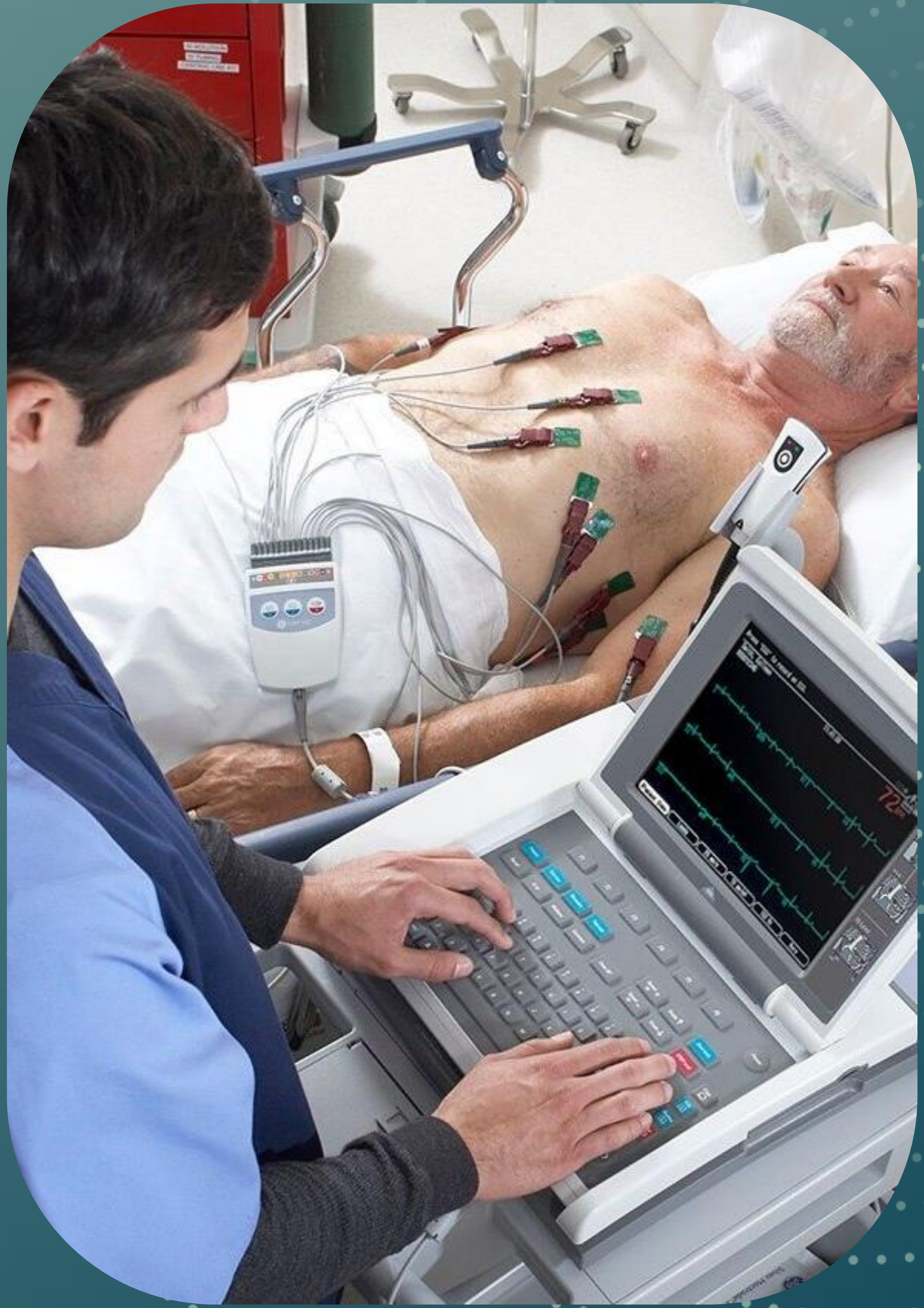
Model	Training Accuracy	Validation Accuracy	Precision	Recall	F1-Score
1D-CNN	0.9987	0.9500	0.9522	0.9500	0.9574
AlexNet (1000 fragments)	0.9898	0.9717	0.9843	0.9540	0.9680
AlexNet (744 fragments)	0.9131	0.8958	0.9020	0.8958	0.8938
Proposed Model (1000 fragments)	0.9999	0.9750	0.9756	0.9750	0.9746
Proposed Model (744 fragments)	0.9944	0.9071	0.9101	0.9071	0.9057

Comparison with other models



Conclusion and Future Work

- Conclusion:
  - Siamese Networks improve ECG classification.
  - Overcome challenges in imbalanced datasets.
- Future directions:
  - Use larger datasets.
  - Real-world deployment and clinical testing.



Thank you!

Do you have any questions?