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Semantic Segmentation for Multi-Class ECG Beat Classification with Emphasis on Aberrant PAC Detection

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Abstract **– This study presents a novel approach to electrocardiogram (ECG) classification using semantic segmentation techniques. Unlike traditional beat-wise classification, our method assigns a class label to each time step, enabling fine-grained waveform interpretation. We propose an algorithm capable of distinguishing between Normal beats, Premature Atrial Contractions (PAC), Premature Ventricular Contractions (PVC), and Aberrancy PAC. Our method segments the raw ECG signal into P, QRS, T waves, and noise components, then identifies and classifies peak locations within QRS regions. The algorithm achieved an overall accuracy of 98.25% and an average sensitivity of 73.31%. These results are significant considering the inclusion of Aberrancy PAC, which is challenging to differentiate from other arrhythmias.**

***Keywords*:** electrocardiogram, premature atrial contraction, deep learning, semantic segmentation

1. Introduction

Electrocardiogram (ECG) beat classification plays a crucial role in the diagnosis and treatment of cardiac diseases. Accurate beat classification is essential for the early detection and prevention of arrhythmias, atrial fibrillation, and other cardiovascular diseases [1]. In particular, automated ECG classification systems enable long-term and continuous monitoring, allowing clinicians to more efficiently evaluate patients' cardiac conditions and develop appropriate treatment plans [2].

The detection of Aberrant Premature Atrial Contractions (Aberrant PACs) in ECG beat classification is a particularly challenging task. Aberrant PACs are characterized by widened QRS complexes due to abnormal ventricular conduction and often resemble the waveform of Premature Ventricular Contractions (PVCs), necessitating accurate diagnosis. Precise identification of these Aberrant PACs is crucial for predicting the risk of atrial fibrillation and other severe arrhythmias [3]. However, existing detection methods have shown limitations in accurately classifying the complex patterns of Aberrant PACs.

Semantic Segmentation is an advanced image processing technique that classifies each pixel of an image into meaningful classes. This method has demonstrated excellent performance in medical image analysis by accurately identifying the location and shape of objects. When applied to ECG analysis, it can capture subtle features of ECG waveforms, enabling accurate classification and exhibiting robustness to noise [4].

In this study, we aim to advance existing ECG beat classification using the semantic segmentation technique. Our goal is to develop an algorithm that can accurately identify and classify not only common beats such as Normal, PVC (Premature Ventricular Contraction), and PAC (Premature Atrial Contraction), but also Aberrant PACs, which are known to be particularly challenging to classify. Through this approach, we expect to significantly improve the accuracy and reliability of ECG analysis, enabling more precise diagnosis and monitoring of cardiac diseases in clinical settings.

2. Methods

2.1. Dataset

In this study, we developed a semantic segmentation model using a dataset of 15,000 one-minute ECG recordings from 300,000 individuals, collected via mobiCARE between October 2020 and December 2024. All data were anonymized to protect patient privacy. Expert medical professionals provided annotations for the ECG recordings, ensuring high-quality labels for model training. The waveform labels consist of eight distinct categories: Baseline, P, QRS[Normal], QRS[PVC(V)], QRS[PAC(S)], QRS[Aberrant PAC], T, and Noise. These labels comprehensively cover the key components of ECG waveforms and various beat types.

Table 1: ORGANIZATION OF THE SPLIT DATA

	Total	Train (90%)	Test (10%)
N-beat	716630	644967	71663
V-beat	48470	43623	4847
S-beat	37530	33777	3753
A-beat	3620	3258	362

As shown in Table 1, the entire dataset consists of 716,630 normal beats, 48,470 PVC beats, 37,530 PAC beats, and 3,620 Aberrancy PAC beats. Before proceeding with the experiment, training data and test data were randomly sampled within each type and split into 90 and 10 ratios.

2.2. Model Architecture

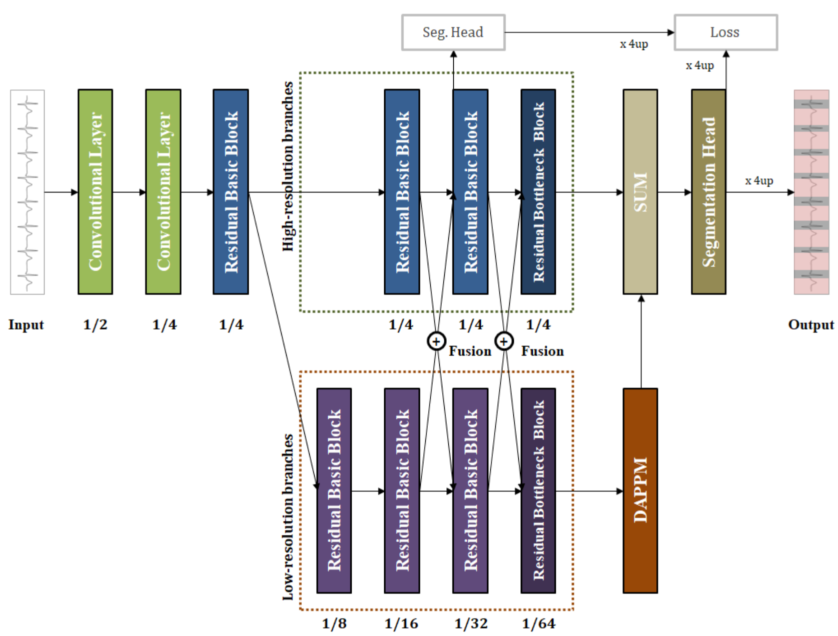

Fig. 1: Overview of the modified DDRNet architecture. “DAPPM” denotes the Deep Aggregation Pyramid Pooling Module.

To identify PAC, we applied semantic segmentation methods from computer vision. Typically, semantic segmentation methods are designed for 2D data as they are used in the image domain, but they can also be applied to 1D data. Recent semantic segmentation models have shown better performance and real-time processing speeds compared to traditional models like U-Net. In this study, we employ the DDRNet-23-slim architecture to consider not only accuracy performance but also real-time processing capabilities. DDRNet demonstrates good performance in terms of accuracy and inference time in the field of real-time semantic segmentation. The model is trained using 16-second segments of 1D ECG data, reflecting the characteristics of ECG signals and arrhythmias. [5, 6]

2.2. Test Methods

The performance of the trained model was evaluated on the test dataset using a two-step process. First, the model performed semantic segmentation on the ECG signals. Then, an algorithm identified the peak positions within the four types of QRS complexes (Normal, PAC, PVC, and Aberrant PAC) in the segmented results. The accuracy of beat detection and classification was assessed using multiple metrics: accuracy, positive predictive value (PPV), sensitivity, and F1-score. These metrics provided a comprehensive evaluation of the model's performance in correctly identifying and classifying the different types of heartbeats.

3. Experiment and Result

As illustrated in Figure 2, the raw ECG undergoes semantic segmentation to classify waveforms into P, QRS[N,S,V,A], T, and Noise components. Subsequently, peak locations are identified within the QRS-classified regions. These peaks are then categorized into Normal Beat[N], PAC beat[S], PVC beat[V], and Aberrancy PAC[A] based on their corresponding QRS labels, enabling beat detection and classification.

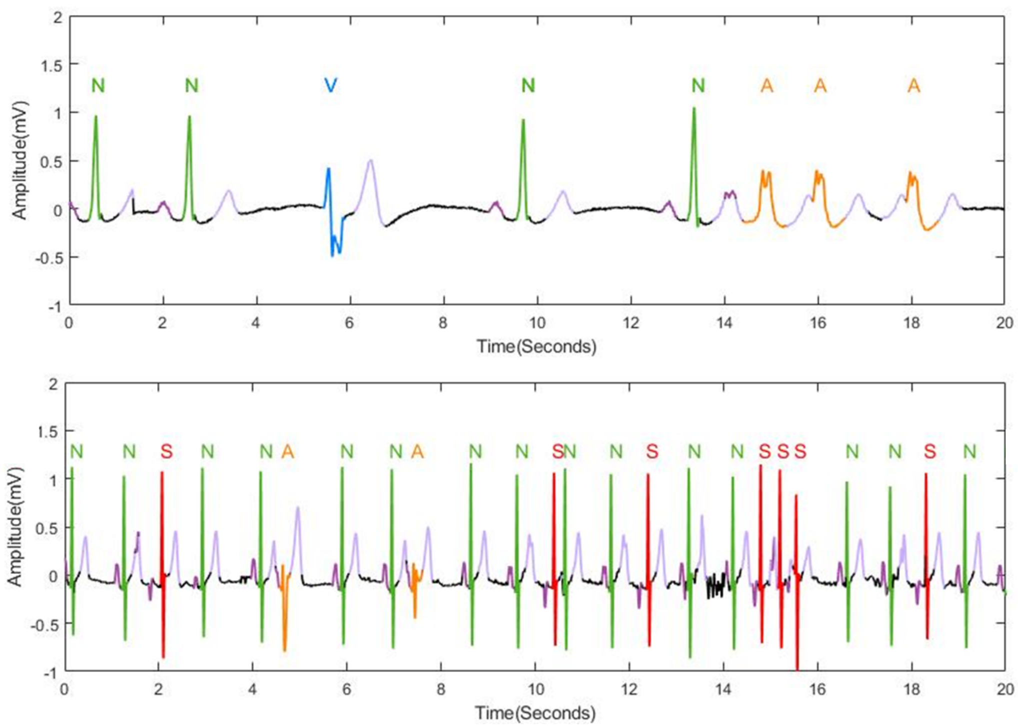

Fig. 2: An example figure showing predicted semantic segmentation of ECG waves using the proposed model

Table 4 shows the test results of the proposed Semantic Segmentation model. The total IoU value is 66.85, and the total F1-score is 79.37. Despite the challenges in segmenting the Noise, PAC, and Aberrancy PAC, the model demonstrates overall good performance. As shown in Table 3, the model achieves high segmentation performance for dominant waveform components such as Baseline (F1-score 90.00), QRS[Normal] (88.93), and T-wave (87.25). In contrast, segmentation of PAC (69.45) and especially Aberrant PAC (61.26) is more difficult, likely due to the limited number of labeled instances and their morphological similarity to PVCs.

Table 3: Semantic Segmentation Model Test Results

	Base	P-Wave	N-QRS	S-QRS	V-QRS	A-QRS	T-Wave	Noise	Total
IoU	81.82	73.72	80.06	53.20	66.75	44.16	77.39	57.69	66.85
F1-score	90.00	84.87	88.93	69.45	80.06	61.26	87.25	73.17	79.37

Table 4 below demonstrates the beat classification performance of the proposed method. With a total accuracy of 98.25, PPV of 80.44, sensitivity of 73.31, and F1-score of 76.54, we confirmed overall high performance in classifying 4 classes, including Aberrancy PAC, which is known to be difficult to classify. Table 4 further illustrates that beat classification performance is excellent for Normal and PVC beats, with F1-scores of 95.51 and 80.25, respectively. For PAC and Aberrant PAC, sensitivity is lower (64.75 and 59.11), indicating some missed detections. However, precision remains high, particularly for Aberrant PAC (PPV 73.29), suggesting that the model is cautious and generally correct when it does predict these rare beats. These results reflect a good balance between specificity and recall and confirm the model's suitability for real-world ECG monitoring.

Table 4: Proposed Algorithm and Test Results

	Accuracy	PPV	Sensitivity	F1 Score
Normal Beat	96.21	95.71	95.32	95.51
PVC	99.37	87.58	74.06	80.25
PAC	98.39	65.18	64.75	64.96
Aberrancy PAC	99.03	73.29	59.11	65.44
Total	98.25	80.44	73.31	76.54

4. Conclusion

Our semantic segmentation-based approach to ECG classification shows significant promise, achieving high accuracy even when including the challenging Aberrancy PAC class. While there is room for improvement in sensitivity, the results are encouraging and open up numerous avenues for further research and application development. With continued refinement and expansion, this approach has the potential to significantly enhance automated ECG interpretation across various clinical and consumer health contexts, ultimately contributing to improved cardiac care and outcomes. While the model performs strongly overall, particularly in precision, further improvement in sensitivity for PAC and Aberrant PAC remains a key objective. Enhancing the detection of these less frequent but clinically important beats could improve the utility of this system in ambulatory or remote ECG monitoring scenarios.

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