Impact of Diffusion-Denoising-Based ECG Augmentation on the Robustness of Beat-Level Arrhythmia Classification

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Introduction

Undiagnosed cardiac arrhythmias can cause serious cardiovascular complications, while continuous ECG monitoring produces large volumes of data requiring automated analysis [1, 2].

However, ambulatory ECG signals are frequently contaminated by baseline wander (BW), muscle artefacts (MA), and electrode-motion (EM) artefacts, reducing classification performance [3].

Research Gap

DeScoD-ECG can mitigate noise-induced degradation in ECG beat classification. However, its iterative denoising process introduces substantial computational overhead at inference, limiting its suitability for real-time deployment.

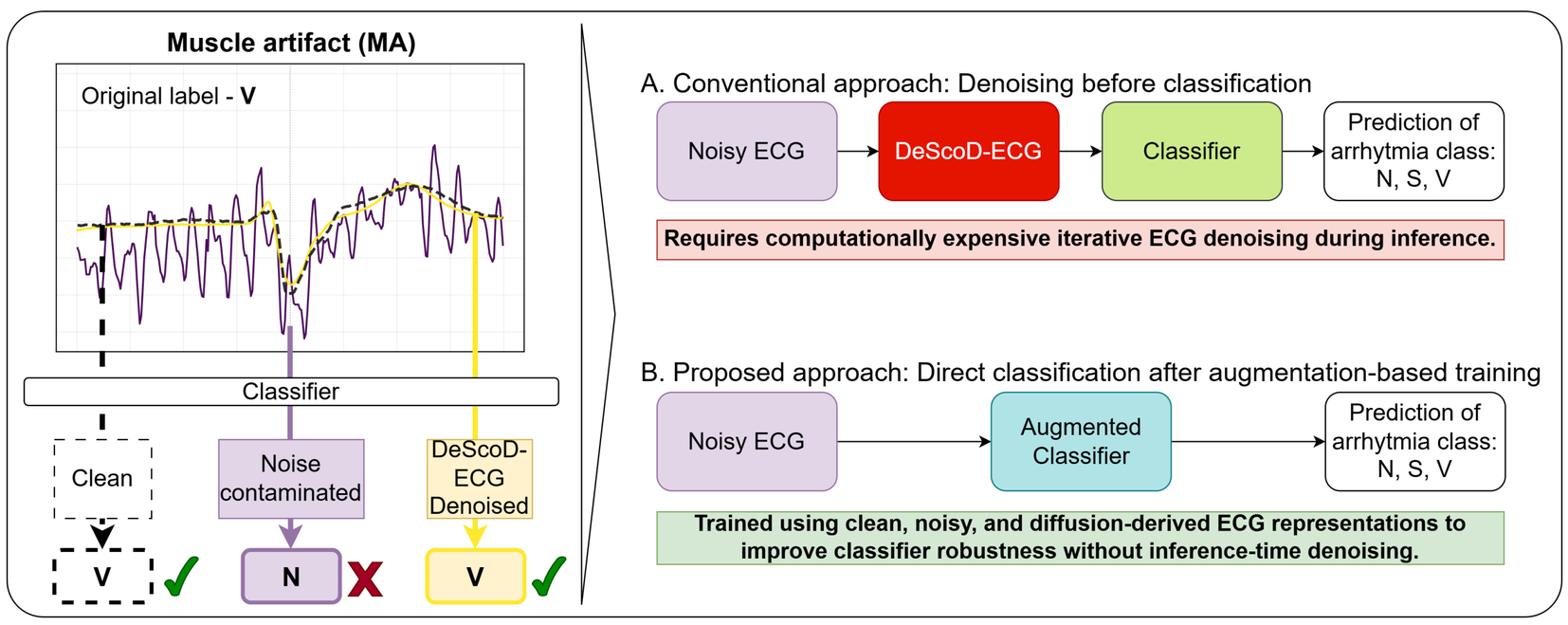

Figure 1. Effects of ECG noise on classification and comparison of inference-time denoising with augmentation-based training.

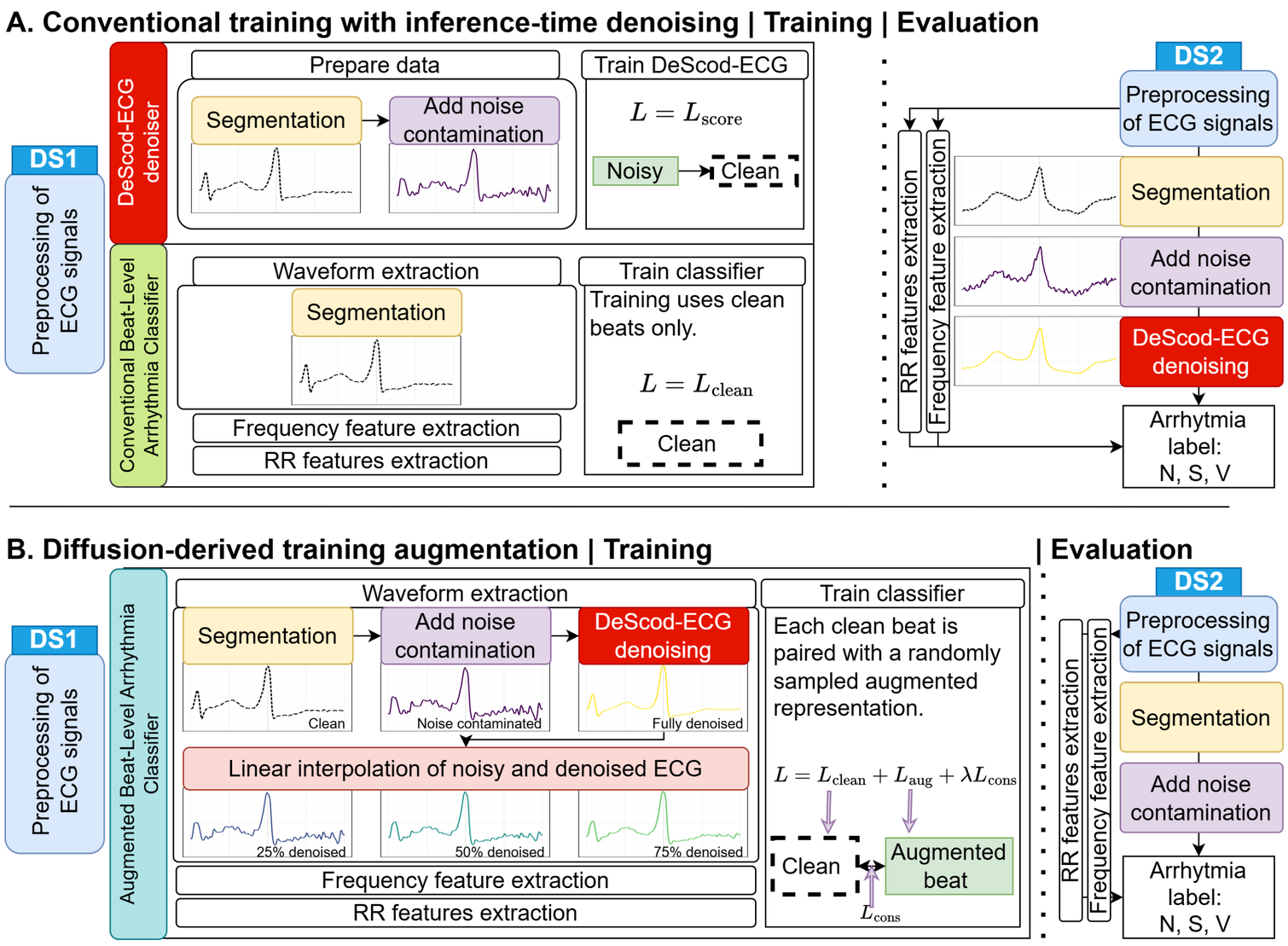

Figure 2. Conventional and diffusion-derived augmentation workflows.

Proposed approach

Diffusion-based ECG restoration is used as a training-time augmentation strategy to improve beat-level arrhythmia classification robustness to physiological noise. Specifically, clean beats are paired with randomly sampled noisy, linearly interpolated, or fully denoised representations, incorporating restoration-derived variability into classifier training without diffusion inference during deployment.

Methods

Dataset: The MIT-BIH Arrhythmia Database (360 Hz, ML II lead) was divided into two patient-independent subsets (DS1 and DS2) with AAMI normal-like (N), supraventricular ectopic (S), and ventricular ectopic (V) beat classes, excluding four paced-beat records [4-5].

Classifier: A fixed hybrid multi-branch architecture integrating multi-scale ECG beat morphology, RR-interval features, and frequency-domain information [6].

Denoiser: DeScoD-ECG, a conditional score-based diffusion model employing iterative restoration and multi-shot averaging for ECG denoising [7]. The denoiser was trained using MA contamination at noise intensities of 0.2-2.0, while augmentation samples were generated from MA-contaminated ECG at intensities of 0.2-0.6.

Experimental setup

Evaluation: Classification robustness was assessed across 12 conditions: three noise types at four noise intensity ranges. Performance was evaluated separately for S and V beats using the F1 score.

Comparison: Five paired augmentation strategies and one conventional clean-only classifier were compared. The conventional classifier was evaluated on both noisy and denoised ECG, yielding seven evaluation configurations.

Results & Discussion

S beats: Diffusion-derived augmentation outperformed conventional training on both noisy and denoised ECG across all 12 conditions. The clean + noisy + denoised + linearly interpolated configuration performed best in 7/12 conditions. At the highest noise intensity (1.5–2.0), F1 increased from 0.591 to 0.697 under MA and from 0.486 to 0.668 under EM, relative to conventional classification of noisy ECG.

V beats: Conventional training combined with inference-time denoising achieved the highest F1 score in 11 of 12 conditions, outperforming augmentation-based approaches in most cases.

Overall: Diffusion-derived augmentation improved robustness primarily for S beats but did not consistently improve V-beat classification, indicating a class-dependent trade-off between training-time augmentation and inference-time denoising.

Future work

Future work will investigate how diffusion-derived augmentation affects classifier decision boundaries and develop sample-selection strategies to preserve informative representations while limiting adverse effects on V-beat classification.

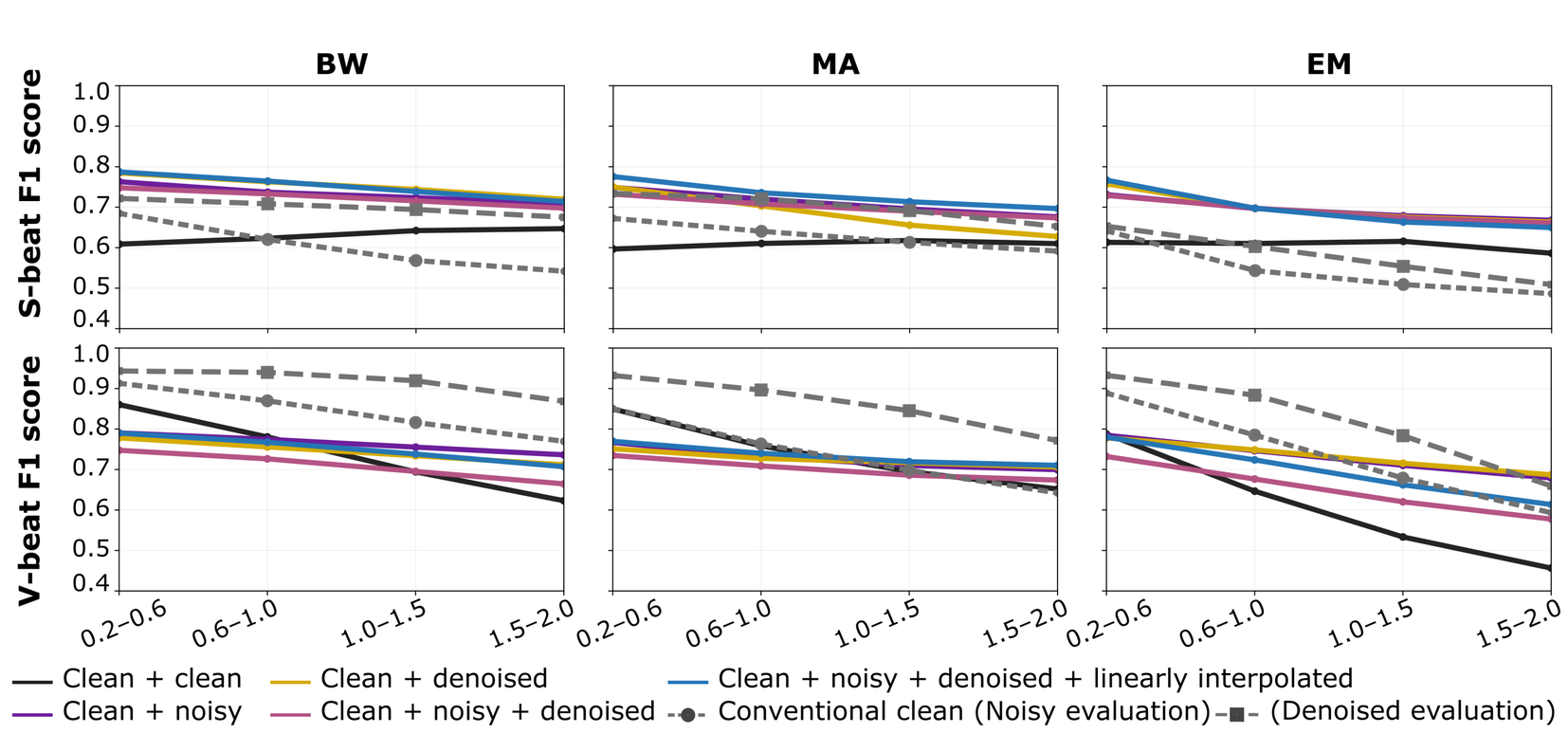

Figure 3. S- and V-beat F1 scores under BW, MA, and EM contamination.

References

GitHub: damss_2026_diffusion-ecg-augmentation-robustness

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