Physiology-Informed Wavelet State-Space Modeling for Interpretable ECG Arrhythmia Classification

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Aims: We propose a physiology-informed architecture, *Wavelet-SSM*, for interpretable single-beat electrocardiogram (ECG) arrhythmia classification. The model builds upon a neural state-space model (SSM) formulation in which latent dynamics evolve in the wavelet coefficient domain, providing a physiologically aligned time–frequency representation consistent with cardiac morphology.

Methodology: In Wavelet-SSM, the state transition matrix ($\mathbf{A}$) is analytically derived from a discrete wavelet basis using High-order Polynomial Projection Operators (HiPPO) and remains fixed during training. Each latent dimension corresponds to a predefined wavelet scale, establishing a deterministic mapping between hidden states and frequency components, unlike standard neural SSMs (e.g., Mamba, S4) where ($\mathbf{A}$) lacks interpretable spectral structure. The input projection ($\mathbf{B}$) and output readout ($\mathbf{C}$) matrices are learned following the selective parameterization of Mamba. Scale bounds are informed by physiological priors on QRS duration, and a QRS-centered HiPPO measure weights projections toward R-peak morphology. A 1-D convolutional stem reduces input sequence length before the SSM layers; a scale-gating module adaptively reweights latent scales before the classification head.

Results: Experiments are conducted on the MIT-BIH Arrhythmia Database; each beat is represented as a 500 ms segment centered on the R-peak, using a fixed patient-disjoint training/validation/test sets with a 60/10/30 split ratio. On the five-class AAMI-style task, Daubechies db3 achieves the strongest Wavelet-SSM result, with an F1 score of 93.23%. The db2, biorthogonal bior3.3, and db4 variants achieve F1 scores of 92.62%, 92.37%, and 91.71%, respectively, demonstrating the impact of basis choice on QRS-scale encoding; scale attribution patterns align with clinical beat characteristics, with ventricular beats consistently activating coarser scales, consistent with their wider QRS complex.

Conclusion: Wavelet-SSM attains performance competitive with state-of-the-art deep learning baselines while exposing scale-level importance patterns consistent with a wider QRS complex for ventricular beats, supporting its use as an interpretable deep model for arrhythmia beat labeling.

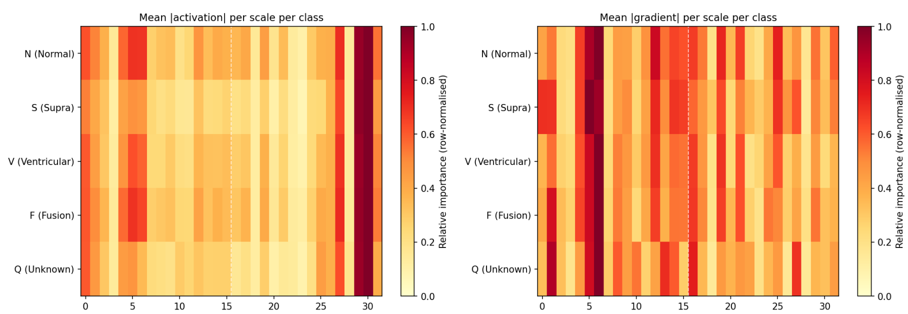

Figure 1: Per-class wavelet scale attribution (Wavelet-SSM, db3, MIT-BIH test set). Right panel: row-normalized mean $|\partial\,\mathrm{logit}_k/\partial\mathbf{h}|$ per scale. V beats activate broader mid-to-coarse scales (wider QRS); N/S beats emphasize fine scales; F beats show mixed activation.

Table 1: Five-class MIT-BIH beat classification performance.

Method	Acc %	PPV %	TPR %	F1 %
Wavelet-SSM, db2	98.29	95.20	90.17	92.62
Wavelet-SSM, db3	98.48	**95.72**	90.86	**93.23**
Wavelet-SSM, bior3.3	98.31	94.80	90.07	92.37
Wavelet-SSM, db4	97.97	93.44	90.05	91.71
S6-Mamba	98.31	94.76	89.72	92.17
S4-HiPPO	97.95	93.72	89.52	91.57
Kiranyaz et al. (2017)	95.90	84.20	88.80	86.40
Zhai et al. (2020)	96.80	87.90	92.00	89.90
Shaker et al. (2021)	**98.70**	90.10	**95.90**	92.90
Li et al. (2021)	92.00	62.80	93.30	75.10
Zhou et al. (2022)	97.90	90.80	89.70	90.20