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Physiologically Anchored Deep Learning Using Paired Sinus Rhythm and Premature Ventricular Contraction Electrocardiograms for Ventricular Ectopic Origin Localization

ABSTRACT

Background: Accurate non-invasive localization of premature ventricular contractions (PVCs) is important for preprocedural planning before catheter ablation. Most artificial intelligence–based electrocardiography (ECG) models evaluate ectopic beats without incorporating patient-specific baseline ventricular conduction patterns. This study aimed to develop and evaluate a patient-referenced, QRS-centered deep learning framework integrating paired sinus rhythm and PVC 12-lead ECG recordings for binary localization of ventricular ectopic origin and to assess the incremental value of sinus rhythm information compared with PVC-only input.

Methods: This retrospective, single-center diagnostic accuracy study included 270 patients with paired sinus rhythm and PVC ECG recordings and procedurally confirmed ventricular ectopic origin. Raw ECG signals were segmented using annotated QRS boundaries and aligned using a QRS-centered strategy. Three input strategies were evaluated: paired PVC + sinus rhythm, PVC-only, and sinus rhythm-only. A 1-dimensional residual convolutional neural network (CNN) (1D ResNet) and a 2-dimensional time-domain CNN (2D time-domain CNN) were trained directly on raw ECG waveforms, with late-fusion probability averaging used for ensemble predictions. Performance was assessed using 5-fold patient-level cross-validation. The primary endpoint was the area under the receiver operating characteristic curve (AUROC).

Results: For paired PVC + sinus rhythm input, pooled AUROC values were 0.753 for the 1D ResNet, 0.743 for the 2D time-domain CNN, and 0.762 for the late-fusion ensemble, with no statistically significant differences among architectures. In the cross-input comparison, ensemble AUROC was 0.762 for paired PVC + sinus rhythm, 0.731 for PVC-only, and 0.551 for sinus rhythm-only input. Paired PVC + sinus rhythm significantly outperformed PVC-only input (DeLong $P = .0313$), whereas sinus rhythm alone showed limited discrimination.

Conclusion: Patient-specific sinus rhythm information provided incremental discriminatory value when combined with PVC morphology for binary left ventricular–right ventricular (LV–RV) localization, while sinus rhythm alone had limited discriminatory value. These findings provide proof-of-concept evidence supporting paired sinus rhythm–PVC modeling as a physiologically informed approach to ventricular ectopic localization. External validation and comparison with established ECG-based localization criteria are required before clinical implementation.

Keywords: Artificial intelligence, deep learning, electrocardiography, premature ventricular contractions, ventricular arrhythmia localization

INTRODUCTION

Accurate anatomical localization of premature ventricular contractions (PVCs) is important for preprocedural planning and optimization of catheter ablation strategies. Surface 12-lead electrocardiography (ECG) remains the primary non-invasive tool for predicting ventricular ectopic origin; however, conventional interpretation relies largely on heuristic morphology criteria and operator-dependent expertise, which may reduce reproducibility and limit generalizability across diverse anatomical substrates.[1]

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Artificial intelligence (AI)-based ECG analysis has increasingly enabled data-driven approaches to ventricular arrhythmia localization beyond conventional morphology-based interpretation. Early deep learning studies demonstrated accurate PVC recognition using transformed ECG representations, including wavelet-based images,[2] and subsequent investigations applied machine learning and convolutional neural networks (CNNs) to anatomical localization tasks.[3-12] Although reported accuracies have been encouraging, most published frameworks have focused primarily on PVC morphology, with limited consideration of patient-specific baseline ventricular conduction characteristics.[3-12]

From a physiological perspective, sinus rhythm reflects individualized ventricular activation patterns influenced by cardiac orientation, myocardial substrate, and intrinsic conduction properties. The morphology of a ventricular ectopic beat may therefore be more informative when interpreted relative to the patient's baseline conduction pattern rather than as a standalone waveform.

Evidence directly evaluating this concept remains limited. Notably, Nakasone et al[13] recently demonstrated in a multicenter cohort that a dual-rhythm model incorporating both sinus rhythm and PVC ECGs improved right- versus left-sided origin prediction compared with a PVC-only model (area under the curve: 0.91 vs. 0.86), supporting the potential complementary value of baseline sinus rhythm information for PVC localization. Nevertheless, studies explicitly investigating physiologically paired sinus rhythm–PVC representations remain scarce, and their performance across different deep learning architectures has not been fully explored.

Therefore, a physiologically anchored, QRS-centered deep learning framework was developed for binary localization of ventricular ectopic origin as left ventricular (LV) versus right ventricular (RV) and evaluated the incremental value of incorporating patient-specific sinus rhythm information by comparing paired sinus rhythm–PVC input with PVC-only and sinus-only strategies. By aligning beats according to annotated QRS boundaries and learning directly from raw time-series data without handcrafted feature extraction or signal transformation, the proposed framework was designed to model ventricular ectopy relative to individualized physiological conduction patterns and to provide a patient-referenced approach for non-invasive anatomical inference in electrophysiology.

HIGHLIGHTS

- Paired sinus rhythm and premature ventricular contraction (PVC) electrocardiograms were integrated into a patient-referenced deep learning framework.
- Paired sinus rhythm–PVC input significantly outperformed PVC-only input for left ventricular–right ventricular localization.
- Sinus rhythm alone showed limited discrimination but provided complementary information when paired with PVC morphology.
- No statistically significant performance differences were observed among the evaluated deep learning architectures.

METHODS

Study Design and Population

This retrospective single-center study included consecutive patients who underwent catheter ablation for PVCs between January 2023 and December 2025. A total of 308 consecutive patients were initially screened for eligibility. Patients were excluded in the presence of poor signal quality, incomplete ECG recordings, paced rhythm, bundle branch block, or prior ablation history. The final study cohort consisted of 270 patients. The inclusion criteria were as follows: (1) availability of an analyzable 12-lead sinus rhythm ECG, (2) availability of an analyzable 12-lead PVC ECG, and (3) procedurally confirmed anatomical origin of the PVC. Premature ventricular contraction origin was procedurally determined during the electrophysiological study using activation mapping and/or pace mapping and was confirmed by successful ablation at the identified site, as detailed below. Baseline demographic and clinical characteristics are summarized in Table 1.

Reference labels were defined as LV origin in 115 patients (42.6%) and RV origin in 155 patients (57.4%) (Table 2). Detailed sublocalization labels, including RV outflow tract septal, papillary muscle, and aortomitral continuity origins, were available but were not used as classification targets. These labels were used only for stratified cross-validation to preserve anatomical diversity across folds.

Ethical Approval

The study protocol was approved by the local ethics committee and was conducted in accordance with the Declaration of Helsinki. The requirement for informed consent was waived owing to the retrospective design of the study.

Electrophysiological Mapping and Procedural Definition of Premature Ventricular Contraction Origin

Premature ventricular contraction origin was determined during the electrophysiological study using activation mapping and/or pace mapping. The earliest local ventricular activation at the successful ablation site was typically 40-60

Table 1. Baseline Demographic and Clinical Characteristics of the Study Population

Characteristic	Overall (n = 270)
Demographic characteristics	
Age, years	58.5 (47.3-71.0)
Male, n (%)	161 (59.6)
Clinical characteristics	
Hypertension, n (%)	78 (28.8)
Diabetes mellitus, n (%)	37 (13.7)
Coronary artery disease, n (%)	45 (16.7)
Heart failure, n (%)	56 (20.7)
Structural heart disease, n (%)	74 (27.4)
Left ventricular ejection fraction (%)	55 (40-60)

Table 2. Baseline Characteristics and Anatomical Distribution of Premature Ventricular Contraction Origins

Major Group	Sub-localization	n	(%)
Left ventricle (LV)	LV—LCC	16	5.9
	LV—LVOT	24	8.9
	LV—RCC	19	7.0
	LV—summit	30	11.1
	LV—AMC papillary (anterior)	7	2.6
	LV—posterior group	19	7.0
Total LV		115	42.6
Right ventricle (RV)	RV—RVOT anterior	40	14.8
	RV—RVOT posterior	88	32.6
	RV—TA lateral	7	2.6
	RV—moderator/TA	7	2.6
	RV—parahisian/TA septal	13	4.8
Total RV		155	57.4
Overall total		270	100

AMC, aortomitral continuity; LCC, left coronary cusp; LVOT, left ventricular outflow tract; RCC, right coronary cusp; RVOT, right ventricular outflow tract; TA, tricuspid annulus.

ms before QRS onset. When pace mapping was used, concordance was assessed using the EnSite™ Electrophysiology System (Abbott), with a match of 96% considered supportive of the presumed origin.

Acute procedural success was defined as complete elimination of the clinical PVC following ablation, with the absence of spontaneous or inducible clinical PVCs during a postablation observation period of 30 minutes, including after isoproterenol administration and/or burst ventricular pacing.

Long-term recurrence was not used to define the reference anatomical label because recurrence after PVC ablation may be influenced by multiple factors beyond localization accuracy. The reference label was therefore based on procedural mapping findings and acute ablation success.

Electrocardiography Acquisition and Data Annotation

All ECG recordings were exported in raw comma-separated values format and included 12-lead sinus rhythm ECG waveforms, 12-lead PVC ECG waveforms, anatomical labels, and annotated QRS onset and offset indices.

QRS annotations and review of the procedural anatomical labels were performed by at least 3 experienced electrophysiologists, and discrepancies were resolved by consensus. No handcrafted features, frequency-domain transformations, or image-based preprocessing were applied. Models were trained directly on raw ECG voltage time-series data in an end-to-end manner.

Electrocardiography Preprocessing and Input Representation

Raw ECG signals were converted into numerical tensors for model training. For both sinus rhythm and PVC recordings, annotated QRS onset and offset boundaries were used for QRS-centered segmentation. Symmetric zero-padding was then applied to generate fixed-length signal representations.

Sinus rhythm and PVC signals were aligned according to annotated QRS boundaries. Three input strategies were evaluated: (1) paired sinus rhythm–PVC input, consisting of a 24×492 tensor comprising 12 sinus rhythm leads and 12 PVC leads; (2) PVC-only input, consisting of a 12×492 tensor; and (3) sinus rhythm–only input, likewise consisting of a 12×492 tensor. Per-patient z-score normalization was applied to reduce inter-individual amplitude variability.

To directly assess the incremental contribution of sinus rhythm information, all 3 input strategies were evaluated within the same modeling framework using identical patient-level cross-validation procedures.

Deep Learning Architectures

A 1-dimensional residual CNN (1D ResNet) was implemented to learn temporal morphological features directly from multichannel raw ECG signals. The network consisted of an initial 1-dimensional convolutional layer followed by 3 residual convolutional stages with progressive channel expansion. The architecture included an initial convolutional layer with a kernel size of 7 and a stride of 2, max-pooling, residual convolutional blocks, adaptive global average pooling, global max pooling, and fully connected classification layers. Rectified linear unit activation functions and dropout regularization were used throughout the network, and batch normalization was applied after convolutional operations.

A 2-dimensional time-domain CNN (2D time-domain CNN) was also implemented using the corresponding raw ECG tensor for each input strategy, represented as a channel-by-time matrix. This model was designed to capture spatial–temporal patterns across leads and time points. Importantly, no image conversion, spectrogram generation, or frequency-domain transformation was performed; the model operated directly on raw ECG voltage signals. The architecture consisted of 2-dimensional convolutional layers, residual connections, adaptive global average pooling, and fully connected classification layers. Batch normalization, rectified linear unit activation functions, and dropout regularization were applied throughout the network.

Both architectures were independently trained and evaluated using the paired sinus rhythm–PVC, PVC-only, and sinus rhythm–only input strategies.

Model Training and Ensemble Strategy

Both models were trained using weighted cross-entropy loss to address class imbalance. The 1D ResNet model was optimized using the AdamW optimizer with a learning rate of 3×10^{-4} and weight decay of 1×10^{-4}. Training was performed with a batch size of 16 for a maximum of 60 epochs. Early stopping was applied by monitoring validation loss, with a patience of 15 epochs and a minimum delta threshold of 0.001.

The 2D time-domain CNN model was optimized using the AdamW optimizer with a learning rate of 5×10^{-5} and weight decay of 1×10^{-4}. Training was performed with a batch size

of 8 for a maximum of 60 epochs. A warm-up learning rate strategy was applied during the initial training epochs. Early stopping was similarly performed by monitoring validation loss, with a patience of 15 epochs and a minimum delta threshold of 0.001.

Late fusion ensembling was performed by probability averaging. The ensemble probability was calculated as the arithmetic mean of the predicted probabilities generated by the independently trained 1D ResNet and 2D time-domain CNN models. Separate ensemble models were generated for the paired sinus rhythm–PVC, PVC-only, and sinus rhythm–only input strategies. Within each input strategy, the 1D ResNet and 2D time-domain CNN models were trained and evaluated using identical patient-level data splits, allowing architectural performance to be compared under the same input conditions.

Cross-Validation Strategy

Five-fold stratified cross-validation was performed at the patient level. Sublocalization labels were grouped into broader anatomical categories and used exclusively for fold stratification to preserve anatomical diversity across data splits. Model classification remained binary, defined as LV versus RV origin.

Within each fold, 20% of patients were reserved as the held-out test set, while the remaining 80% were allocated to the training/validation set. From this training/validation set, 20% was further separated for validation. No patient-level overlap occurred between training, validation, and testing datasets. The same patient-level fold assignments were used across the paired sinus rhythm–PVC, PVC-only, and sinus rhythm–only input strategies to enable direct comparison of model performance under identical data partitions. Class imbalance was addressed using class-weighted loss functions during model training.

Statistical Analysis

Model performance was primarily assessed using the area under the receiver operating characteristic curve (AUROC). Secondary performance metrics included accuracy, sensitivity (recall), precision, F1-score, and area under the precision–recall curve (AUPRC). These metrics were reported for the 1D ResNet, 2D time-domain CNN, and late-fusion ensemble models across the evaluated input strategies. Area under the receiver operating characteristic curve values were calculated using pooled out-of-fold test predictions across the 5 cross-validation folds. Pairwise comparisons between model ROCs were performed using DeLong tests for correlated curves. In particular, the AUROC of the paired sinus rhythm–PVC ensemble was compared with that of the PVC-only ensemble to assess the incremental discriminative value of incorporating patient-specific sinus rhythm information. Statistical significance was defined as a 2-sided $P < .05$. All analyses and model development procedures were performed using Python with the PyTorch and scikit-learn libraries.

RESULTS

Study Cohort and Data Processing

A total of 270 patients with paired 12-lead sinus rhythm and PVC ECG recordings were included in the analysis. All subjects were successfully incorporated into the 5-fold stratified cross-validation pipeline without data loss. Sublocalization labels were used exclusively for fold stratification to maintain anatomical balance across data splits, while the classification task remained binary, defined as LV versus RV origin. Strict patient-level separation was maintained between training, validation, and testing partitions.

To evaluate the incremental contribution of patient-specific sinus rhythm information, 3 input strategies were analyzed using the same modeling framework: paired PVC + sinus rhythm, PVC-only, and sinus rhythm–only inputs. Each input strategy was evaluated using the 1D ResNet, 2D time-domain CNN, and their late-fusion ensemble.

QRS-Centered Input Representation

The overall model architecture is illustrated in Figure 1.

QRS-centered waveform overlays are shown in Figure 2 for PVC waveforms and Figure 3 for sinus rhythm waveforms. Premature ventricular contraction waveforms demonstrated substantial inter-patient morphological variability, particularly across the precordial leads, whereas sinus rhythm waveforms showed comparatively narrower dispersion.

In both figures, the red trace represents the median waveform across 270 patients, and the vertical dashed line indicates the QRS alignment reference point. The observed alignment confirms consistent QRS-centered signal representation across the study cohort and illustrates the distinct morphological information contained in PVC and sinus rhythm recordings.

Model Discrimination Performance

Across 5-fold patient-level cross-validation, both deep learning architectures demonstrated consistent discrimination performance for binary ventricular ectopic origin localization.

For the paired PVC + sinus rhythm input, pooled AUROC values were 0.753 for the 1D ResNet, 0.743 for the 2D time-domain CNN, and 0.762 for the late-fusion ensemble model. Pairwise DeLong comparisons revealed no statistically significant differences among these architectures (all $P > .05$), although the late-fusion ensemble achieved the highest numerical AUROC.

Architecture-specific ROC analyses for the paired PVC + sinus rhythm, PVC-only, and sinus–only input strategies are provided in Supplementary Figures 1-3, respectively.

Secondary performance metrics, including accuracy, sensitivity (recall), precision, F1-score, and AUPRC, are summarized in Table 3.

Input Representation Analysis

In the cross-input comparison, the late-fusion ensemble AUROC was 0.762 for PVC + sinus rhythm, 0.731 for PVC-only, and 0.551 for sinus–only input. The paired PVC + sinus rhythm model significantly outperformed the PVC-only model (DeLong $z = 2.153$, $P = .0313$) and the sinus-only model ($P < .0001$). Premature ventricular contraction-only also

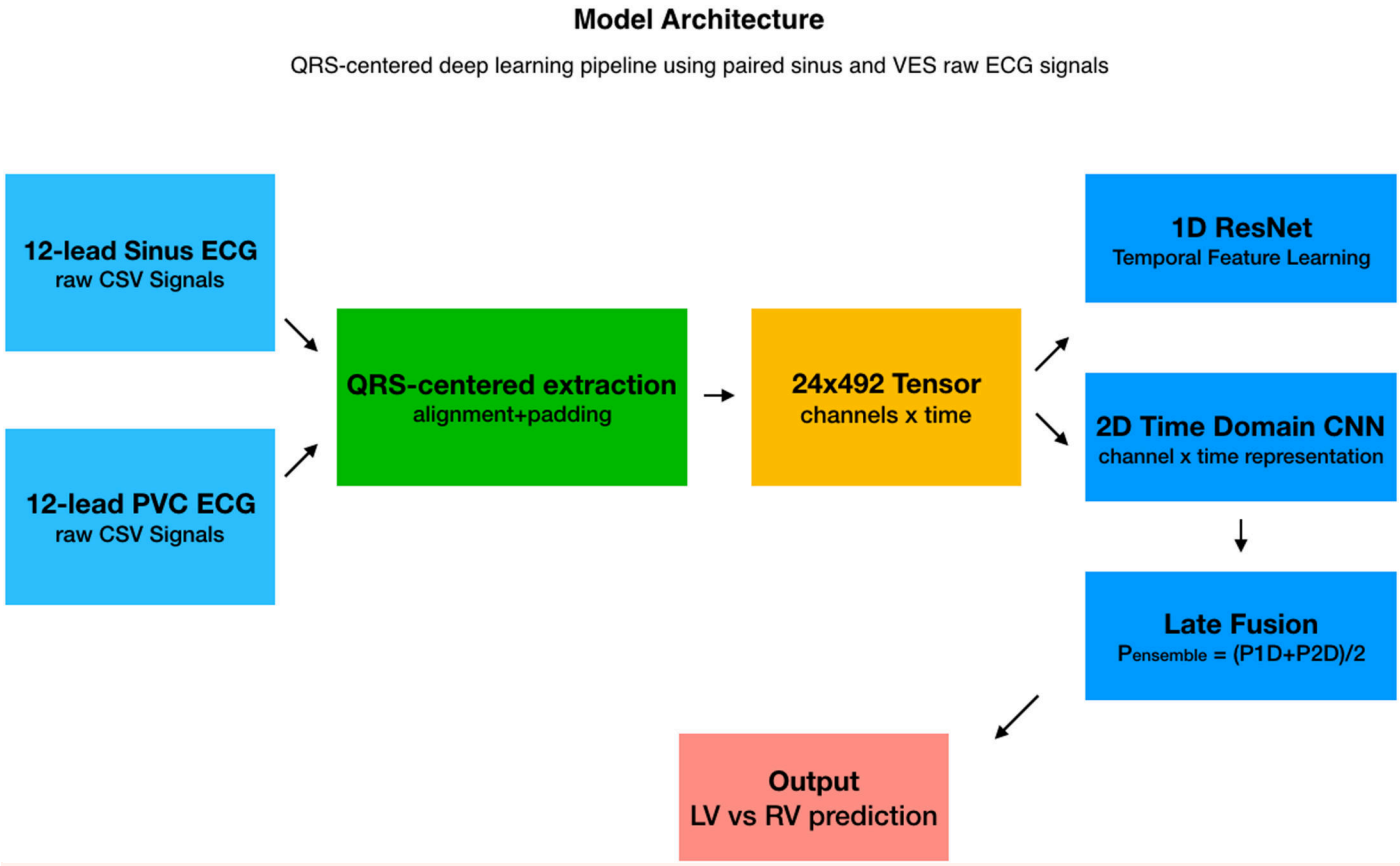

Figure 1. Model architecture. Overview of the proposed QRS-centered deep learning pipeline. Paired sinus rhythm and premature ventricular contraction raw ECG segments were combined into a 24 × 492 tensor and processed by 2 parallel models: a 1-dimensional residual convolutional neural network for temporal feature learning and a 2-dimensional time-domain convolutional neural network for channel–time representation learning. Final predictions were combined using late-fusion probability averaging. ECG, electrocardiography; LV, left ventricular; PVC, premature ventricular contraction; RV, right ventricular.

significantly outperformed sinus-only ($P < .0001$). These findings demonstrate a significant incremental discriminative contribution of sinus rhythm when incorporated alongside PVC morphology, while sinus rhythm alone provided limited discriminatory information (Figure 4).

DISCUSSION

This study developed a patient-referenced, QRS-centered deep learning framework for binary anatomical localization of ventricular ectopic beats and directly evaluated the incremental contribution of patient-specific sinus rhythm information. The paired PVC + sinus rhythm late-fusion ensemble achieved an AUROC of 0.762, compared with 0.731 for PVC-only and 0.551 for sinus rhythm–only input. Importantly, paired PVC + sinus rhythm significantly outperformed PVC-only input (DeLong $P = .0313$), providing direct evidence that patient-specific sinus rhythm information contributes incremental discriminatory value when combined with PVC morphology. Within the paired input strategy, no statistically significant performance differences were observed between the 1D ResNet, 2D time-domain CNN, and late-fusion ensemble models.

Artificial intelligence–based PVC localization has been extensively investigated in recent years 3-12. Several studies have reported high classification performance using CNNs, hybrid CNN–long short-term memory (LSTM) models, transformer-based architectures, semantic segmentation frameworks, or large-scale machine learning systems trained on ablation-confirmed datasets. Some investigations have demonstrated very high accuracy for multisite classification, 6, 12 whereas others have achieved strong discrimination using image-based ECG representations or signal transformation pipelines.[4,8,10] However, direct comparison across studies should be interpreted with caution. Many prior models rely on signal transformation techniques such as wavelet decomposition or spectrogram generation, image-based rendering of ECG traces, manually engineered indices, or hierarchical rule-augmented decision strategies.[4,7,8,11] In addition, several high-accuracy studies were derived from highly curated, homogeneous, ablation-confirmed cohorts, which may not fully reflect broader clinical variability.[5,12] Notably, most of these approaches derive localization information predominantly from the ectopic beat itself, whereas relatively few studies have directly examined whether

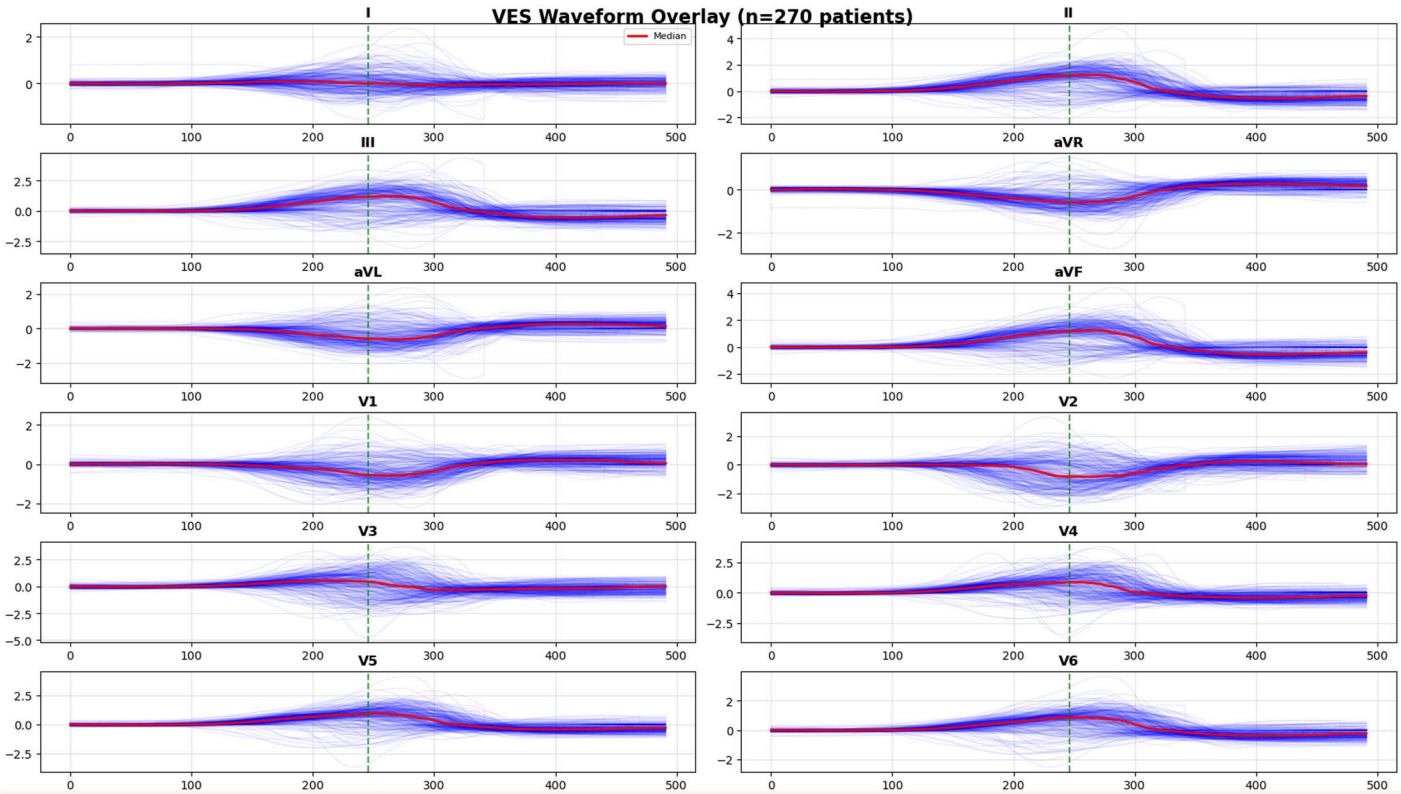

Figure 2. Premature ventricular contraction waveform overlay. QRS-centered overlay of premature ventricular contraction waveforms across 270 patients. Individual patient signals are shown in blue, and the median waveform is shown in red. The dashed green vertical line indicates the QRS alignment reference.

patient-specific sinus rhythm provides incremental information beyond PVC morphology alone.[13]

The present findings are consistent with the recent multicenter study by Nakasone et al, in which a dual-rhythm model incorporating both sinus rhythm and PVC ECGs outperformed a PVC-only model for right- versus left-sided PVC origin prediction (AUROC: 0.91 vs. 0.86). In the cohort, the corresponding late-fusion ensemble AUROC increased from 0.731 with PVC-only input to 0.762 with paired PVC + sinus rhythm input, with a statistically significant difference between the 2 strategies. Importantly, sinus rhythm alone showed limited discrimination (AUROC: 0.551), suggesting that its value lies not in independently encoding ectopic origin, but in providing complementary patient-specific information when interpreted alongside PVC morphology. Together, these observations support the concept that baseline ventricular activation may provide useful contextual information for ECG-based PVC localization.

In contrast, the present framework deliberately avoids handcrafted features, frequency-domain transformations, and image conversion. All models were trained directly on raw time-domain ECG signals using a unified tensor representation. More importantly, the framework explicitly incorporates patient-specific baseline sinus rhythm morphology alongside PVC morphology within a QRS-centered input representation. Most prior approaches analyze ectopic morphology in isolation.[3-12] However, surface ECG morphology is not determined solely by the site of ectopic origin; it is also influenced by cardiac orientation, baseline conduction pathways, ventricular mass distribution, and thoracic geometry. By aligning sinus rhythm and PVC QRS complexes within a structured 24×492 tensor, the model was designed to learn ectopic activation in relation to individualized physiological conduction rather than relying only on absolute PVC morphology. This approach conceptualizes PVC localization as a relative electrophysiological contrast problem rather than solely as a morphology-based classification task.

Within the paired PVC + sinus rhythm strategy, the 1D ResNet, 2D time-domain CNN, and late-fusion ensemble achieved AUROC values of 0.753, 0.743, and 0.762, respectively. Although the late-fusion ensemble showed the highest numerical discrimination, pairwise DeLong comparisons did not demonstrate statistically significant differences among the architectures. Accordingly, the present findings should not be interpreted as evidence that model architecture is unimportant, but rather that no statistically significant performance advantage of 1 evaluated architecture over another was demonstrated in this cohort. Larger datasets and external validation will be required to determine whether architectural differences become relevant with greater statistical power or more granular localization tasks.

Although some studies have reported AUROC values exceeding 0.90 for more granular localization tasks,[6,12] performance magnitude should be interpreted in the context of dataset design, labeling granularity, cross-validation strategy, preprocessing pipeline, and external validation structure. The present study focused on binary LV–RV discrimination as

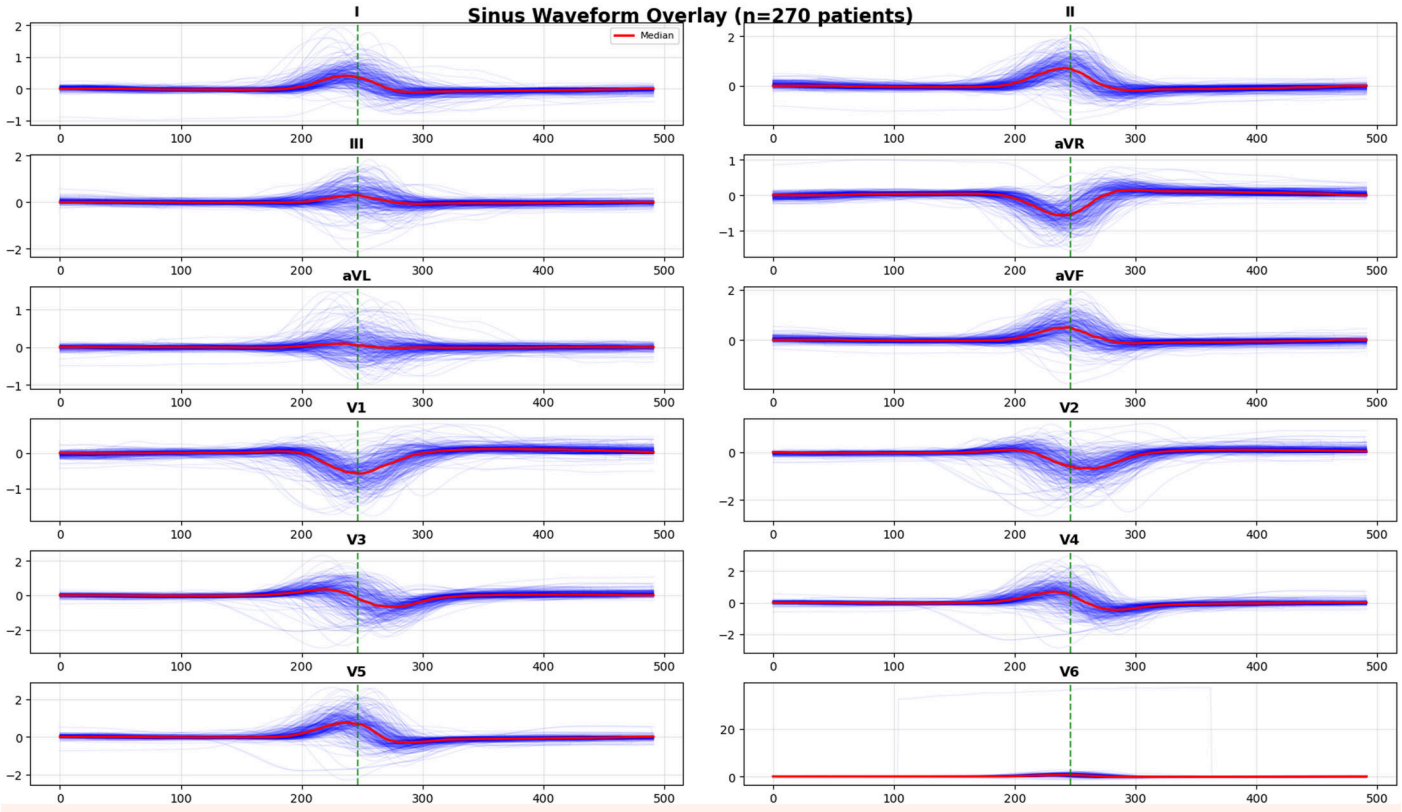

Figure 3. Sinus rhythm waveform overlay. QRS-centered overlay of sinus rhythm waveforms across 270 patients. Individual patient signals are shown in blue, and the median waveform is shown in red. The dashed green vertical line indicates the QRS alignment reference.

an initial proof-of-concept evaluation of the paired input framework before extension to more granular anatomical subclassification. The AUROC range observed in this study reflects moderate discrimination under strict patient-level separation, raw waveform input, and physiologically structured modeling without signal transformation or rule-based augmentation. Thus, the present framework emphasizes physiologically structured representation learning while maintaining methodological simplicity and transparency.

From a clinical perspective, non-invasive differentiation between LV and RV ectopic origins may provide useful information for procedural planning, vascular access strategy, and mapping preparation during catheter ablation. However, the present study should be regarded as a proof-of-concept evaluation rather than evidence of clinical readiness. Although the QRS-centered framework operates directly on raw ECG signals without feature engineering or frequency-domain transformation, its potential clinical utility requires confirmation through independent multicenter external validation, prospective evaluation, and comparison with established ECG-based localization algorithms and expert interpretation.

Table 3. Performance Metrics According to Input Strategy and Model Architecture

Input Strategy	Model	AUROC	Accuracy	Sensitivity (Recall)	Precision	F1-score	AUPRC
PVC + Sinus	1D ResNet	0.753	0.722 ± 0.094	0.728 ± 0.105	0.771 ± 0.082	0.748 ± 0.094	0.823 ± 0.092
PVC + Sinus	2D CNN	0.743	0.737 ± 0.070	0.748 ± 0.057	0.784 ± 0.069	0.766 ± 0.063	0.807 ± 0.079
PVC + Sinus	Ensemble	0.762	0.752 ± 0.092	0.754 ± 0.089	0.800 ± 0.084	0.776 ± 0.086	0.825 ± 0.083
PVC-only	1D ResNet	0.724	0.707 ± 0.070	0.743 ± 0.103	0.744 ± 0.039	0.742 ± 0.071	0.811 ± 0.056
PVC-only	2D CNN	0.708	0.685 ± 0.062	0.692 ± 0.104	0.741 ± 0.031	0.713 ± 0.069	0.792 ± 0.075
PVC-only	Ensemble	0.731	0.707 ± 0.055	0.724 ± 0.098	0.756 ± 0.023	0.737 ± 0.060	0.807 ± 0.052
Sinus-only	1D ResNet	0.556	0.548 ± 0.053	0.606 ± 0.190	0.613 ± 0.067	0.595 ± 0.085	0.622 ± 0.036
Sinus-only	2D CNN	0.492	0.544 ± 0.030	0.841 ± 0.195	0.571 ± 0.008	0.670 ± 0.067	0.586 ± 0.044
Sinus-only	Ensemble	0.551	0.541 ± 0.053	0.606 ± 0.174	0.605 ± 0.068	0.593 ± 0.079	0.614 ± 0.045

AUROC values were calculated from pooled out-of-fold predictions. Accuracy, sensitivity (recall), precision, F1-score, and AUPRC are presented as mean ± SD across the 5 patient-level cross-validation folds.
AUROC, area under the receiver operating characteristic curve; AUPRC, area under the precision–recall curve; CNN, convolutional neural network; PVC, premature ventricular contraction.

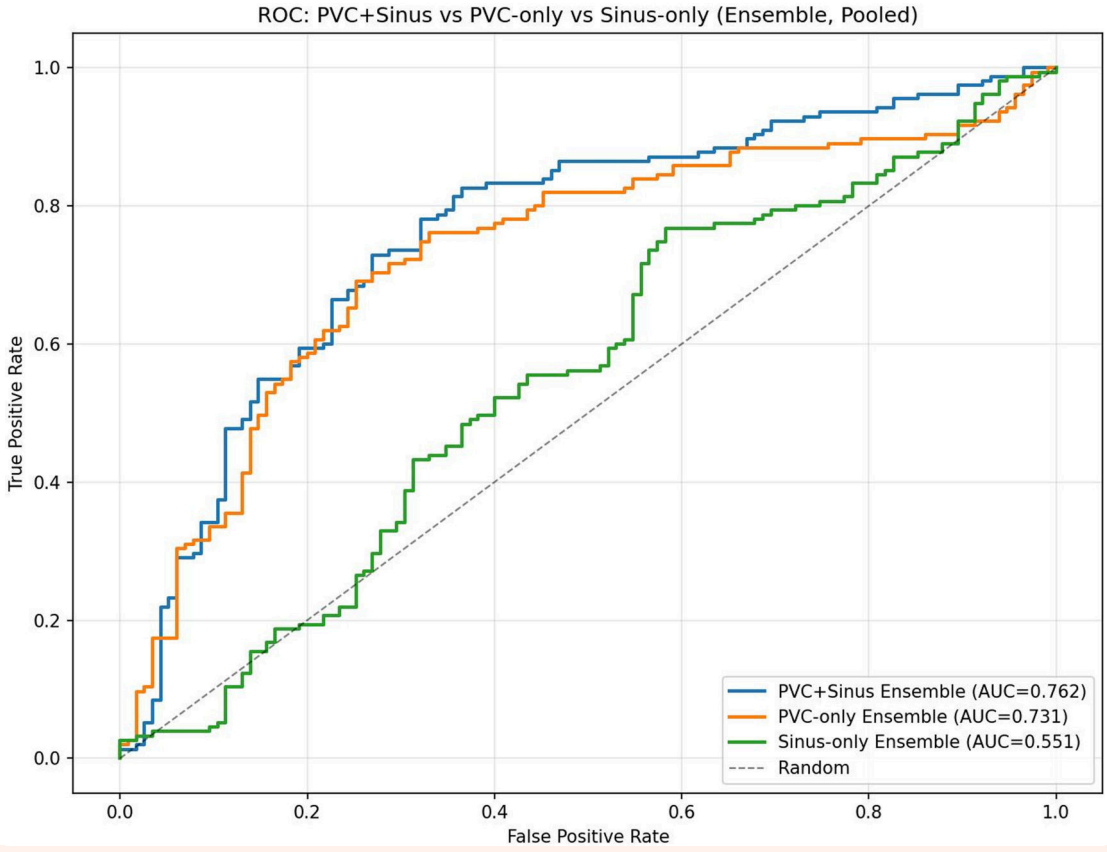

Figure 4. Receiver operating characteristic curve comparison across input strategies. Receiver operating characteristic curves comparing the late-fusion ensemble models using paired PVC + sinus rhythm, PVC-only, and sinus rhythm–only inputs based on pooled out-of-fold test predictions. The paired PVC + sinus rhythm model achieved an AUROC of 0.762, compared with 0.731 for PVC-only and 0.551 for sinus-only input. AUROC, area under the receiver operating characteristic curve; PVC, premature ventricular contraction.

Study Limitations

Several limitations should be acknowledged. First, this was a retrospective, single-center study, which may limit the generalizability of the findings to broader and more heterogeneous populations. Although strict patient-level cross-validation was applied, no independent external validation cohort was available; therefore, the performance of the proposed model across different institutions, ECG acquisition systems, and patient populations remains to be established.

Second, the classification task was restricted to binary left ventricular versus right ventricular discrimination, and detailed anatomical sublocalization labels were not incorporated into model training. Accordingly, the performance of this framework for finer anatomical subclassification, including outflow tract, fascicular, papillary muscle, annular, or epicardial origins, remains unknown.

Third, anatomical origin was determined based on procedural confirmation rather than an independent imaging- or pathology-based reference standard. Nevertheless, labeling was independently performed by at least 3 experienced electrophysiologists, and discrepancies were resolved by consensus, which enhanced label reliability.

Finally, although the incremental value of incorporating sinus rhythm was directly evaluated against PVC-only and sinus rhythm–only input strategies, these comparisons were performed within the same retrospective single-center cohort and without independent external validation.

CONCLUSION

In this study, a patient-referenced, QRS-centered deep learning framework integrating paired sinus rhythm and PVC ECG signals demonstrated moderate discriminatory performance for binary localization of ventricular ectopic origin directly from raw 12-lead ECG waveforms. By incorporating individualized baseline ventricular conduction patterns, this approach may provide a physiologically informed representation of ectopic activation without requiring handcrafted feature extraction or signal transformation.

The paired PVC + sinus rhythm strategy significantly outperformed PVC-only input, whereas sinus rhythm alone showed limited discriminatory performance. These findings provide proof-of-concept evidence that patient-specific sinus rhythm information may add complementary discriminatory value when interpreted alongside PVC morphology. No statistically significant performance differences were observed among the evaluated 1D ResNet, 2D time-domain CNN, and late-fusion ensemble architectures.

Nevertheless, the present results should be interpreted as an initial proof-of-concept rather than a clinically validated localization tool. External validation in independent and multicenter cohorts, direct comparison with established ECG-based localization criteria, and evaluation of more detailed anatomical sublocalization are warranted before clinical implementation.

Ethics Committee Approval: This study was approved by the Ethics Committee of Kocaeli City Hospital Scientific Research (Approval No.: 2026-75; Date: June 11, 2026).

Informed Consent: Informed consent was not required because the study was conducted retrospectively using anonymized ECG data.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – A.Ş., T.A., N.K., S.B.; Design – A.Ş., N.K., S.B., E.A.; Supervision – A.Ş., S.B., T.E.G., N.K.; Resources – A.Ş., S.B., S.S., M.Ç., Y.K., N.K.; Materials – A.Ş., S.G., S.S., A.B.D., Ş.E.Ö.; Data Collection and/or Processing – A.Ş., Ş.E.Ö., Ş.N.D., H.Ü., Y.K., S.G., S.S.; Analysis and/or Interpretation – A.Ş., M.Ç., S.B., N.K., T.A.; Literature Search – A.Ş., S.B., N.K.; Writing – A.Ş., S.B., Ş.E.Ö., M.Ç.; Critical Review – A.Ş., T.A., N.K., S.B., E.A., T.E.G., S.S., M.Ç., Y.K., S.G., A.B.D., Ş.E.Ö., Ş.N.D., H.Ü.

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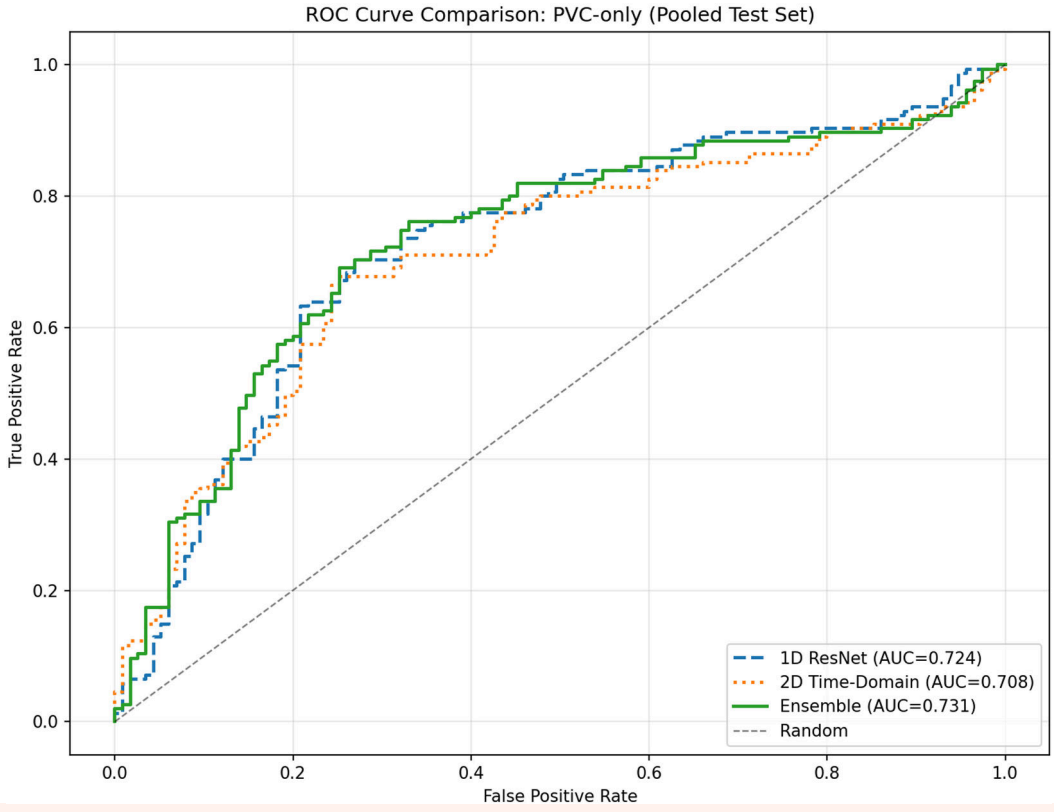
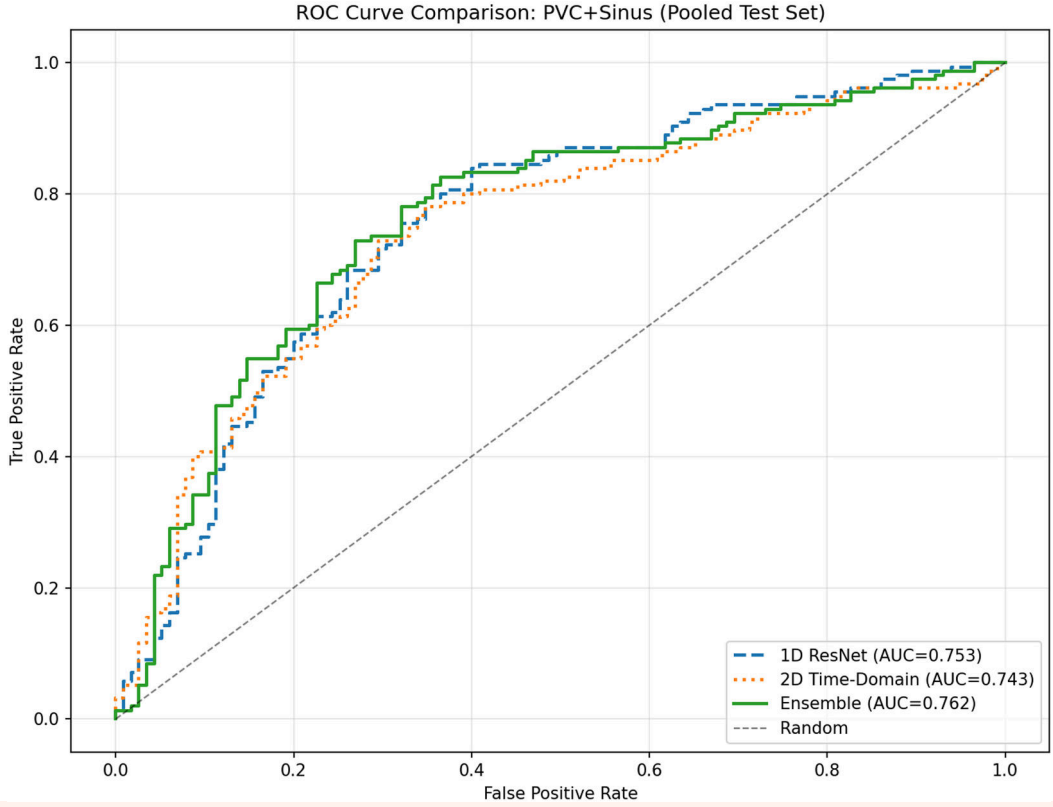
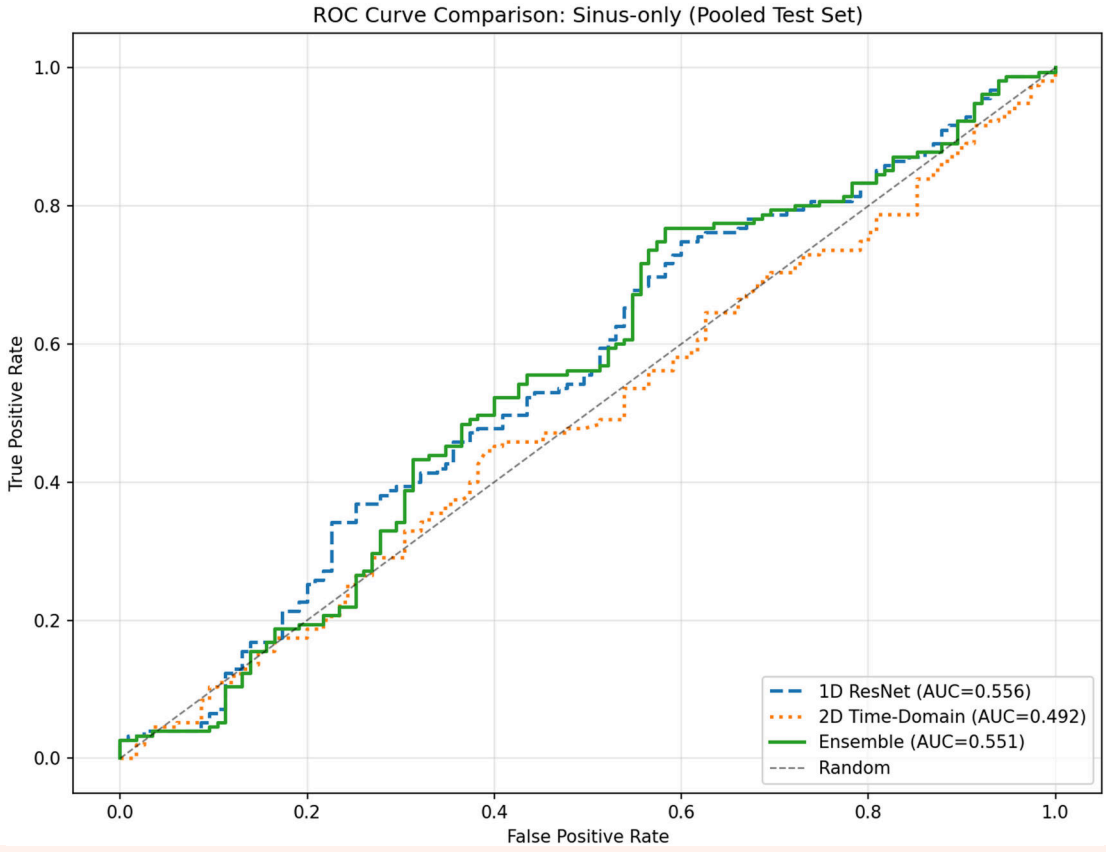


Supplementary Figure 1. Architecture-Specific ROC Analysis for Paired PVC+Sinus Rhythm Input. Receiver operating characteristic curves comparing the 1D ResNet, 2D time-domain CNN, and late-fusion ensemble models using paired PVC+sinus rhythm input.



Supplementary Figure 2. ROC curves comparing 1D ResNet, 2D CNN, and late-fusion ensemble models using PVC-only input.



Supplementary Figure 3. Architecture-Specific ROC Analysis for Sinus Rhythm-Only Input. Receiver operating characteristic curves comparing the 1D ResNet, 2D time-domain CNN, and late-fusion ensemble models using sinus rhythm-only input.