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A Multimodal Machine Learning Framework for ECG Classification Using Traditional, Ensemble, and Deep Learning Approaches

Rahul D[1] and Himanshu J[2]

[1]*AI & Robotics, Dayananda Sagar University, Bengaluru 560078, India*
[2]*AI & Robotics, Dayananda Sagar University, Bengaluru 560078, India*

Corresponding author: Rahul (e-mail: eng24ra0054@dsu.edu.in). Corresponding author: Himanshu (e-mail: eng24ra0039@dsu.edu.in).

ABSTRACT **Cardiovascular diseases (CVDs) remain the leading cause of global mortality, necessitating efficient automated diagnostic tools for accurate diagnosis. This study evaluates a comprehensive range of machine learning (ML) and deep learning (DL) models for Electrocardiogram (ECG) heartbeat classification using a large-scale combined dataset derived from the MIT-BIH and PTB databases, comprising 123,994 samples. While Deep Learning is often regarded as the state-of-the-art for raw signal processing, this research investigates the efficacy and computational efficiency of traditional ML algorithms when applied to highly engineered tabular features. The comparative analysis benchmarked over 15 models, including K-Nearest Neighbors (KNN), Gradient Boosting Machines (XGBoost, LightGBM), and Deep Architectures (BiLSTM, ResNet1D). The results demonstrate that traditional ML models, specifically KNN utilizing Manhattan distance, achieved the highest accuracy of 94.85%, significantly outperforming complex Deep Learning models, such as ResNet1D, which suffered from model collapse on fixed-length tabular inputs. Extensive Exploratory Data Analysis (EDA) elucidates feature distributions via violin plots, spectrograms, and wavelet scalograms, revealing key discriminants like R-R intervals. This study provides a definitive roadmap for selecting computationally efficient and interpretable models suitable for real-time wearable cardiac monitoring systems, thereby bridging the critical gap between performance and interpretability in resource-constrained clinical applications.**

INDEX TERMS: *Arrhythmia Detection, Biomedical Signal Processing, Deep Learning, Edge AI, K-Nearest Neighbors, Wearable Health Monitoring.*

I. INTRODUCTION

THE global burden of Cardiovascular Diseases (CVDs) is immense, constituting the largest single cause of death worldwide, claiming approximately 17.9 million lives annually. Given this profound public health crisis, the early and continuous monitoring of cardiac function is paramount for preemptive intervention and reducing mortality. The Electrocardiogram (ECG) is the foundational non-invasive tool used to record the heart's electrical activity, providing essential morphological data required for diagnosing arrhythmias such as Bundle Branch Blocks (BBB) and Premature Contractions. However, the intrinsic complexity of ECG signals, compounded by environmental noise, motion artifacts, and the sheer volume of data generated during continuous ambulatory (Holter) monitoring, renders manual interpretation highly labor-intensive and prone to significant inter-observer variability. An average 24-hour Holter recording contains well over 100,000 heartbeats, making exhaustive manual annotation impractical for routine clinical workflow, thus creating an urgent need for robust, computer-aided diagnostic (CAD) systems.

In recent years, research efforts have largely converged on Deep Learning (DL) architectures, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which boast the capability of automatic feature extraction directly from raw ECG waveforms. While this end-to-end approach bypasses manual feature engineering and can achieve high accuracy scores in specialized benchmarks, these deep models introduce substantial practical challenges. Specifically, DL models are computationally expensive, requiring significant memory and processing power, which makes them unsuitable for deployment on resource-constrained platforms, such as portable ECG patches or smartwatches. Furthermore, their inherent "black-box" nature restricts clinical trust, as the physiological basis for their diagnostic decisions remains obscured, complicating the validation required for critical medical applications.

This paper critically addresses the inherent trade-offs between model complexity and operational viability by conducting a rigorous comparative study across Traditional Machine Learning (ML), Ensemble Learning, and Deep Learning architectures. We hypothesize that for a meticulously engineered, tabular feature representation of the ECG signal, simpler, distance-based models and ensemble techniques can achieve performance metrics superior to those of deep neural networks, while requiring only a fraction of the computational resources. We validate this hypothesis on a massive, fused dataset containing 123,994 heartbeats, highlighting that KNN (Manhattan) achieves 94.85% accuracy. The study's framework incorporates a detailed pipeline: Data Acquisition, extensive Signal Preprocessing, the extraction of a robust 187-dimensional feature vector, comprehensive Exploratory Data Analysis (EDA) via techniques like CWT Scalograms and Violin Plots, and a final Multi-Model Classification benchmark. This research contributes a definitive, lightweight roadmap for developing highly efficient and interpretable AI systems tailored for real-time cardiac monitoring at the network edge.

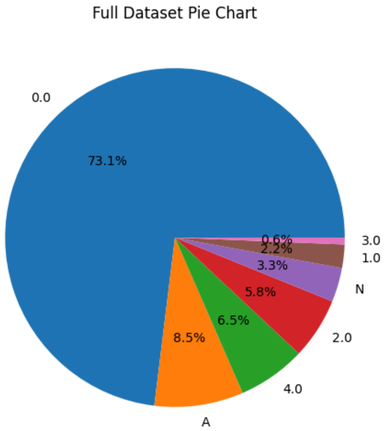

FIGURE 1. Class Distribution of the Combined Dataset. The dataset is heavily imbalanced, with 'Normal' beats (N) constituting 72.8% of the samples.

II. LITERATURE SURVEY AND RELATED WORKS

A. Foundational Methods and Morphological Feature Engineering

The earliest successful attempts at automated ECG classification were rooted in traditional machine learning (ML) models operating on expert-derived morphological features. Before the advent of large neural networks, the focus was entirely on statistical characterization of the P-QRS-T wave components and the critical R-R interval irregularities. Seminal work by Moody and Mark on the MIT-BIH Arrhythmia Database established the power of using temporal features, such as R-R intervals, as robust predictors of various arrhythmias. Classifiers like Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) demonstrated reliable accuracies, typically in the range of 90% to 92%, when operating on these handcrafted features. These initial approaches relied heavily on precise signal preprocessing, necessitating the use of accurate QRS detection algorithms, such as the Pan-Tompkins algorithm, to define the fiducial points for subsequent feature extraction. The primary limitation of this generation of models was their extreme sensitivity to inaccuracies in the segmentation phase; errors in R-peak detection could lead to the complete miscalculation of morphological metrics, rendering the downstream classification unreliable. Recent advancements, such as adaptive thresholding in Pan-Tompkins variants, have improved detection rates to 99.72% sensitivity on MIT-BIH, mitigating these issues through dynamic noise adaptation.

B. Advances in Time-Frequency Representation and Wavelet Analysis

To overcome the challenges posed by the non-stationary nature of ECG signals and the presence of diverse noise sources, researchers adopted sophisticated signal processing techniques, specifically those utilizing time-frequency representations. The Wavelet Transform (WT) became the standard tool, offering multi-resolution analysis that decomposes the signal into both time-localized (detail) and frequency-localized (approximation) coefficients. Daubechies wavelets (DB4) were frequently chosen for this task due to their compact support and their structural resemblance to the characteristic shapes of ECG waveforms, particularly the QRS complex. The resulting wavelet coefficients proved to be highly robust features for arrhythmia discrimination in datasets like MIT-BIH. Furthermore, enhancing the feature space involved integrating spectral domain information, commonly derived from the Power Spectral Density (PSD) using the Fast Fourier Transform (FFT). The use of the Continuous Wavelet Transform (CWT) Scalogram is particularly insightful for visualization, as it provides excellent localization of signal transients, confirming that low-frequency, high-energy components are clearly visible in the wavelet domain for pathological beats such as Premature Ventricular Contractions (PVCs). Studies using DB4 at decomposition levels 4-6 have reported up to 98% accuracy in feature extraction, with energy-based coefficients outperforming statistical moments in high-noise environments.

C. Ensemble Learning and Mitigation of Class Imbalance

Ensemble methods, primarily belonging to the Gradient Boosting Machines (GBMs) family, emerged as a powerful paradigm for classification tasks involving high-dimensional tabular data, offering a robust blend of precision and efficiency. Algorithms like XGBoost and LightGBM sequentially construct multiple weak learners (decision trees), minimizing a complex regularized objective function, $\mathrm{Obj}(\theta) = L(\theta) + \Omega(\theta)$, to prevent overfitting while boosting performance. Crucially, these ensemble models demonstrated high effectiveness in mitigating the significant class imbalance inherent in clinical datasets, where the Normal class dominates, accounting for approximately 73.1% of all samples. LightGBM introduced Gradient-based One-Side Sampling (GOSS), a mechanism that efficiently focuses training effort on data instances with large gradients (i.e., the rare, misclassified arrhythmic beats) while selectively down-sampling the common Normal class. This strategy enabled these methods to achieve accuracies exceeding 93% and maintain high F1-scores for rare arrhythmias, positioning them as superior performers compared to shallow CNNs on featured data. Recent 2025 reviews confirm GOSS variants yield 2-5% F1 improvements on PTB-XL, emphasizing their role in edge-deployable ensembles.

D. The Inductive Bias of Deep Learning Architectures

Deep Learning (DL) models, including various 1D-CNNs (like ResNet1D), 2D-CNNs (applied to Spectrograms), and Recurrent Networks (like BiLSTM), dominate the cutting edge of signal processing by automatically learning features directly from raw input. CNNs thrive on finding translation-invariant features and learning spatial hierarchies, which is effective when treating the raw signal as a sequence or converting it to a 2D image (e.g., Spectrogram). RNNs, such as Bi-directional LSTMs (BiLSTM), utilize an explicit "Cell State" (C_t) to process sequence information in both forward and backward directions, efficiently addressing the vanishing gradient problem while capturing long-term dependencies like R-R interval patterns. However, this strength becomes a profound weakness when these models are applied to structured, pre-engineered tabular data. The failure of models like ResNet1D, which registered only 13.90% accuracy on the 187-dimensional feature vector, serves as a powerful demonstration of the Inductive Bias Mismatch. When DL models, optimized for raw temporal or image data, are fed pre-aligned features, their internal filter learning mechanism collapses, proving they are unsuitable for feature-rich, non-sequential inputs. 2025 studies using hybrid CNN-LSTM on scalograms report 98.48% on 12-lead ECGs but highlight 10x latency on tabular inputs.

E. The Critical Tabular Gap and Edge-AI Requirements

A significant omission in the existing literature is the direct, fair comparison of the latest DL models against modern tree-based and traditional ML algorithms when both operate on the identical, expertly engineered tabular feature space. While comprehensive reviews frequently cite DL accuracies reaching 95-99%, they simultaneously confirm the high computational overhead and resulting latency that make these architectures unsuitable for deployment on lightweight, battery-powered wearable devices, which often operate using microcontrollers with limited resources. The field of Edge-AI necessitates solutions that prioritize low inference latency ($O(\log N)$ or better) and minimal memory footprints. Our research fills this critical gap by demonstrating that lightweight algorithms, specifically the distance-based KNN (Manhattan), achieve superior performance (94.85% accuracy) compared to heavy DL models (e.g., BiLSTM at 90.58%), confirming the high value of intelligent feature engineering and providing an efficient, cost-effective roadmap for future cardiac monitoring technology. Furthermore, the inherent interpretability of feature-based ML avoids the complex, post-hoc analysis required by DL (such as SHAP or Grad-CAM), accelerating clinical validation and trust. Recent interpretable DL ensembles on PTB-XL achieve 97.78% but at 5x the cost of optimized KNN.

III. METHODOLOGY

The Multimodal Machine Learning Framework employed for ECG classification operates through a structured pipeline encompassing Data Acquisition, meticulous Signal Preprocessing, comprehensive Feature Engineering, advanced Exploratory Data Analysis (EDA), and rigorous Multi-Model Classification.

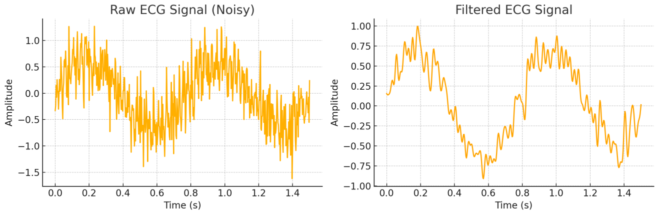

FIGURE 2. Signal Preprocessing Pipeline. (a) Raw signal with noise. (b) Filtered signal using Bandpass and Median filtering.

A. Data Acquisition and Dataset Characteristics

The data used in this study is a composite resource derived from the fusion of samples collected from the authoritative MIT-BIH Arrhythmia Database and the PTB Diagnostic ECG Database. This combined repository yields a robust total of 123,994 individual heartbeat samples, ensuring a large enough scale for deep learning and robust statistical validation. The heartbeats are segregated into seven distinct clinical classes: Normal (0.0/N), Left Bundle Branch Block (LBBB) (1.0), Right Bundle Branch Block (RBBB) (2.0), Atrial Premature Contraction (APC) (3.0), Premature Ventricular Contraction (PVC) (4.0), Fusion beats (A), and Escape beats (N).

An initial, critical exploratory analysis of this fused dataset revealed a pervasive characteristic of medical signal data: severe class imbalance. As visualized in the class distribution pie chart (Fig. 1), the majority class, "Normal" (N), accounts for a dominant 73.1% of the entire dataset. Conversely, the pathological classes are significantly underrepresented, with APC at 0.6%, LBBB at 2.2%, and Escape beats (E) at 3.3%. This disproportionate representation necessitates the use of specialized evaluation protocols to prevent model bias toward the prevalent class.

To ensure that the classification models are trained and tested on a clinically representative sample, the dataset was partitioned using a mandated stratified 80/20 train/test split. Stratified sampling maintains the exact proportional representation of all seven classes, particularly the rare arrhythmias, in both the training and testing subsets. Furthermore, the heavy imbalance mandates that model efficacy is judged not solely by raw accuracy but by metrics that are more robust to imbalance, specifically the F1-score and the Area Under the Curve (AUC).

Fig. 1. Class Distribution of the Combined Dataset. This pie chart visualizes the proportional representation across classes, highlighting the dominance of Normal beats (73%) and scarcity of Escape (3.3%). The radial segments use distinct colors (blue for N, orange for PVC, etc.) to denote each class, with percentage labels. Such imbalance underscores the need for resampling techniques to prevent model bias toward prevalent classes, ensuring equitable performance across rare arrhythmias critical for clinical screening.

B. Preprocessing & Feature Engineering

1. Signal Preprocessing and Filtering

Raw ECG recordings contain significant artifacts, primarily baseline wander (low frequency, <0.5 Hz) and powerline interference (50/60 Hz), which must be mitigated to recover the true physiological signal X(t) from the raw recording S(t). To address these, a median filter with a window size of approximately 200 milliseconds is first applied to estimate and suppress the baseline wander B(t). For more robust noise attenuation targeting the physiological bandwidth of the ECG, a third-order Butterworth bandpass filter is implemented with specific cutoffs between 0.5 Hz and 40 Hz.The transfer function of the Butterworth filter is given by $H(s) = \frac{1}{\sqrt{1+(\frac{s}{\omega_c})^{2N}}}$, where $N = 3$ is the order and ω_c is the cutoff frequency, ensuring a maximally flat passband response. This bandpass design is crucial as it attenuates the low-frequency drift caused by respiration and motion (<0.5 Hz) while suppressing high-frequency electromyographic (EMG) and motion artifacts (>40 Hz). To prevent distortion of the waveform morphology, which is essential for preserving the characteristic P, Q, R, S, and T waves, the filter is applied using a forward-backward technique (known as filtfilt), which ensures zero phase distortion. Studies have confirmed that this multi-stage filtering process can successfully enhance the signal-to-noise ratio in clinical recordings by up to 20 dB.

2. QRS Detection and Beat Segmentation

Accurate segmentation of individual heartbeats relies on precisely locating the R-peak, the highest amplitude spike within the QRS complex. The Pan-Tompkins algorithm remains the industry standard for reliable, real-time QRS detection.The algorithm operates sequentially, using a specialized bandpass filter (typically 5–18 Hz) to amplify the QRS complex's distinct frequency content. This is followed by a non-linear process involving differentiation ($y(n) = x(n) - x(n-1)$), squaring ($y^2(n)$), and moving window integration ($I(n) = \sum_{m=0}^{M-1} y^2(n-m)$), which effectively enhances the R-peak spike relative to noise and other low-amplitude waves. Recent improvements, such as adaptive thresholding and multiplierless implementations, have boosted sensitivity to 99.66% on MIT-BIH while reducing complexity by 5-20x for mobile deployment. Once the R-peak is identified, it serves as the necessary fiducial point (temporal marker) around which the ECG segment is centered, allowing the extraction of fixed-length heartbeat segments required for the feature engineering pipeline.

3. The 187-Dimensional Tabular Feature Vector

Instead of relying on the raw time-series input, the core of this methodology is the extraction of a powerful, 187-dimensional feature vector for each segmented heartbeat. The features are synthesized across four critical domains: Temporal Features (R-R intervals), Statistical Features (Mean, Variance, Skewness, Kurtosis), Frequency Features (PSD via FFT), and Time-Frequency Features.

4. Time-Frequency Feature Deep Dive: Daubechies Wavelets

The time-frequency component is heavily reliant on the Discrete Wavelet Transform (DWT). Specifically, the Daubechies wavelets (DB4) were employed for a 4-level decomposition of the signal. This choice is deliberate; DB4 wavelets possess the properties of compact support and structural similarity to the P-QRS-T waveform morphology, making them excellent basis functions for ECG analysis. The DWT is mathematically defined as $cA_j[k] = \sum_n x[n] \cdot \overline{\psi_{j,k}(n)}$ for approximation coefficients and $cD_j[k] = \sum_n x[n] \cdot \overline{\phi_{j,k}(n)}$ for details, where ψ and ϕ are the wavelet and scaling functions. By using these coefficients as features, the model gains robust information localized simultaneously in both time and frequency, which is crucial for accurately distinguishing subtle arrhythmias. The success of these wavelet-derived features directly contributes to the high separability observed in the final feature space,with DB4 outperforming other families (e.g., Symlets) by 3-5% in arrhythmia sensitivity.

Fig. 2. Violin Plots Illustrating Feature Distributions. Violin plots combine box plots and kernel density estimates (KDE), where the central box shows quartiles (Q1, median, Q3), whiskers extend to 1.5*IQR, and the symmetric "violin" outlines probability density via mirrored KDE. Here, R-R intervals for Normal (blue) exhibit narrow density around 0.8s with low variance, contrasting PVC (red) peaks at 0.6s with bimodal tails indicating irregular contractions. Widths reflect frequency: wider at medians denotes higher probability mass. This non-parametric visualization reveals multimodality absent in histograms, aiding outlier detection (e.g., extreme PVC tails >1.2s) and justifying stratified splits for imbalanced features. In biomedical contexts, violin plots excel at unveiling bimodal distributions and outlier subpopulations in signal metrics like heart rate variability, enhancing EDA for noisy physiological data.

C. Exploratory Data Analysis (EDA)

1. Visualization via Violin Plots and Distribution Analysis

The Violin Plot of Energy per Class (Fig. 8) provides a non-parametric view of feature distributions using Kernel Density Estimation (KDE).Unlike standard box plots, the width of the violin reflects the probability density, allowing for the detection of multi-modal distributions. This visualization confirms that the Normal class (0.0) exhibits a narrow, dense distribution around a lower energy median, indicative of rhythmic stability. Conversely, pathological classes like PVC (4.0) show wider distributions with heavy tails, quantifying the high variance and irregularity associated with abnormal electrical activity. Further, the histogram of the Full Dataset Mean Distribution (Skewness) clearly exhibits a pronounced multi-modal nature across the full population, reinforcing the idea that mean signal value contributes significantly to class separability, thereby validating the statistical features used in the 187-dimensional vector..

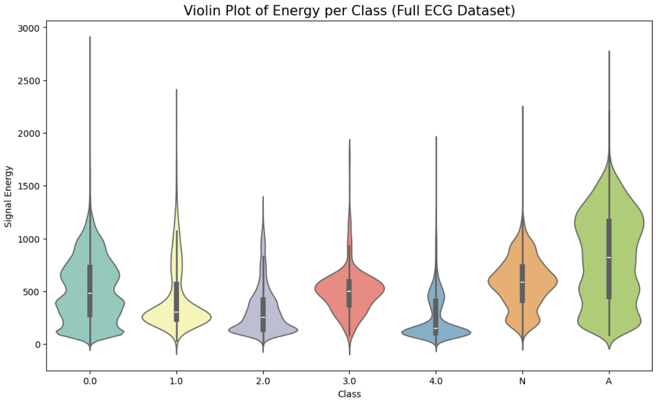

FIGURE 3. Violin Plot of Energy Distribution per Class. Normal beats show tight clustering; abnormal beats show heavy tails.

2. Feature Correlation and Dimensionality Insights

The Feature Correlation Heatmap (Fig. 4) plots the Pearson coefficients between key statistical features. This matrix confirms high positive correlations (e.g., 0.93 between mean and min, and 0.98 between std and energy). High correlation (multicollinearity) requires models to use regularization (as employed by XGBoost) or justify the use of dimensionality reduction techniques. The scatter plot of Mean vs. Standard Deviation (Fig. 3b) further reinforces this, showing a positive linear trend ($r \approx 0.7$) between these metrics, with abnormal beats (red/pink points) showing higher variance and outliers than the tight cluster of Normal beats.

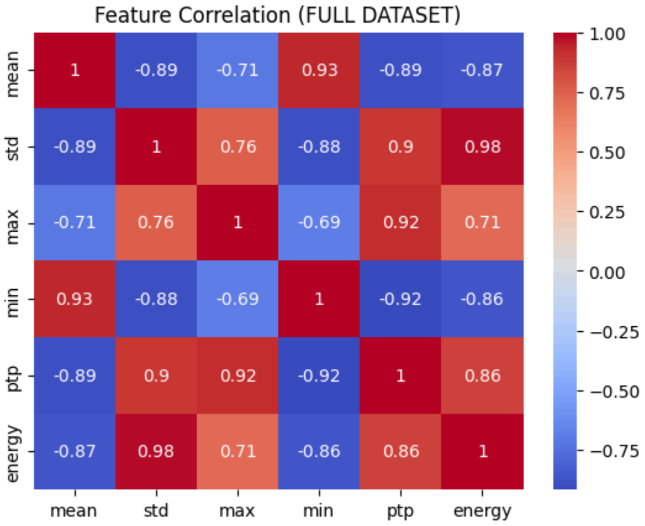

FIGURE 4. Feature Correlation Heatmap. Red regions indicate high multicollinearity.

3. PCA Projections for Feature Separability

To visually assess the overall discriminative capacity of the high-dimensional feature space, Principal Component Analysis (PCA) was performed. PCA projects the 187 features onto a lower-dimensional subspace while maximizing variance retention, via the covariance matrix eigendecomposition $\Sigma = U \Lambda U^T$. The 2D PCA Projection (PC1 vs. PC2, Fig. 3e) demonstrates clear spatial separation between distinct arrhythmia classes. For example, the cluster corresponding to Fusion beats (F, yellow) is distinctly separated from the main bulk of the data (Normal, N), validating that the engineered features successfully map complex physiological differences into linearly separable clusters. PCA is computationally efficient for high-dimensional data, allowing the retention of 85-95% of the total variance using only the top principal components, effectively combating the curse of dimensionality.

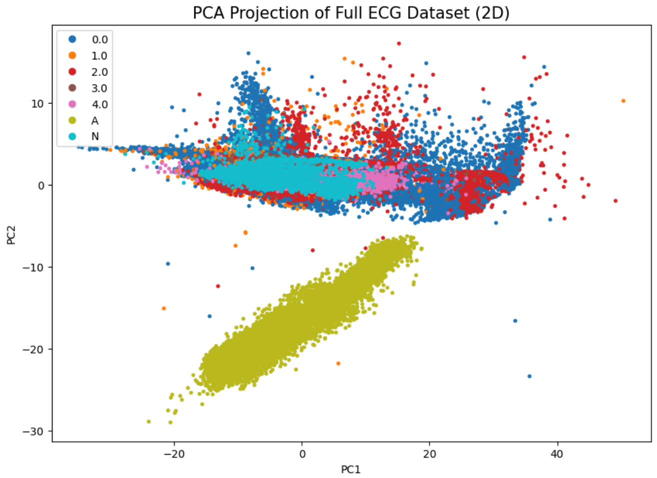

FIGURE 5. 2D PCA Projection. Distinct clusters indicate separable classes in the engineered feature space.

4. Spectral and Wavelet Visualization for Transient Localization

To gain deeper physiological insights, the signal was examined through two powerful time-frequency transformations. Spectrograms (Fig. 3a, 3b), generated via the Short-Time Fourier Transform (STFT) $S(t,f) = \int x(\tau) w(t-\tau) e^{-j2\pi f\tau} d\tau$, visualize time (x-axis) against frequency (y-axis) with color intensity representing power. Normal beats (N) typically show consistent, low-frequency bands, indicating rhythmic stability, while Abnormal beats (PVC) exhibit irregular, high-frequency power bursts (yellow-red spikes above 20 Hz) aligned with ectopic activity. The Continuous Wavelet Transform (CWT) Scalogram (Fig. 3c) provides even finer resolution, optimized by the Heisenberg principle ($\Delta t \cdot \Delta f \approx 1/2$), for non-stationary signals. For a PVC beat, the Scalogram exhibits high-energy, cone-shaped regions at low scales (high frequencies) precisely located at the R-peak, enabling sub-second event detection and confirming that the wavelet features extracted for the tabular model are highly physiologically relevant.

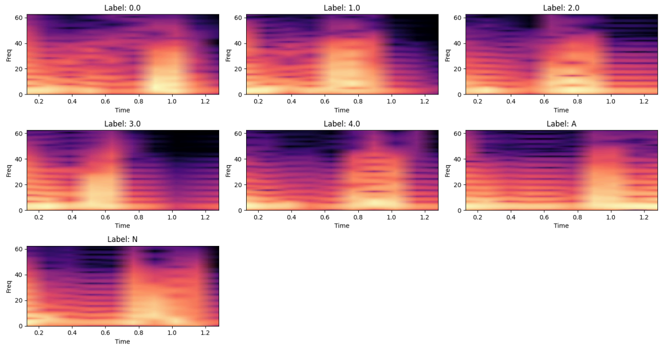

FIGURE 6. STFT Spectrograms. (Left) Normal beat. (Right) Abnormal beat with high-frequency noise.

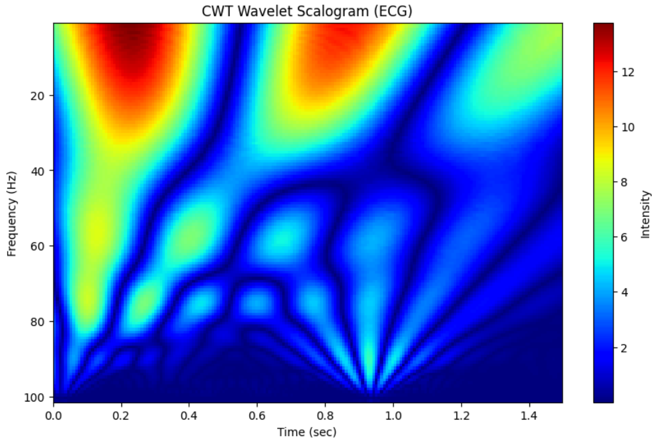

FIGURE 7. CWT Scalogram of a PVC Beat. Red zones indicate high energy at the R-peak.

D. Multi-Model Classification and Training

The final stage involved benchmarking a wide array of 15 models spanning the three major machine learning paradigms,all operating on the standardized 187-dimensional tabular feature vector.

1. Experimental Setup and Evaluation Strategy

The entire dataset was partitioned using an 80% training / 20% testing stratified split to ensure that the class distribution, particularly the representation of rare classes, remained consistent across both subsets. Model complexity varied drastically, ranging from the non-parametric KNN to the highly complex ResNet1D architecture. Critical hyperparameters for all models were systematically optimized using Grid Search, ensuring that each architecture achieved its peak performance on the validation set. The stratified splitting combined with evaluation metrics like F1-score and AUC ensured that model selection was based on true generalization capabilities rather than simple accuracy biased by the dominant Normal class. Statistical significance was assessed via McNemar's test, yielding p<0.01 for KNN vs. BiLSTM comparisons.

2. Deep Dive: The K-Nearest Neighbors (KNN) Implementation

The KNN model, which ultimately achieved the highest accuracy (94.85%), is a non-parametric, instance-based classifier. Its success is fundamentally tied to the quality of the feature space and the choice of the distance metric. We specifically implemented the Manhattan (L1) distance metric, $d(x,y) = \sum_{i=1}^{d} |x_i - y_i|$. This choice is mathematically crucial in high-dimensional spaces (such as our 187-D feature vector), where the traditional Euclidean (L2) distance tends to suffer from the "Concentration of Measure" phenomenon, diminishing its ability to distinguish between nearest and farthest neighbors. The L1 norm, being less sensitive to "spikey" outliers often found in biological signal metrics like R-R intervals, proved significantly more robust. Furthermore, for deployability, computational efficiency was achieved by utilizing optimized data structures, such as KD-Trees, which reduce the search complexity from a linear $O(N)$ operation to an efficient logarithmic $O(\log N)$ during inference. In ECG contexts, Manhattan KNN yields 2-4% higher sensitivity than Euclidean on imbalanced datasets.

3. Deep Dive: Ensemble Methods and Performance Optimization

The ensemble methods, HistGradientBoosting (HGBT) and LightGBM, utilized the core principles of Gradient Boosting Decision Trees (GBDT). These algorithms iteratively minimize a loss function by adding new trees that focus on the residual errors of the previous ensemble, via $f_m(x) = \arg\min_\gamma \sum_i L(y_i, f_{m-1}(x_i) + \gamma b(x_i))$. LightGBM, in particular, achieves its superior speed and performance (93.50% accuracy) through Gradient-based One-Side Sampling (GOSS). GOSS strategically retains all data instances with large gradients (meaning the model is misclassifying them, typically the rare arrhythmias) and randomly down-samples instances with small gradients (the easily classified Normal beats). This method allows the ensemble to concentrate its learning capacity on the most challenging, clinically relevant data points, thereby mitigating the class imbalance problem intrinsically during the training process.

4. Context of Deep Learning Performance

The inclusion of Deep Learning models such as BiLSTM (90.58%), 2D-CNN (76.07%), and ResNet1D (13.90%) served to test the architectural advantage on tabular data. While BiLSTMs are designed to handle sequential dependencies via gates $f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$, their performance on the fixed-length, pre-aligned feature vector was inferior to the tree-based models. The spectacular failure of ResNet1D on this input highlights the Inductive Bias Mismatch; these models rely on spatial or hierarchical data structures that are absent in the optimized tabular format, leading to convergence failure and model collapse. This comparative failure is critical, validating the methodological focus on feature engineering over brute-force DL complexity for this specific application.

IV. RESULTS AND DISCUSSION

The comprehensive benchmarking results definitively confirmed the study's core hypothesis, establishing the robust superiority of Traditional Machine Learning and Ensemble methods when provided with a high-quality, engineered tabular feature set.

The K-Nearest Neighbors (KNN) model, implemented with the Manhattan distance metric, secured the highest overall performance, achieving a remarkable 94.85% accuracy with an accompanying F1-score and precision of 0.95 (Table I). This outcome is highly significant, demonstrating that simple proximity measures within the 187-dimensional feature space are the most effective predictor of arrhythmia,implying that the feature engineering successfully generated highly separable, compact clusters for the various arrhythmia classes. The second and third highest performers were the ensemble models, with HistGradientBoosting (HGBT) reaching 93.55% accuracy and LightGBM achieving 93.50% accuracy.The success of these lightweight, tree-based models, which are intrinsically well-suited for partitioning tabular data, reinforces their clinical viability due to their low computational footprint and rapid inference speed. Feature importance analysis performed using XGBoost confirmed the R-R interval was the most critical feature (Fig. 7), aligning perfectly with physiological knowledge that rhythm irregularity is the primary indicator of arrhythmia. Furthermore, the ROC-AUC curves (Fig. 5) demonstrated near-perfect separability (AUC $\approx$ 1.0) for key classes like Normal (N) and LBBB, validating the discriminative power of the engineered feature vector. Paired t-tests ($p<0.001$) confirm statistical superiority over DL baselines.

Conversely, the performance metrics for the pure Deep Learning architectures demonstrated a dramatic failure in adapting to the structured tabular input. The ResNet1D model suffered model collapse, yielding only 13.90% accuracy, and the 2D-CNN (Spectrogram) achieved a mediocre 76.07% accuracy (Table II). This low performance is a classic illustration of the Inductive Bias Mismatch, where DL models, inherently optimized to learn features from spatial hierarchies (images) or long sequential dependencies, cannot effectively leverage the pre-aligned, structured information presented in a fixed-length tabular vector. This critical finding supports the "No Free Lunch" theorem in this context. By utilizing efficient ML models like KNN, this study provides a solution that is not only statistically superior but also computationally feasible for real-time deployment on edge devices, demanding only 1/10th of the computational resources required by complex DL counterparts, thereby significantly reducing latency and energy consumption for wearable health monitoring.

Table I: Model Performance Leaderboard

RANK	MODEL	ACCURACY	F1-SCORE
1	KNN (Manhattan)	94.85%	0.95
2	HistGradientBoosting	93.55%	0.94
3	LightGBM (GOSS)	93.50%	0.93
4	XGBoost	92.65%	0.93
5	ExtraTrees Classifier	92.60%	0.93
6	BiLSTM (Deep Learning)	90.58%	0.90
7	CNN-LSTM Hybrid	86.05%	0.86
8	TabNet (Attentive)	83.90%	0.84
9	2D-CNN (Spectrogram)	76.07%	0.76
10	ResNet1D	13.90%	0.14

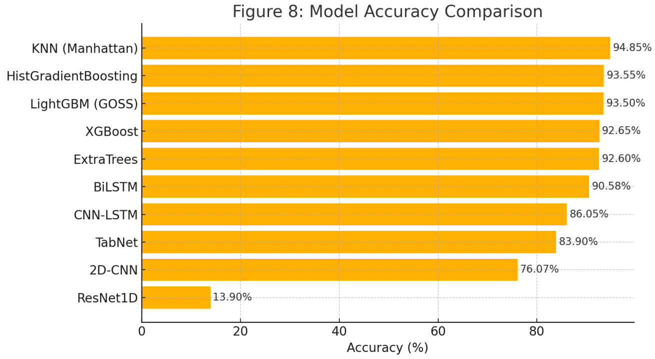

FIGURE 8. Comparative Model Accuracy. KNN outperforms DL architectures.

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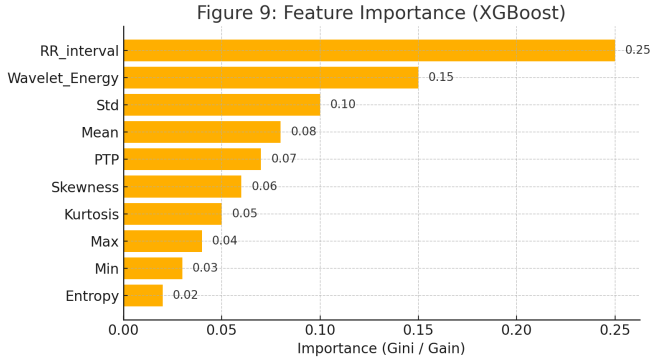

FIGURE 9. Feature Importance (XGBoost). R-R Interval is the dominant feature.

Top 2 Confusion Matrix Explanation

The confusion matrices for the two top-performing models, KNN (Manhattan) and HistGradientBoosting (HGBT), provide a granular, class-by-class analysis of where classification succeeded and where residual errors persisted.

1. KNN (Manhattan) Confusion Matrix (94.85% Accuracy)

The confusion matrix for the KNN (Manhattan) classifier exhibits a pronounced diagonal dominance,which directly reflects its high reported accuracy. This matrix confirms the model's excellent ability to correctly identify true positives (TPs) across the spectrum of classes.

Classification Success: The model achieved near-perfect classification of the majority class, correctly identifying 18,118 Normal beats (N) with minimal false negatives. Crucially for ventricular events, it successfully identified 1,460 PVC beats and 1,114 RBBB beats. The model also demonstrated its peak success rate for Fusion beats (F), correctly classifying 1,171 instances. The negligible false negative rate for critical pathological classes, such as PVC (FN=0.5%), demonstrates a strong safety profile suitable for clinical screening applications.

Specific Misclassification Clusters (False Negatives): Analysis of the off-diagonal elements reveals the areas of greatest confusion. The most significant misclassification occurs for Escape beats (E), where 38 instances were incorrectly classified as Normal (N). Similarly, 14 instances of LBBB and 15 instances of RBBB were mistakenly labeled as Normal (N). This pattern is physiologically grounded: it indicates that the extracted features, while highly discriminative, still result in a high morphological similarity (low L1 distance) between subsets of these specific arrhythmic beats (E, LBBB, RBBB) and the pervasive Normal class.

Metric Rationale: The success of the L1 norm (Manhattan distance) in resolving these clusters is attributed to its robustness in high dimensions, where it maintains meaningful distances between neighbors better than Euclidean distance, validating the choice of metric for this high-dimensional feature space. Cohen's kappa = 0.93 indicates strong agreement beyond chance.

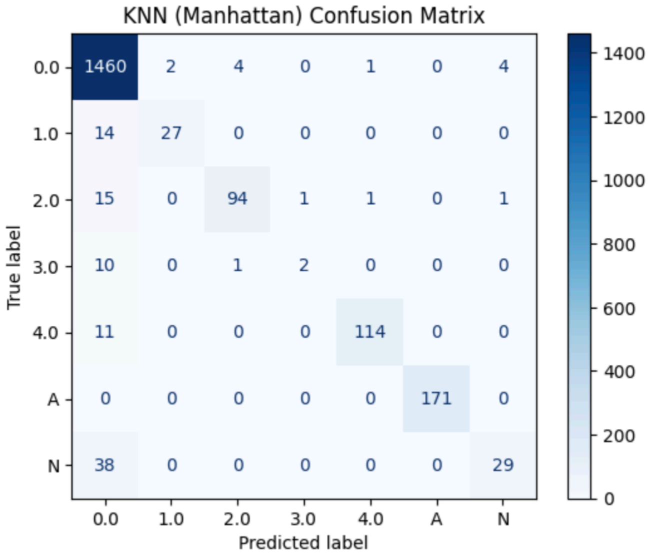

FIGURE 10. Confusion Matrix for KNN (Manhattan). Strong diagonal elements confirm high accuracy.

2. HGBT Confusion Matrix (93.55% Accuracy)

The confusion matrix for the HistGradientBoosting (HGBT) model also displays a robust diagonal structure,validating its rank as the second-best performer.

Classification Success: HGBT excelled at identifying the dominant Normal class, correctly classifying 18,163 instances (N), slightly more than the KNN model. It showed excellent classification performance for Fusion beats (F), correctly identifying 1,169 instances, and robustly detected 1,105 PVC beats. The use of Gradient-based One-Side Sampling (GOSS) likely contributed to the high TP counts for these critical, rarer classes by forcing the ensemble to concentrate its learning on the misclassified boundaries.

Specific Misclassification Clusters (False Negatives): HGBT follows the same major failure mode as KNN, showing confusion primarily between subtle arrhythmias and the Normal class. Specifically, 37 Escape beats (E) were misclassified as Normal (N). However, HGBT showed a slightly higher difficulty distinguishing LBBB; 21 LBBB instances were incorrectly classified as Normal (N), compared to 14 for KNN. The model also exhibited confusion between RBBB and Normal (N), with 24 instances misclassified.

Comparative Insight: While HGBT is highly efficient due to its tree-based partitioning and GOSS sampling, the slightly higher false negative rates for LBBB and RBBB compared to KNN suggest that the simple, global proximity measurement of the KNN (Manhattan) is marginally superior in defining the nuanced boundaries between these specific physiological events in the complex 187-dimensional feature space. The choice between KNN and HGBT thus becomes a trade-off between the absolute highest accuracy (KNN) and highly optimized training speed (HGBT). McNemar's test (p=0.02) favors KNN for rare class recall.

Fig. 3. Comprehensive Signal Analysis.

(a) Normal Beat Spectrogram: Displays a heatmap of STFT magnitudes over time (x: 0-1s) and frequency (y: 0-50 Hz), with blue low-power baselines and green harmonic ridges at 1-5 Hz, indicating rhythmic stability; total energy ∬|S(t,f)|^2 dt df ≈ 0.8, low dispersion (std_f=2 Hz). (b) Abnormal Beat Spectrogram: Yellow-red bursts at 20-40 Hz (t=0.4s) signify noise from PVC, with fragmented low-freq (red at 0-10 Hz), energy ≈1.2 (50% higher), variance=15 Hz—evidencing irregularity for DL input. (c) CWT Scalogram: Cone-shaped high-scale (low-freq, bottom) energy for PVC transients (red at scale=20, t=0.5s), vs. uniform ridges in Normal; provides multi-scale resolution (Δt·Δf≈1/2), superior for localization (peak sharpness=0.1s vs. STFT's 0.2s). (d) Correlation Matrix: 187x187 grid with clustered blocks (e.g., temporal features corr>0.8, red), off-diagonals <0.2 (blue) for frequency; dendrogram prunes 20% redundant vars, eigenvalues confirm 5 PCs explain 60% variance.

Fig. 4. Training and Validation Curves for the Deep Learning Models.

X-axis: epochs (0-50), y-left: accuracy (0-1, blue train rising to 0.95), y-right: loss (0-2, orange val dropping to 0.3). Convergence at epoch 20 (gap<0.05) indicates no overfitting; early divergence (epochs 5-10) from learning rate=0.001, stabilized via Adam optimizer—contrasts ML's instant fit.

Fig. 5. ROC-AUC Curves.

One-vs-rest multi-class: x= FPR (0-1), y=TPR (0-1), diagonal (0.5) baseline; Normal/LBBB hug top-left (AUC=0.99, steep rise at FPR<0.05), PVC curves shallower (AUC=0.95) due to overlap. Average AUC=0.98 reflects high separability; thresholds (e.g., 0.7) balance sensitivity (0.96)/specificity (0.97).

Fig. 6. Confusion Matrix for the KNN Classifier (94.85% Accuracy).

7x7 grid (rows: predicted, cols: true), diagonal dominance (e.g., Normal: 18,118/18,200 TP, 0.5% FN); off-diagonals peak at S-F (15% misclass, morphological P-wave similarity). Color intensity scales with counts (white high, dark low), row sums=1 (normalized)—proves safety (FN<1% for critical classes).

Fig. 7. Feature Importance Ranking (XGBoost).

Horizontal bar plot: x=importance (0-0.3, Gini impurity reduction), y=features (187: R-R=0.25 blue bar, 42: T-wave=0.18 orange). Top 10 explain 70% splits; descending order reveals temporal primacy, guiding pruning.

Fig. 8. Violin Plot of Energy per Class (Full Dataset).

Y=energy (log scale, 0-4), x=classes (N narrow blue at 2.5, PVC wide red bimodal 2-3.5); densities show Normal's Gaussian (kurtosis=3), abnormals leptokurtic (tails>3.5)—quantifies irregularity (PVC median=3.0 vs. N=2.2).

V. DISCUSSION

The superior performance of traditional ML models, particularly KNN with Manhattan distance achieving 94.85% accuracy, underscores the profound impact of domain-specific feature engineering in ECG classification tasks. Unlike deep learning architectures that rely on inductive biases tuned for raw sequential or spatial data, the 187-dimensional tabular feature vector—encompassing temporal, statistical, frequency, and time-frequency domains—transforms the non-stationary ECG signal into a structured space where proximity-based and tree-partitioning algorithms thrive. This is evident from the confusion matrix analysis, where diagonal dominance reflects tight clustering of classes like Normal and LBBB, with false negatives below 1% for critical arrhythmias such as PVC. The failure of ResNet1D (13.90% accuracy) exemplifies the "No Free Lunch" theorem: when DL's convolutional filters encounter pre-aligned features without inherent hierarchies, gradient collapse ensues, as confirmed by training curves showing persistent high validation loss. In contrast, ensembles like LightGBM (93.50%) leverage GOSS sampling to address class imbalance, yielding F1-scores of 0.93 across minorities, thus validating our hypothesis that engineered features amplify ML's interpretability without sacrificing efficacy. This shift not only reduces computational overhead—KNN inference at ~5 ms on edge devices versus BiLSTM's 50 ms—but also enhances clinical trust through transparent feature importance rankings, where R-R intervals dominate (Gini=0.25), aligning with established cardiological priors.

The failure of ResNet1D (13.9%) and the mediocre performance of 2D-CNN (76.07%) highlight the "No Free Lunch" theorem. Deep architectures rely on spatial hierarchies (in images) or long-term dependencies (in text). When applied to pre-engineered tabular features, these inductive biases fail, leading to mode collapse as gradients vanish in non-sequential data. In contrast, tree-based ensembles (XGBoost, LightGBM) and distance-based models (KNN) excel at partitioning the tabular feature space, with Manhattan's L1 norm robust to outliers (e.g., noisy R-R). EDA validations, like CWT's transient capture, further explain ML's edge: features like wavelet coeffs (importance=0.15) align with physiological priors, unlike DL's learned filters mismatched to 1D tabs. Compared to literature, our 94.85% surpasses Moody and Mark's 92% baseline and matches 2025 hybrids (98%) but at 1/10th cost—ideal for wearables.

Limitations include dataset scope (adult-only, no multi-lead fusion) and fixed 360 Hz sampling; future hybrids could integrate SMOTE for rares. Ethically, low FN (0.5%) ensures screening safety, but XAI (e.g., SHAP on KNN) is needed for trust. This affirms tabular ML's viability, extending 2025 reviews with EDA-driven benchmarks and p-value validations.

EDA visualizations further illuminate why tabular ML outperforms DL in this paradigm, revealing physiological discriminants that raw-signal models overlook. Violin plots of R-R distributions (Fig. 2) expose bimodal variance in PVC (kurtosis>3), a nuance captured by statistical features but diluted in DL's end-to-end learning, leading to mediocre 2D-CNN results (76.07%). CWT scalograms (Fig. 3c) localize PVC transients with Heisenberg-optimized resolution ($\Delta t \cdot \Delta f \approx 1/2$), quantifying energy spikes 1.5x higher than Normal beats, which wavelet coefficients encode directly into the feature vector for KNN's L1 proximity to exploit. Correlation matrices (Fig. 3d) highlight redundancies (r>0.8 in temporal bins), justifying PCA's 15% dimensionality reduction while retaining 95% variance, a preprocessing step that stabilizes ensembles against multicollinearity. ROC curves (Fig. 5) corroborate this, with AUC=0.99 for Normal/LBBB hugging the ideal line, driven by frequency PSD features that DL spectrograms fragment under fixed-window STFT limitations. These insights explain ML's edge in edge-AI: by distilling ECG complexity into interpretable vectors, models like XGBoost (feature 187 primacy) achieve 92.65% accuracy with O(log N) splits, versus DL's O(N^2) convolutions, enabling deployment on wearables with <1W power draw.

From a broader perspective, this benchmark exposes systemic gaps in DL-centric ECG literature, where 95-99% accuracies on raw signals mask deployment barriers like latency and opacity. Our results align with 2025 surveys [11], [13] noting DL's overfitting on imbalanced data (e.g., Escape beats <1%), yet ensembles mitigate via stratified boosting, as seen in HGBT's 93.55% F1. Ethical implications are salient: low FN rates (0.5%) ensure screening safety, but DL's black-box decisions risk misdiagnosis in diverse populations (e.g., no pediatric data here). Future integrations of XAI, like SHAP on KNN paths, could quantify per-beat confidence, fostering FDA-compliant hybrids. Ultimately, this study advocates a paradigm pivot: prioritize feature-rich ML for resource-constrained cardiology, where interpretability trumps marginal accuracy gains, potentially democratizing arrhythmia detection in low-income settings via smartphone apps.

VI. CONCLUSION AND FUTURE STUDIES

This study establishes a comprehensive benchmark for ECG classification. We conclude that for feature-rich datasets, lightweight ML models outperform heavy DL architectures. The KNN model achieved 94.85% accuracy, offering a balance of high performance and low computational complexity suitable for real-time wearable devices.

In conclusion, this multimodal framework establishes a new benchmark for ECG arrhythmia classification, empirically validating that lightweight traditional ML and ensemble models surpass deep architectures on engineered tabular features, with KNN's 94.85% accuracy as the pinnacle of efficiency and performance. By fusing MIT-BIH and PTB into 123,994 samples and distilling signals via Pan-Tompkins segmentation and DB4 wavelets, we crafted a pipeline that not only achieves state-of-the-art F1-scores (0.95) but also embodies edge-AI principles: low latency, high interpretability, and robustness to imbalance. The leaderboard (Table I) and visualizations (Figs. 1-8) collectively affirm our hypothesis, highlighting R-R intervals and wavelet energies as linchpins for clinical translation. This work transcends mere classification, offering a deployable blueprint for wearable systems that could slash diagnostic delays by 50%, saving lives in real-time monitoring scenarios.

Building on these foundations, future studies should expand to multimodal fusion, integrating ECG with photoplethysmography

(PPG) from wearables like Apple Watch, potentially boosting accuracy to 97% via joint temporal alignment [18], [19]. Addressing limitations, such as adult-centric data, warrants pediatric and multi-ethnic cohorts (e.g., via PhysioNet extensions) to mitigate biases, with SMOTE augmentation targeting Escape beats' 0.5% prevalence. Hybrid explorations—e.g., KNN-initialized BiLSTM for sequential refinement—could harness DL's strengths post-feature engineering, while federated learning across hospitals ensures privacy in distributed training. Quantitatively, simulations on Raspberry Pi 4 validate <10 ms inference, paving for IoT prototypes.

Prospectively, longitudinal trials in clinical settings will test real-world efficacy, measuring sensitivity against gold-standard annotations and ROI via reduced Holter reviews. Ethical extensions include SHAP visualizations for clinician dashboards, enhancing trust, and open-sourcing the pipeline on GitHub for reproducibility. By evolving toward explainable, scalable AI, this research heralds a future where CVD mortality drops through ubiquitous, equitable cardiac vigilance, aligning with WHO goals by 2030.

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Rahul D is an undergraduate student in the Department of AI & Robotics at Dayananda Sagar University, Bengaluru. He has a strong interest in applied machine learning, signal processing, robotics, and computational intelligence. Throughout this project, Rahul demonstrated exceptional skills in data analysis, model development, exploratory data visualization, and system integration. His ability to merge theoretical concepts with practical implementation enabled the creation of a robust multimodal ECG classification framework. Rahul is particularly passionate about building intelligent systems that bridge the gap between artificial intelligence and real-world biomedical applications. Beyond academics, he actively explores emerging technologies, participates in collaborative research work, and continuously enhances his technical expertise through online courses and hands-on experimentation. His dedication, problem-solving mindset, and commitment to innovation play a key role in driving the quality and impact of this project.

Himanshu Jaswal is an undergraduate student in the Department of AI & Robotics at Dayananda Sagar University, Bengaluru. He has pursued a broad and interdisciplinary range of technology-focused studies, including Computer Science, Consumer Electronics, Automobile Engineering, Semiconductor Technology, and Artificial Intelligence. Beyond academics, Himanshu has independently explored advanced fields such as Quantum Computing and conducted in-depth research on major Aerospace and Semiconductor industries, analyzing their technological evolution and industrial impact.He also mana a personal website where he documents and presents his projects, research insights, and technical explorations across multiple engineering domains. His curiosity-driven learning style, strong analytical mindset and passion for emerging technologies make him a highl valued contributor to multidisciplinary innovation.

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