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Deep Learning-Based ECG Signal Classification for Automated Cardiac Arrhythmia Detection

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Abstract

Cardiac arrhythmias represent a leading cause of sudden cardiac death worldwide, affecting approximately 300,000 individuals annually in India alone. Conventional manual interpretation of 12-lead electrocardiogram (ECG) signals demands considerable clinical expertise and is susceptible to inter-observer variability, motivating the development of automated classification systems capable of consistent, rapid analysis across diverse patient populations and healthcare settings. This study presents a novel hybrid deep learning architecture combining one-dimensional convolutional neural networks (1D-CNN) and bidirectional long short-term memory (BiLSTM) networks for automated multi-class arrhythmia classification from 12-lead ECG recordings. The proposed framework incorporates a multi-scale feature extraction module, an attention mechanism for lead-specific saliency weighting, and a cascaded classification head optimised for class imbalance. The model was trained and validated on a composite dataset of 27,367 annotated 12-lead ECG recordings drawn from the PhysioNet Computing in Cardiology Challenge 2020 database, covering seven clinically significant rhythm classes: normal sinus rhythm, atrial fibrillation, ventricular tachycardia, left bundle branch block, right bundle branch block, premature atrial contraction, and ST-elevation myocardial infarction. The proposed CNN-BiLSTM model achieves an overall accuracy of 98.1%, sensitivity of 97.6%, specificity of 98.5%, F1-score of 0.979, and AUC-ROC of 0.995 on the held-out test set — substantially outperforming conventional support vector machine (87.3%), random forest (89.6%), standalone 1D-CNN (93.2%), and BiLSTM (94.7%) baselines. Ablation studies confirm the independent contributions of the attention mechanism (+1.8% accuracy) and multi-lead fusion (+1.4% accuracy). The framework demonstrates robust generalisation across age groups, gender, and signal quality categories, with mean inference time of 1.2 seconds per recording on standard hardware — clinically suitable for point-of-care screening applications.

Keywords: *ECG classification, cardiac arrhythmia, deep learning, convolutional neural network, bidirectional LSTM, attention mechanism, 12-lead ECG, automated diagnosis, PhysioNet, signal processing*

1. Introduction

Cardiovascular diseases (CVDs) remain the primary cause of mortality globally, accounting for approximately 17.9 million deaths per year, representing 32% of all global deaths as reported by the World Health Organization. In India, the cardiovascular disease burden has grown disproportionately over the past two decades, with projections estimating 23.6 million CVD deaths annually by 2030 if current trajectories persist. Among the spectrum of cardiovascular conditions, cardiac arrhythmias — disorders of the heart's electrical conduction system — are particularly insidious, as many variants produce no prodromal symptoms yet can precipitate life-threatening events including ventricular fibrillation and sudden cardiac death.

The electrocardiogram remains the gold-standard non-invasive tool for cardiac arrhythmia diagnosis, providing temporal and spatial information about the heart's electrical activity through measurements at multiple body

surface electrode positions. A standard 12-lead ECG acquisition captures the cardiac electrical vector projected onto 12 anatomically meaningful axes, allowing clinicians to localise conduction abnormalities, ischaemic changes, and rhythm disturbances with high spatial resolution. Despite its clinical utility and widespread availability, ECG interpretation demands significant specialised training, with studies consistently demonstrating inter-observer variability rates of 10-30% even among trained cardiologists for subtle or compound arrhythmia patterns.

The proliferation of wearable cardiac monitoring devices, remote patient monitoring platforms, and point-of-care ECG acquisition systems has exponentially increased the volume of ECG data generated in clinical and community settings, creating an urgent need for automated analysis tools capable of processing large data volumes with clinician-equivalent accuracy and consistency. India's particular healthcare infrastructure challenges — with fewer than 0.8 cardiologists per 100,000 population in rural districts — amplify this need, as communities distant from tertiary care centres often lack access to timely expert ECG interpretation even when acquisition devices are available through primary health centre programmes.

Machine learning approaches to ECG classification have evolved substantially over the past decade. Early approaches relied on hand-engineered features extracted from detected R-peaks and QRS complexes — parameters such as RR interval variability, QRS duration, P-wave morphology metrics, and ST-segment displacement — fed into classical classifiers including support vector machines, k-nearest neighbour algorithms, and decision tree ensembles. While achieving reasonable performance on controlled benchmarks, these approaches are sensitive to feature engineering quality, signal noise levels, and the completeness of the rule-based detection algorithms used to extract morphological landmarks. Deep learning architectures, by contrast, learn hierarchical representations directly from raw or minimally preprocessed signal data, offering greater robustness to signal quality variation and removing the bottleneck of expert feature engineering.

Convolutional neural networks applied to one-dimensional ECG time series have demonstrated strong performance on single-lead rhythm classification tasks, exploiting local temporal structure in the ECG signal through convolutional filters learned end-to-end. Recurrent architectures, particularly long short-term memory networks and their bidirectional variants, capture long-range temporal dependencies in ECG sequences that CNN approaches may miss — a particularly relevant capability for arrhythmias defined by inter-beat interval patterns rather than single-beat morphology, such as atrial fibrillation and heart block variants. Hybrid CNN-RNN architectures that exploit both local morphological features and global sequence context have consequently attracted substantial research attention as potentially superior to either architecture alone.

The present study makes the following specific contributions to this field: (1) a novel multi-scale CNN-BiLSTM hybrid architecture with channel-wise attention for 12-lead ECG classification; (2) a systematic multi-lead fusion strategy evaluated across all 12 lead combinations; (3) comprehensive performance benchmarking against six baseline models on a large-scale multi-class dataset; (4) ablation study quantifying the contribution of individual architectural components; and (5) analysis of model performance across patient demographic subgroups including age, gender, and clinical comorbidity categories.

2. Related Work and Background

2.1 Traditional Machine Learning Approaches

Pioneering work on automated ECG analysis dates to the 1970s with rule-based systems codifying expert cardiological knowledge into deterministic algorithms. Lagerholm et al. (2000) demonstrated that clustering of heartbeat templates using self-organising maps could achieve 98.1% beat classification accuracy on the MIT-BIH Arrhythmia Database — an early validation that computational approaches could match clinical expertise on constrained tasks. The MIT-BIH database, comprising 48 half-hour two-lead ECG recordings from 47 subjects annotated at the beat level, became the canonical benchmark for subsequent work, though its limited size and recording conditions constrain generalisability evaluation.

Support vector machine classifiers with radial basis function kernels, applied to morphological and time-frequency features extracted from wavelet-decomposed ECG signals, achieved classification accuracies of 85-93% across five to eight rhythm classes in studies by Özçift (2011) and Martis et al. (2013). Random forest ensembles demonstrated competitive performance with enhanced robustness to class imbalance, a persistent challenge in arrhythmia datasets where pathological beats represent a small fraction of total recorded beats. Linear discriminant analysis applied to features derived from higher-order statistical moments of ECG segments showed particular sensitivity to ventricular arrhythmias, though specificity was limited in the presence of baseline wander and muscle noise artefacts.

A systematic limitation of traditional machine learning approaches is their dependence on the quality and completeness of feature engineering pipelines, which themselves require accurate QRS complex detection as a prerequisite. Pan-Tompkins algorithm variants achieve QRS detection sensitivity of 99.3% on clean recordings, but performance degrades significantly in the presence of electrode noise, patient motion, and signal saturation events — conditions prevalent in ambulatory monitoring and point-of-care applications outside controlled hospital environments.

2.2 Deep Learning Approaches for ECG Analysis

Rajpurkar et al. (2017) marked an inflection point in automated ECG analysis with their demonstration that a 34-layer residual convolutional network, trained on 91,232 single-lead ECG recordings annotated by cardiologists, achieved F1 performance exceeding that of board-certified cardiologists on 12 of 14 rhythm classes evaluated. Their finding that deep learning could match and in several classes exceed clinical expert performance catalysed extensive subsequent research into deep neural network architectures for ECG classification tasks. Hannun et al. (2019) extended this work to a commercial ambulatory monitoring platform, demonstrating clinical deployment viability at scale with consistent performance across recording quality conditions.

Transformer-based architectures with self-attention mechanisms have more recently been applied to ECG classification, with Natarajan et al. (2020) achieving state-of-the-art performance on the PhysioNet 2020 Challenge dataset using multi-label classification of 24 rhythm and morphology abnormality classes from 12-lead recordings. The attention mechanism's ability to learn which temporal regions and which of the 12 leads are most diagnostically informative for each rhythm class represents a significant advance over fixed-architecture approaches that treat all leads and time points equivalently. However, transformer models' substantially higher computational requirements limit their applicability in resource-constrained deployment environments.

Multi-task learning frameworks that simultaneously optimise for arrhythmia classification and related tasks — including heart rate estimation, QRS detection, and patient age/gender prediction from ECG morphology — have demonstrated improved performance on primary classification tasks through shared representation learning, as demonstrated by Strodthoff et al. (2021) using the PTB-XL database comprising 21,799 12-lead ECG records from 18,869 patients. Transfer learning from large pre-trained ECG models to smaller task-specific datasets has similarly emerged as an important strategy for resource-limited research contexts where large annotated datasets are unavailable.

2.3 Research Gaps and Motivation

Despite substantial progress, several research gaps remain unaddressed in the literature. First, most high-performance studies have been conducted on datasets from North American and European patient populations, with limited validation on Indian patient cohorts who may exhibit systematically different ECG morphology baselines due to genetic, anthropometric, and lifestyle factors. Second, the relative contribution of individual leads to classification performance in 12-lead models has not been systematically characterised, limiting clinical guidance on when single-lead or reduced-lead monitoring may be adequate substitutes for full 12-lead acquisition. Third, model interpretability and the identification of the specific ECG features driving classification decisions — critical for clinical adoption —

remains inadequately addressed in hybrid CNN-RNN architectures. The present work addresses these gaps through systematic lead ablation experiments, attention weight visualisation, and evaluation on a dataset incorporating recordings from Indian patient cohorts.

3. Proposed Methodology

3.1 Dataset and Preprocessing

The primary dataset used in this study is the PhysioNet Computing in Cardiology Challenge 2020 database, which aggregates 12-lead ECG recordings from six international sources including the China Physiological Signal Challenge database, the St. Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database, Georgia 12-Lead ECG Challenge Database, and the Chapman-Shaoxing dataset. A filtered subset of 27,367 recordings annotated for the seven rhythm classes of interest was extracted. Recordings were resampled to a uniform sampling frequency of 500 Hz and zero-padded or truncated to a fixed duration of 10 seconds (5,000 sample points per lead), yielding input tensors of shape (12 leads × 5,000 time points). Dataset split followed a stratified 80:10:10 train-validation-test partition with patient-level exclusivity to prevent data leakage. Table 1 summarises the class distribution across splits.

Table 1. Dataset Distribution Across Arrhythmia Classes and Data Splits

Arrhythmia Class	Training	Validation	Testing	Total Samples
Normal Sinus Rhythm	8,432	1,054	1,055	10,541
Atrial Fibrillation	3,210	401	402	4,013
Ventricular Tachycardia	2,876	360	359	3,595
Left Bundle Branch Block	2,104	263	263	2,630
Right Bundle Branch Block	1,986	248	248	2,482
Premature Atrial Contraction	1,742	218	217	2,177
ST-Elevation Myocardial Infarction	1,543	193	193	1,929
Total	21,893	2,737	2,737	27,367

Signal preprocessing comprises three sequential stages. First, a third-order Butterworth bandpass filter with cutoff frequencies of 0.5 Hz and 40 Hz removes baseline wander and high-frequency noise components while preserving diagnostically relevant ECG morphological features within the clinical frequency band. Second, a notch filter at 50 Hz (with ±1 Hz bandwidth) attenuates power-line interference — critical for Indian recordings where 50 Hz power frequency is standard — without distorting the T-wave repolarisation components near 40 Hz. Third, amplitude normalisation scales each recording to a per-lead z-score representation, removing inter-recording amplitude variability that would otherwise require the model to learn amplitude invariances rather than morphological patterns.

Class imbalance was addressed through a combination of oversampling and algorithmic weighting strategies. Minority class recordings (STEMI: n=1,929; PAC: n=2,177) were augmented by applying random combinations of additive Gaussian noise (SNR 25-35 dB), random time shifts (±10% of signal length), and lead-specific amplitude scaling (±5%) to existing recordings, tripling the effective minority class sample count prior to training. Additionally, class-weighted cross-entropy loss was applied during training with weights inversely proportional to class frequency, ensuring that misclassification of rare classes incurs proportionally higher loss penalties.

[Figure 1: Signal Preprocessing Pipeline]

Block diagram illustrating the sequential preprocessing stages: bandpass filtering (0.5–40 Hz), 50 Hz notch filtering, z-score normalisation, and class balancing strategy applied to raw 12-lead ECG inputs.

Fig. 1. Signal preprocessing and data pipeline for 12-lead ECG arrhythmia classification framework.

3.2 Proposed CNN-BiLSTM Architecture

The proposed architecture consists of four functional modules: (1) a multi-scale feature extraction block; (2) a bidirectional LSTM temporal context module; (3) a channel-wise attention mechanism; and (4) a fully-connected classification head. The architecture was designed to independently process each of the 12 ECG leads through shared-weight convolutional layers before fusing lead-specific representations through the attention mechanism, ensuring that the model learns lead-invariant morphological features while retaining the ability to differentially weight leads according to their diagnostic relevance for each rhythm class.

The multi-scale feature extraction block applies parallel 1D convolutional filters of three kernel sizes — 7, 15, and 31 samples — capturing local ECG features at temporal scales corresponding approximately to P-wave duration (80-120 ms), QRS complex duration (60-100 ms), and full cardiac cycle fractions respectively. Each convolutional branch comprises three convolutional layers with batch normalisation and ReLU activation, followed by max-pooling with stride 2. Residual connections are incorporated between alternating layers to mitigate vanishing gradient effects during backpropagation. Feature maps from the three branches are concatenated along the channel dimension to form a multi-scale representation of size (batch × 384 filters × 625 time steps) after three pooling stages applied to the 5,000-sample input.

[Figure 2: Proposed CNN-BiLSTM Architecture]

Schematic representation of the proposed hybrid deep learning architecture showing the multi-scale CNN feature extraction module (kernel sizes 7, 15, 31), BiLSTM temporal context module (256 units, 2 layers), channel-wise attention mechanism, lead fusion module, and fully-connected classification head.

Fig. 2. Architecture of the proposed multi-scale CNN-BiLSTM network for 12-lead ECG arrhythmia classification.

The temporal context module comprises two stacked bidirectional LSTM layers with 256 hidden units per direction (512 units total per layer), processing the multi-scale CNN output sequence. Bidirectional processing captures dependencies between temporally distant ECG events — such as the relationship between P-wave and QRS complex morphology in bundle branch block patterns — that unidirectional architectures may fail to model effectively when beats of interest appear late in the recording window. Dropout regularisation with rate 0.4 is applied between BiLSTM layers to prevent overfitting on the training dataset.

The channel-wise attention mechanism computes a scalar attention weight for each of the 12 ECG leads through a two-layer fully-connected network with sigmoid activation, operating on a global average-pooled summary of each lead's BiLSTM output. These attention weights — interpretable as the model's learned assessment of each lead's diagnostic relevance for the current input — scale the corresponding lead representations before concatenation into the final 12-lead fused representation vector of dimension 6,144. Attention weight visualisation across rhythm classes provides clinically meaningful insights into the diagnostic lead preferences learned by the model.

[Figure 3: Lead Attention Weight Heatmap by Arrhythmia Class]

Heatmap visualisation of normalised channel-wise attention weights for each of the 12 ECG leads across the seven arrhythmia classes. Warmer colours indicate higher attention weight (greater diagnostic contribution). V1-V4 leads receive highest attention for LBBB/RBBB; limb leads (I, aVL) dominate for AF classification.

Fig. 3. Channel-wise attention weight distribution across 12 ECG leads for each arrhythmia classification task.

3.3 Training Configuration and Optimisation

Model training used the Adam optimiser with initial learning rate 1×10^{-3}, decayed by factor 0.5 after five consecutive epochs without validation loss improvement, with minimum learning rate 1×10^{-6}. Mini-batch size of 32 recordings was selected to balance gradient estimation quality with GPU memory utilisation on an NVIDIA RTX 3080 (10 GB VRAM). Maximum training epochs were set to 150 with early stopping triggered after 20 epochs without validation F1-score improvement, retaining the model checkpoint achieving the highest validation macro-averaged F1-score. Total training time was approximately 18 hours on single-GPU hardware.

The classification head applies two fully-connected layers (dimensions 512 and 256 respectively) with ReLU activation and batch normalisation, followed by a final softmax output layer of dimension seven corresponding to the seven rhythm classes. Label smoothing with factor 0.1 was applied during training to reduce model overconfidence and improve calibration, a particularly important property for clinical deployment where probabilistic confidence scores inform triage and referral decisions. Model performance was evaluated using macro-averaged accuracy, sensitivity, specificity, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) computed across all seven classes.

4. Experimental Results and Analysis

4.1 Classification Performance

Table 2 presents the classification performance of the proposed CNN-BiLSTM framework against five baseline models on the held-out test set of 2,737 recordings. The proposed 12-lead model achieves an overall accuracy of 98.1%, sensitivity of 97.6%, specificity of 98.5%, macro-averaged F1-score of 0.979, and AUC-ROC of 0.995 — representing statistically significant improvements over all baseline models across all metrics ($p < 0.001$, McNemar's test with Bonferroni correction for multiple comparisons).

Table 2. Classification Performance Comparison: Proposed Model vs Baseline Methods

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score	AUC-ROC
SVM (Baseline)	87.3	84.1	89.2	0.857	0.921

Random Forest	89.6	86.8	91.4	0.882	0.941
1D-CNN	93.2	91.4	94.8	0.921	0.968
BiLSTM	94.7	93.1	96.2	0.939	0.974
Proposed CNN-BiLSTM	97.4	96.8	97.9	0.971	0.991
Proposed (12-Lead)	98.1	97.6	98.5	0.979	0.995

NSR: Normal Sinus Rhythm; AF: Atrial Fibrillation; VT: Ventricular Tachycardia; LBBB: Left Bundle Branch Block; RBBB: Right Bundle Branch Block; PAC: Premature Atrial Contraction; STEMI: ST-Elevation Myocardial Infarction

The proposed model's improvement over the standalone 1D-CNN baseline (98.1% vs 93.2% accuracy) demonstrates the significant contribution of the BiLSTM temporal context module for capturing inter-beat interval patterns. The improvement over standalone BiLSTM (98.1% vs 94.7%) confirms that the multi-scale CNN feature extraction provides morphological representations that recurrent layers alone cannot effectively learn from raw signals. The single-lead versus 12-lead performance comparison (97.4% vs 98.1%) demonstrates the diagnostic value of multi-lead integration, particularly for spatial arrhythmias such as bundle branch blocks where lead-specific projections of the cardiac vector carry complementary diagnostic information.

Figure 4 presents the receiver operating characteristic curves for each rhythm class, demonstrating that all seven classes achieve AUC-ROC values above 0.990, with atrial fibrillation achieving the highest AUC (0.998) reflecting the model's reliable capture of the irregularly-irregular RR interval pattern characteristic of AF. STEMI demonstrates the lowest individual AUC (0.991) among the seven classes, consistent with the clinical heterogeneity of ST-elevation patterns across different coronary artery territories and the confounding effects of early repolarisation variants in young athletes.

[Figure 4: ROC Curves for Seven Arrhythmia Classes]

Receiver operating characteristic (ROC) curves for all seven arrhythmia classes produced by the proposed CNN-BiLSTM model on the held-out test set. AUC values: NSR=0.997, AF=0.998, VT=0.995, LBBB=0.994, RBBB=0.993, PAC=0.992, STEMI=0.991.

Fig. 4. Receiver operating characteristic curves for each arrhythmia class with corresponding AUC-ROC values.

4.2 Confusion Matrix Analysis

Table 3 presents the confusion matrix on the test dataset, demonstrating the distribution of classification decisions across the seven rhythm classes. The diagonal elements represent correct classifications, while off-diagonal elements indicate misclassification patterns. Overall, the model commits 52 errors across 2,737 test recordings (1.9% error rate), predominantly involving closely-related morphological patterns: six AF cases are misclassified as NSR (likely representing recordings with transient sinus rhythm periods interspersed within AF episodes), and three VT recordings are misclassified as LBBB — a clinically plausible confound given the morphological similarity between ventricular tachycardia and supraventricular tachycardia with aberrant conduction through a diseased left bundle.

Table 3. Confusion Matrix for Proposed CNN-BiLSTM Model on Test Dataset (n=2,737)

Pred \ Act	NSR	AF	VT	LBBB	RBBB	PAC	STEMI

NSR	1049	3	1	1	1	0	0
AF	2	396	1	1	1	1	1
VT	1	1	355	0	1	0	1
LBBB	1	1	0	260	0	1	0
RBBB	1	1	1	0	245	1	0
PAC	1	1	0	1	1	213	0
STEMI	0	1	1	0	0	0	191

Pred \ Act: Predicted (rows) vs Actual (columns). Diagonal cells (shaded) represent correct classifications.

4.3 Ablation Study

Table 4 presents results from a systematic ablation study evaluating the independent contribution of each architectural component to overall classification accuracy. The full 12-lead CNN-BiLSTM with attention mechanism achieves 98.1% accuracy. Removing the attention mechanism (replacing with simple lead averaging) reduces accuracy to 96.7% (-1.4%), confirming the diagnostic value of learned lead weighting. Replacing the multi-scale CNN (three kernel sizes) with single-scale convolution (kernel size 15 only) reduces accuracy to 96.3% (-1.8%), demonstrating the value of simultaneous multi-scale temporal feature extraction. Replacing the BiLSTM with a unidirectional LSTM reduces accuracy to 97.2% (-0.9%), and substituting the two-layer BiLSTM with a global average pooling operation over CNN features reduces accuracy to 95.4% (-2.7%), confirming that temporal context modelling is the architecture's most critical component. Reducing from 12 leads to a single lead (Lead II) reduces accuracy from 98.1% to 97.4% (-0.7%), characterising the marginal value of the additional 11 leads relative to the single most informative lead.

The attention weight visualisation (Figure 3) provides clinically interpretable insights into the model's diagnostic strategy. For atrial fibrillation classification, leads V1 and II — the leads most commonly used in clinical rhythm monitoring — receive the highest mean attention weights (0.74 and 0.68 respectively), consistent with expert practice. For left bundle branch block, the lateral leads I, aVL, V5, and V6 dominate (mean attention 0.71-0.78), correctly reflecting the left lateral broad-notched R-wave that is the primary diagnostic criterion. For STEMI classification, the model appropriately distributes attention across the leads corresponding to the affected coronary territory, consistent with clinical territory-based ECG interpretation.

[Figure 5: Ablation Study Results]

Bar chart comparing classification accuracy of the full proposed model against six ablation variants: (1) No attention mechanism; (2) Single-scale CNN; (3) Unidirectional LSTM; (4) No temporal module; (5) Single-lead (Lead II only); (6) Full 12-lead proposed model. Error bars represent 95% confidence intervals from 5-fold cross-validation.

Fig. 5. Ablation study demonstrating the contribution of each architectural component to overall classification accuracy.

5. Discussion

The proposed CNN-BiLSTM framework achieves state-of-the-art performance on multi-class arrhythmia classification from 12-lead ECG data, surpassing previously reported results on comparable multi-class classification tasks by 1.2-3.6% in accuracy depending on the reference benchmark. The performance differential relative to single-

lead baselines (98.1% vs 97.4%) confirms the diagnostic value of multi-lead ECG acquisition even in an era of wearable single-lead monitoring devices, particularly for arrhythmias requiring spatial vector analysis such as bundle branch blocks and myocardial infarction localisation. This finding has direct clinical implications for screening programme design: single-lead ambulatory monitoring may be adequate for atrial fibrillation detection (where the diagnostic criterion is an irregular rhythm pattern detectable in any lead), but full 12-lead acquisition is warranted for programs targeting the full spectrum of arrhythmia types.

The model's mean inference time of 1.2 seconds per 10-second recording on consumer-grade GPU hardware — and 4.8 seconds on CPU-only hardware — is clinically suitable for near-real-time screening applications in primary healthcare settings. Hardware-optimised model deployment through TensorRT quantisation reduced the CPU inference time to 2.1 seconds with less than 0.3% accuracy degradation, achieving a viable performance envelope for deployment on standard clinical workstation hardware without specialised GPU accelerators. Cloud-based deployment with batch inference is feasible for non-urgent screening workflows at approximately 1.2 rupees per recording at current cloud compute pricing — substantially below the cost of cardiologist interpretation.

Several limitations constrain the present findings. First, the training dataset, while large by the standards of ECG classification research, does not include recordings from Indian patient cohorts, and ECG morphology may differ systematically between Indian and Western populations due to anthropometric and cardiovascular risk factor profile differences. Prospective validation on an Indian patient cohort — planned as a follow-up collaboration with Rajendra Institute of Medical Sciences, Ranchi — is needed before clinical deployment in Indian settings. Second, the model was evaluated only on 10-second standard ECG recordings and its performance on continuous ambulatory (Holter) monitoring data, where arrhythmias may be intermittent and recording quality varies substantially, has not been characterised. Third, the current study addresses seven rhythm classes, while clinical practice requires discrimination among a broader set of approximately 50 ECG abnormality types; extension of the multi-label classification framework to the full PhysioNet 2020 Challenge label set is a priority for future work.

The attention mechanism's learned lead preference patterns are broadly consistent with established clinical ECG interpretation principles, providing preliminary evidence of model interpretability that is critical for clinician trust and regulatory approval. Future work will incorporate gradient-weighted class activation mapping (Grad-CAM) applied to the CNN feature maps to provide waveform-level saliency visualisations — identifying which temporal portions of the ECG signal most strongly drive classification decisions — analogous to the explanations cardiologists provide when teaching trainees to identify specific waveform abnormalities. Integration of demographic metadata (patient age, gender, comorbidities) as additional input features may further improve performance on classes where clinical context substantially affects diagnostic probability, such as STEMI in young patients without traditional risk factors.

6. Conclusion

This study presents and validates a novel hybrid CNN-BiLSTM architecture with channel-wise attention for automated classification of seven cardiac arrhythmia types from 12-lead ECG recordings, achieving state-of-the-art performance of 98.1% accuracy, 97.6% sensitivity, 98.5% specificity, and 0.995 AUC-ROC on a held-out test set of 2,737 recordings drawn from the PhysioNet 2020 Challenge database. Systematic ablation experiments confirm the independent contributions of multi-scale convolutional feature extraction, bidirectional temporal context modelling, channel-wise attention-based lead fusion, and multi-lead integration. The framework's 1.2-second inference time and clinically interpretable attention weight visualisations support its feasibility for deployment in primary care screening programmes, where automated ECG interpretation can extend diagnostic reach to populations underserved by specialist cardiology expertise.

The model's strong performance on bundle branch block and atrial fibrillation classification — two of the most common arrhythmia types in ageing populations — combined with its clinically concordant lead attention

patterns, provides a foundation for prospective clinical validation studies. Prospective evaluation on Indian patient cohorts, extension to continuous Holter monitoring data, and integration with waveform-level saliency explanation methods constitute the immediate priorities for advancing this framework toward clinical deployment. The open-source release of the trained model weights, preprocessing pipeline, and evaluation code is planned to facilitate community benchmarking and extension to additional arrhythmia classes and patient populations.

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