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Adaptive Attention-Driven ALEXIS Framework for High-Precision ECG Signal Classification

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Abstract **Accurate classification of electrocardiogram (ECG) signals is essential for the early identification of cardiac abnormalities and for supporting timely clinical decision-making. However, conventional machine learning and deep learning approaches often assume stationary signal characteristics and therefore struggle to model the complex non-linear, non-stationary, and patient-specific nature of ECG signals. These limitations reduce their ability to capture subtle morphological variations and temporal dependencies associated with abnormal cardiac rhythms. To address these challenges, this paper proposes an Adaptive Attention-Driven ALEXIS Framework, a hybrid deep learning architecture that integrates multiscale signal decomposition, hierarchical feature learning, and adaptive attention-guided fusion for five-class ECG abnormality classification. The proposed framework combines the Stockwell Transform (ST) for time-frequency analysis, Empirical Mode Decomposition (EMD) for adaptive extraction of intrinsic oscillatory modes, and Local Phase Quantization (LPQ) for robust morphological feature representation. The extracted multiscale features are processed through an AlexNet-based spatial learning module and an LSTM-based temporal modeling module, followed by an attention-guided feature fusion mechanism and Support Vector Machine (SVM) classifier for robust decision making. The framework was evaluated using the MIT-BIH Arrhythmia Database comprising 109,494 annotated ECG beats, which were partitioned into 80% training (approximately 87,595 beats) and 20% testing (approximately 21,899 beats) using a stratified beat-level split. Experimental evaluation on the independent test set achieved an overall accuracy of 98.43%, sensitivity of 98.27%, specificity of 98.78%, and F1-score of 98.31%. These results demonstrate that the proposed ALEXIS framework effectively captures complementary spectral, temporal, and morphological ECG characteristics, providing accurate and interpretable ECG abnormality classification while establishing a strong foundation for future validation using inter-patient evaluation protocols and cross-database clinical studies.**

Keywords **Electrocardiogram (ECG); Cardiovascular-Disease (CVD) Detection; Adaptive Attention Mechanism; Stockwell Transform (ST); Empirical Mode Decomposition (EMD); Local Phase Quantization (LPQ); AlexNet–LSTM Fusion**.

I. Introduction

Cardiovascular diseases (CVDs) are among the major causes of death across the world, with the World Health Organization (WHO) indicating that they cause around 32% of all deaths. Timely detection of cardiac defects is essential to avoid irreversible cardiac damage and to optimize patient outcome [1]. The electrocardiogram (ECG) signal is one of the most common non-invasive diagnostic signals which can provide useful information regarding the electrical activity of the heart. The traditional approach to ECG interpretation, however, is highly dependent upon clinical experience, and there are significant inter-observer variation, diagnostic challenge, and delayed diagnosis. As a result,

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automated ECG analysis systems have become more significant for the accurate and timely diagnosis of cardiac diseases.

Automated ECG classification has seen significant improvement in the last few years due to advancement in machine learning and deep learning [2-4]. CNNs have proven to be effective in extracting spatial and morphological features from ECG waveforms, while the LSTM network is adept at capturing temporal relationships between cardiac cycles. Many classification systems for ECGs have been reported, but there are a number of important limitations. Most of the current methods are mainly based on temporal or spatial feature learning, thereby limiting the ability to fully utilize the complementary information represented in both the time-frequency and the morphological and texture-based ECG [5,6]. In addition, traditional deep learning models generally process every region of the signal with uniform importance, and do not have mechanisms to selectively enhance diagnostic components of the signal, including the QRS complex, ST-segment deviations, and T-wave abnormalities [7].

In order to solve these problems, this study presents an Adaptive Attention-Driven ALEXIS Framework for ECG abnormality classification. The framework incorporates the Stockwell Transform (ST), the Empirical Mode Decomposition (EMD) and the Local Phase Quantization (LPQ) to learn complementary spectral, temporal, and morphological features of ECG signals. In the same way, deep networks, such as AlexNet and LSTM networks, were used to learn spatial and temporal representations, and an attention-guided

Table 1. Comparative Analysis of ECG Classification Methods.

Study	Dataset	Methodology	Validation Strategy	Reported Performance	Main Limitation	Improvement Introduced by ALEXIS
Zhang et al. [13]	ECG Heart Failure Dataset	CNN–LSTM–SE with Attention	Dataset-specific train/test evaluation	High classification accuracy reported	No multiscale features	ST + EMD + LPQ integration
Eleyan et al. [14]	MIT-BIH and BIDMC ECG Databases	CNN–LSTM Hybrid Network	Multi-class ECG classification	Superior performance over conventional methods	Noise sensitive; limited interpretability	Attention-guided feature fusion
Sankar et al. [26]	ECG Cardiac Disease Dataset	Deep CNN	Train/test evaluation	Accuracy ≈94.2%	Spatial features only	Spatial + temporal learning
Reshan et al. [19]	Heart Disease Dataset	Hybrid CNN–LSTM Deep Network	Comparative experimental evaluation	Improved prediction accuracy	No attention mechanism	Attention-enhanced classification
Maulani et al. [20]	Heart Disease Dataset	CNN–LSTM with Hyperparameter Optimization	Grid Search and Random Search	Improved classification performance	Expensive optimization	Multiscale feature extraction
Proposed ALEXIS	MIT-BIH Arrhythmia Database	ST + EMD + LPQ + AlexNet + LSTM + Attention + SVM	Stratified 80/20 Train-Test Evaluation	Accuracy: 98.43%; Sensitivity: 98.27%; Specificity: 98.78%	Single-dataset evaluation	Multiscale, interpretable framework

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fusion mechanism dynamically focuses on the diagnostically informative features. The fused representations were then classified using a Support Vector Machine (SVM) for better discrimination and generalization between ECG patterns. The proposed framework is a combination of multiscale decomposition, attention-guided learning, and hybrid classification to enhance classification accuracy and interpretability.

II. Related Work

ECG classification remains a critical research area for early detection of cardiovascular abnormalities [8]. Traditional machine learning methods rely on handcrafted features and often struggle with noise and inter-patient variability, while deep learning models such as CNNs and LSTMs improve representation learning but face challenges in interpretability and adaptive feature selection [9]. Consequently, recent research has focused on hybrid and attention-based architectures to enhance robustness, diagnostic accuracy, and clinical relevance [10]. Recent ECG classification research has focused on improving diagnostic accuracy through deep learning, optimization, and hybrid signal-processing frameworks. Optimization-based approaches incorporating feature selection and metaheuristic algorithms have demonstrated improved convergence and feature relevance, although they remain dependent on handcrafted representations and often suffer from limited interpretability [11,12]. Hybrid CNN–LSTM architectures have shown strong capability in capturing both spatial ECG morphology and temporal rhythm dynamics, leading to improved classification performance for arrhythmia and heart-failure detection; however, these methods generally lack adaptive feature fusion and robustness to noisy signals [13,14,19,20]. Deep learning models combined with evolutionary optimization have further enhanced predictive accuracy, though at the expense of increased computational complexity and reduced explainability [15,16]. Multiscale signal analysis techniques such as Stockwell Transform and advanced feature representation methods have demonstrated the importance of time–frequency characterization for biomedical signal interpretation, yet often fail to integrate ECG-specific temporal dependencies and attention-guided learning mechanisms [17,18]. Large-scale AI frameworks and multimodal diagnostic systems have also achieved promising results in cardiovascular prediction, but they frequently lack signal-level interpretability and fine-grained ECG analysis [21–24]. The MIT-BIH Arrhythmia Database remains the most widely adopted benchmark for validating ECG classification algorithms due to its standardized annotations and diverse arrhythmia patterns [25]. Furthermore, CNN-based ECG classification studies have reported encouraging

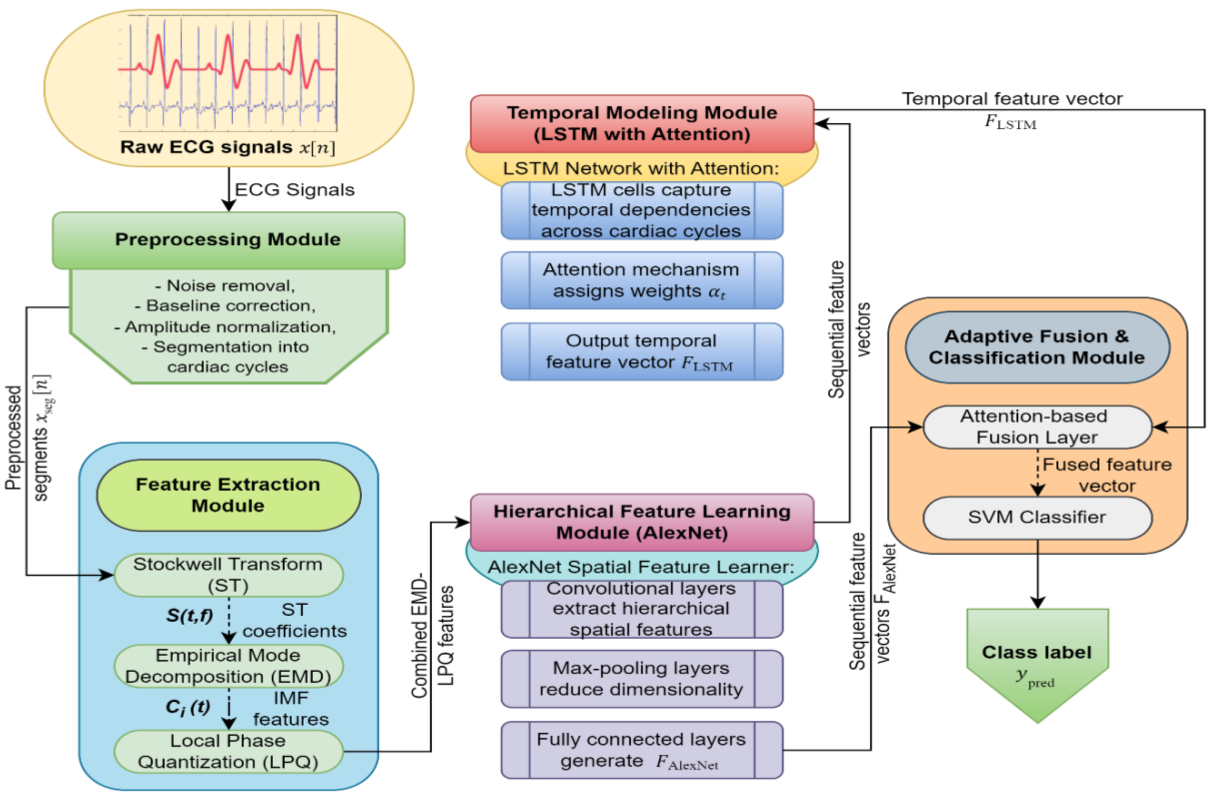

Fig. 1. Proposed Adaptive Attention-Driven ALEXIS Framework.

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performance; however, limitations remain in capturing complementary spectral, temporal, and morphological information within a unified framework [26]. As summarized in Table 1, the existing ECG classification studies primarily focused on either spatial feature learning, temporal dependency modelling, or attention-based enhancement. However, most approaches lack a unified framework capable of jointly exploiting multiscale time-frequency decomposition, adaptive mode extraction, texture-phase representation, spatial-temporal deep learning, and attention-guided feature fusion. The proposed ALEXIS framework addresses these limitations, thereby integrating Stockwell Transform (ST), the Empirical Mode Decomposition (EMD), and the Local Phase Quantization (LPQ), AlexNet, LSTM, and adaptive attention mechanisms within a single architecture, resulting in improved classification performance and enhanced interpretability for ECG abnormality analysis.

III. Method

The proposed Adaptive Attention-Driven ALEXIS Framework is a highly accurate and interpretable deep learning model designed for ECG-based cardiac abnormality classification as shown in Fig. 1. The ALEXIS model consists of a hybrid integration approach based on signal decomposition, multiscale texture encoding, deep hierarchical feature learning, and temporal attention mechanisms into a unified and adaptive diagnostic pass. The framework surpasses the shortcomings of the traditional deep learning frameworks that usually assume the ECG signals as stationary and cannot capture the more complex temporal-spectral variations and inter-beat dynamics of the ECG signals [27-29].

A. Preprocessing of ECG Signals

Raw ECG signals obtained from the MIT-BIH Arrhythmia Database were first processed using a fourth-order Butterworth band-pass filter with cutoff frequencies of 0.5 Hz and 40 Hz to suppress baseline wander, motion artifacts, muscle noise, and high-frequency interference, while preserving the morphological characteristics of the P-wave, QRS complex, and T-wave [30]. Following band-pass filtering, residual low-frequency baseline drift was corrected using polynomial detrending, which removes slow-varying signal components without affecting diagnostically relevant ECG morphology [31]. After denoising, the amplitude normalization was done using z-score standardization given by the following Eq. (1) as follows [2] where $x(t)$ denotes the denoised ECG signal at time instant t, $x_{norm}(t)$ represents the normalized ECG signal, μ_x, where μ_x and σ_x are the mean and standard deviation of the ECG signal respectively.

$$x_{norm}(t) = \frac{x(t)-\mu_x}{\sigma_x} \tag{1}$$

In this case, normalization removes variability in subjects and differences in inter-recordings of amplitudes and allows the scaling of features to be consistent across all input samples [32]. The uniform windowing eases the matter of synchronization to extract temporal features with LSTM, enhancing interpretability and temporal granularity of the extracted features [33-35].

B. Multiscale Time–Frequency Decomposition Using Stockwell Transform (ST)

Arguably, the nature of non-stationary and transient characteristics in ECG signals necessitates the accuracy of analysis of temporal and spectral variation in ECG signals. Traditional Fourier Transform (FT) methods give frequency-domain information and require signal stationarity, whereas the Short-Time Fourier Transform (STFT) method adds an additional fixed window creating a time-frequency trade-off between time and frequency resolution [36].

The proposed ALEXIS framework could be used to overcome these drawbacks by using the multiscale time frequency Stockwell Transform (ST), a time frequency decomposition method that retains phase information and offers a high-resolution joint representation of time and frequency properties. Stockwell Transform of a continuous-time signal $x(t)$ is mathematically defined as the sum of the Stockwell Transforms of the signal, i.e. $S(t,f)$ equals to Eq. (2) as follows [3], where $S(t,f)$ denotes the Stockwell Transform coefficient at time t and frequency f, $x(\tau)$ represents the input ECG signal evaluated at the integration variable τ, $j=\sqrt{-1}$ is the imaginary unit, and $|f|$ denotes the magnitude of the frequency, which determines the adaptive Gaussian window width for multiresolution analysis.

$$S(t,f) = \int_{-\infty}^{\infty} x(\tau)\,\frac{|f|}{\sqrt{2\pi}}\,e^{-\frac{(t-\tau)^2 f^2}{2}}\,e^{-j2\pi f\tau}\,d\tau \tag{2}$$

C. Adaptive Feature Extraction Using Empirical Mode Decomposition (EMD)

The ECG signal is inherently non-linear and non-stationary, exhibiting time-varying amplitude and frequency characteristics that traditional linear transforms cannot fully capture. To extract physiologically meaningful features adaptively, the proposed ALEXIS framework employs Empirical Mode Decomposition (EMD), a data-driven technique that decomposes the signal into a set of Intrinsic Mode Functions (IMFs) without requiring predefined basis functions. Mathematically, the input ECG signal $x(t)$ can be represented as the sum of $n$intrinsic mode functions (IMFs) and a residual component as defined in Eq. (3) as follows [9]:

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where $x(t)$ denotes the ECG signal at time instant t, $C_i(t)$ represents the i^{th} intrinsic mode function corresponding to the oscillatory component at a particular frequency scale, $r_n(t)$ denotes the final residual component representing the non-oscillatory trend, $i$is the IMF index $(i = 1,2, \dots, n)$, and n is the total number of intrinsic mode functions determined adaptively according to the signal characteristics [37].

$$x(t) = \sum_{i=1}^{n} C_i(t) + r_n(t) \quad (3)$$

D. Texture and Phase Encoding Using Local Phase Quantization (LPQ)

Although multiscale decomposition using Stockwell Transform (ST) and adaptive oscillatory analysis using Empirical Mode Decomposition (EMD), extricate spectral and temporal data are present, but localized texture and phase analysis are needed to detect subtle changes in the morphology of ECG signals, including minor distortions in the QRS complex, P-waves, and T-waves. The ALEXIS framework proposed to extract such high-resolution micro-patterns utilizes Local Phase Quantization (LPQ) as an additional method of extracting the feature. LPQ is founded on short-term fourier transform (STFT) on a local region of every sample. Given a 1-D ECG sample, the LPQ transform at a local window with the center at sample x_n can be calculated by the following Eq. (4) as follows [3] where $F(u, x_n)$ denotes the local Fourier coefficient at frequency $u$centered on sample x_n, x_n is the current ECG sample, $x_{n+k}$is the signal value at position $n + k$, k is the local neighborhood index $(k = -K, \dots, K)$, K is the half-window size, $u$represents the discrete frequency set $\{u_0, u_1, \dots, u_{M-1}\}$, M denotes the number of discrete frequency groups, and $j = \sqrt{-1}$ is the imaginary unit. The phase of the local Fourier coefficient is subsequently quantized Eq. (5) as follows [7], where $\phi_q(x_n)$ is the binary LPQ descriptor of the q^{th} frequency component, u_q denotes the q^{th} discrete frequency, $q = 0,1, \dots, M - 1$ is the frequency index, and $\angle(\cdot)$ represents the phase angle of the complex Fourier coefficient.

$$F(u, x_n) = \sum_{k=-K}^{K} x_{n+k} e^{-j2\pi uk}, \ u \in \{u_0, u_1, \dots, u_{M-1}\} \quad (4)$$

$$\phi_q(x_n) = \{1, if \ \angle F(uq, xn) \geq 0 \ 0, if \ \angle F(uq, xn) < 0, \quad q = 0,1, \dots, M - 1 \quad (5)$$

The binary code of each local neighborhood is then the LPQ code, which codes phase changes without regard to amplitude, and thus very resistant to changes in signal intensity and noise. The end result is the final LPQ feature vector of an ECG segment based on the combination of the LPQ codes of all of the neighborhoods as in Eq. (6) as follows [4], where $LPQ_{segment}$ denotes the LPQ feature vector corresponding to one ECG segment, $\phi_q(x_n)$ represents the binary LPQ descriptor obtained from the q^{th}frequency component at sample x_n, N is the total number of ECG samples within the segment, and x_1 and x_N denote the first and last samples of the segmented ECG signal, respectively. The resulting LPQ feature vector is subsequently concatenated with the intrinsic mode functions obtained from EMD and the time-frequency coefficients extracted using ST to construct a unified multiscale feature representation for hierarchical learning by the AlexNet network.

$$LPQ_{segment} = [\phi_0(x_1), \phi_1(x_1), \dots, \phi_{M-1}(x_N)] \quad (6)$$

E. Hierarchical Feature Learning with AlexNet

The extracted multiscale features, comprising Stockwell Transform (ST) maps, EMD-based intrinsic mode functions (IMFs), and Local Phase Quantization (LPQ) descriptors are hierarchically processed using a deep convolutional neural network (CNN) based on the AlexNet architecture. The convolution operation extracts local spatial patterns from the input feature maps and is mathematically defined as in Eq. (7) as follows [11],

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) \, g(t - \tau) d\tau \quad (7)$$

where $(f * g)(t)$ denotes the convolution output evaluated at time t, $f(\tau)$ represents the input feature map, $g(t - \tau)$ denotes the convolution kernel shifted by $t - \tau$, t is the output sample index (or time instant), and $\tau$is the integration variable. In discrete form for 1-D ECG signals as defined in Eq. (8) as follows [13], $x[n + k]$ is the input sequence (concatenated ST, EMD, LPQ features), $w[k]$ is the learnable kernel, and $y[n]$ is the output feature map, K is the kernel length, n denotes the output sample index, and k is the kernel index. Max-pooling layers are applied to reduce dimensionality and retain dominant features as defined in Eq. (9) as follows [9], where $y_{pool}[i]$ denotes the pooled output at the i^{th} pooling window, p is the pooling window size, s is the stride, and j represents the index within each pooling window. Finally, fully connected layers integrate high-level features from all spatial regions, producing a hierarchical feature representation suitable for temporal modeling via LSTM [38-40]. Unlike conventional CNNs that operate on raw ECG signals, the proposed framework feeds AlexNet with fused multiscale representations as defined in Eq. (10) as follows [7].

$$y[n] = \sum_{k=0}^{K-1} x[n + k] \cdot w[k] \quad (8)$$

$$ypool[i] = max\{y[si + j] \mid j = 0, \dots, p - 1\} \quad (9)$$

$$XAlexNet = concat(S(t, f), IMFs, LPQ) \quad (10)$$

F. Temporal Pattern Learning Using LSTM Network

While AlexNet captures hierarchical spatial features from multiscale ECG representations (ST, EMD, LPQ), the sequential nature of cardiac signals requires explicit

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modeling of temporal dependencies to identify rhythm patterns, beat-to-beat variations, and transient abnormalities. To this end, the ALEXIS framework employs a Long Short-Term Memory (LSTM) network, which is specifically designed to learn long-range temporal dependencies in sequential data. An LSTM unit consists of cell states and gating mechanisms (input, forget, and output gates) that regulate information flow. The hidden state h_t at time step t is computed as defined in Eq. (11) to (16) as follows [9], where x_t is the input feature vector obtained from AlexNet at time step t, h_{t-1} is the previous hidden state, C_{t-1} and C_t denote the previous and current cell states, respectively, $\tilde{C}_t$ is the candidate cell state, f_t, i_t, and o_t represent the forget, input, and output gates, W_f, W_i, W_C, and W_o are the trainable weight matrices corresponding to each gate, b_f, b_i, b_C, and b_o are the associated bias vectors, $[x_t]$ denotes the concatenation of the previous hidden state and the current input vector, $\sigma(\cdot)$ is the sigmoid activation function, $tanh(\cdot)$ is the hyperbolic tangent activation function, and $\odot$ represents element-wise multiplication.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (11)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (12)$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (13)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (14)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (15)$$

$$h_t = o_t \odot tanh(C_t) \quad (16)$$

To further enhance the discriminative power, an adaptive temporal attention mechanism was integrated, enabling the model to focus on informative time steps that contribute most to disease classification. The attention score α_t for each time step $t$was computed as defined in Eq. (17) as follows [13]. The final context vector c summarized the temporal information as defined in Eq. (18) as follows [7], where e_t denotes the unnormalized attention score at time step t, α_t represents the normalized attention weight obtained using the softmax function, W_a is the trainable attention weight matrix, b_a is the attention bias vector, h_t is the hidden-state vector generated by the LSTM at time step t, k is the summation index used in the softmax normalization, T denotes the total number of time steps in the input sequence, c is the attention-weighted context vector summarizing the entire sequence, and $exp(\cdot)$ denotes the exponential function used in softmax normalization.

$$e_t = tanh(W_a h_t + b_a),\ \alpha_t = \frac{exp(e_t)}{\sum_{k=1}^{T} exp(e_k)} \quad (17)$$

$$c = \sum_{t=1}^{T} \alpha_t h_t \quad (18)$$

G. Feature Fusion and Attention Integration Layer

The accurate classification of ECG signals relies on the effective integration of spatial and temporal features. While AlexNet extracts hierarchical spatial patterns from multiscale features (ST, EMD, LPQ), and LSTM with attention captures temporal dependencies, the ALEXIS framework introduces a novel adaptive feature fusion layer that dynamically combines these complementary representations. Furthermore, $F_{AlexNet} \in R^{d_s}$ denotes the spatial feature vector from AlexNet, $F_{LSTM} \in R^{d_t}$ denotes the attention-weighted temporal feature vector from LSTM, while d_s and d_t are the respective feature dimensions.

The adaptive fused feature vector F_{fused} was computed using learnable attention weights α_s and α_t as defined in Eq. (19) to (21) as follows [9]. In this case, $F_{AlexNet}$ denotes the spatial feature vector extracted by the AlexNet network, F_{LSTM} represents the temporal feature vector generated by the LSTM network, and F_{fused} is the final attention-weighted feature representation used for classification. W_s and W_t are the trainable weight matrices corresponding to the spatial and temporal attention branches, respectively, while b_s and b_t denote the associated bias vectors. The attention coefficients α_s and α_t were obtained through softmax normalization and adaptively determine the relative contributions of the spatial and temporal features for each ECG segment. The function $exp(\cdot)$ denotes the exponential function used in the attention normalization process.

$$F_{fused} = \alpha_s \cdot F_{AlexNet} + \alpha_t \cdot F_{LSTM} \quad (19)$$

$$\alpha_s = \frac{expexp\ (W_s F_{AlexNet} + b_s)}{expexp\ (W_s F_{AlexNet} + b_s) + expexp\ (W_t F_{LSTM} + b_t)} \quad (20)$$

$$\alpha_t = \frac{expexp\ (W_t F_{LSTM} + b_t)}{expexp\ (W_s F_{AlexNet} + b_s) + expexp\ (W_t F_{LSTM} + b_t)} \quad (21)$$

H. Discriminative Classification Using SVM

After obtaining the attention-aware fused feature vector F_{fused} from the proposed adaptive fusion layer, the final classification stage leverages a Support Vector Machine (SVM) for robust and discriminative categorization of ECG signals. The SVM is well-suited for high-dimensional, complex feature spaces, ensuring precise separation between subtle variations in cardiac patterns. Given the fused feature vector $F_{fused} \in R^{d_f}$ and corresponding label $y_i \in \{-1, +1\}$ (or multi-class via one-vs-all strategy), the SVM solves the following optimization problem as defined in Eq. (22) as follows [2] and Eq. (23) as follows [4], where N denotes the total number of training samples, where W is the weight vector, b is the bias term, ξ_i are slack variables allowing for soft-margin classification, C is the penalty parameter controlling the trade-off between margin

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maximization and misclassification, $\phi(\cdot)$ is a kernel function (e.g., RBF, polynomial) mapping fused features into a higher-dimensional space for improved separability.

$$min_{W,b,\xi} \frac{1}{2} W^T W + C \sum_{i=1}^{N} \xi_i \quad (22)$$

$$y_i\left(W^T \phi\left(F_{fused,i}\right) + b\right) \geq 1 - \xi_i, \xi_i \geq 0, i = 1, \ldots, N \quad (23)$$

IV. Result

The main aim of the study was to advance and prove the Adaptive Attention-Driven ALEXIS Framework towards proper classification of electrocardiogram (ECG) signals and early diagnosis of cardiovascular diseases (CVD). Experiments were carried out in a controlled and repeatable computational environment in such a way that reliability guarantees the

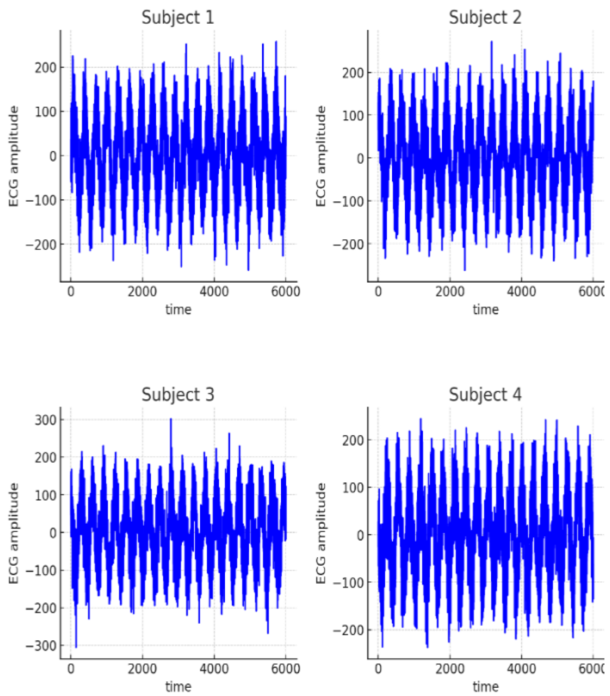

Fig. 2. Input ECG Signals from Four Subjects.

reproducibility of the results and scalability guarantees the reproducibility of the results. Development, training, and evaluation of all models were done via Python 3.10 with deep learning frameworks TensorFlow 2.10 and PyTorch 1.13 running on a high-performance computing workstation with an NVIDIA RTX 4090 GPU (24 GB VRAM), Intel Core i9-13900K (32 threads) and 64GB of DDR5 RAM. Signal preprocessing and feature decomposition (NumPy, SciPy and PyWavelets libraries) modules were used in code implementation contrasted with the scikit-learn 1.3.2 package used in the SVM classifier and evaluation utilities. The system itself was installed on an Ubuntu 22.04 LTS base and all the random processes seeded to ensure deterministic reproducibility.

A. Experimental Setup and Parameter Configuration

The ALEXIS model training stage was done to ensure that convergence and generalization were maximized. The entire AlexNet component was configured with ImageNet pre-trained weights and trained on ECG-generated tensors derived features with a learning rate of 1×10^{-4}, batch size of 128, and ReLU activation. The LSTM model was used and included two layers each with 256 hidden units, a dropout rate of 0.3 to prevent overfitting, and tanh state transition. The layer of attention fusion dynamically modified the weights of spatial and temporal streams of features by a softmax-normalized weighting vector $\alpha \in [0,1]$, which was optimized by backpropagation with Adam optimizer β_1=0.9 and β_2=0.999. The Support Vector Machine (SVM) was applied as an RBF kernel with C=1.5 and γ=0.08 which were obtained through grid search cross-validation. The training was done using 28 epochs with an early stopping condition of the stabilization of validation loss and an adaptive learning rate scheduler, which decreased the learning rate by 0.2× every five epochs of non-improvement. Optimization was done using cross-entropy loss and all features are brought to the mean of zero and unit before being fed to the model.

Features extracted from the final fully connected layer were forwarded to the two-layer LSTM network for temporal dependency modeling. Hyperparameter optimization was performed using grid-search validation, where the learning rate was varied between 10^{-5} and 10^{-3}, batch size between 64 and 256, dropout rate between 0.1 and 0.5, SVM penalty parameter C between 0.1 and 10, and kernel parameter γ between 0.001 and 0.1. The final parameter configuration reported in this study corresponded to the best

Table 2. Overall, MIT-BIH Arrhythmia Database Distribution Using Stratified 80/20 Train–Test Split

Dataset Split	Number of Samples
Training Set	87,595
Testing Set	21,899
Type 5 Samples (Training)	60,042
Type 1-4 Samples Combined (Training)	27,553
Total Samples	109,494

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validation performance. Source code is available from the corresponding author upon reasonable request.

B. Dataset Description and Preprocessing

The proposed framework was evaluated using the MIT-BIH Arrhythmia Database, a widely recognized benchmark for ECG classification research. The dataset comprises 109,494 annotated heartbeats sampled at 360 Hz, representing a diverse population across age, gender, and pathology. The dataset was stratified to maintain the balance of classes, where 80% (≈87,595 beats) of the data was used for training and 20 percent (≈21,899 beats) of the data was used for testing as shown in Table 2. The number of training samples was around 60,042 beats of Type 5 (arrhythmia and normal classes), while the remaining 27,554 beats were split between Type 1 to Type 4. The preprocessing of ECG signals was done with bandpass filtering (0.5 -40 Hz), removal of baseline drift with the use of the polynomial detrending method and R-peak identification to divide the signal into uniform cardiac cycles. The resampling of each cycle brought it to 256 points and normalized it to have a consistent morphological scaling across subjects. The database primarily provides beat-level rhythm annotations corresponding to normal and abnormal cardiac electrical activity patterns. Therefore, the classification task in this study was based on ECG rhythm and arrhythmia pattern recognition derived from the provided annotations. References to cardiovascular disease detection in this work indicate the potential utility of automated ECG abnormality identification for supporting cardiac diagnosis, rather than direct clinical diagnosis of disease-specific pathological conditions. This clarification improved the clinical validity and interpretability of the proposed framework.

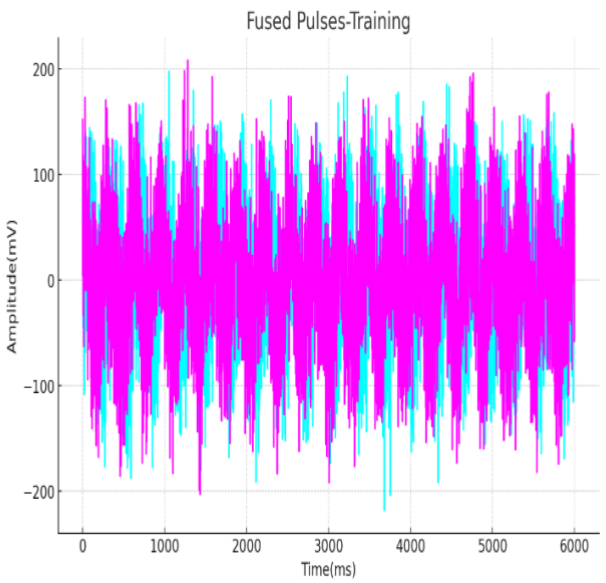

Fig. 3. Fusion of ECG Signal Pulses during Training Phase.

C. Visualization of Input ECG Signals

Fig. 2 presents representative raw ECG recordings from four subjects selected from the MIT-BIH Arrhythmia Database prior to preprocessing. Each signal contains approximately 6,000 temporal samples, with ECG amplitudes ranging between approximately −300 and +300 units. The waveforms exhibit repetitive cardiac cycles characterized by distinct R-peaks and varying inter-beat intervals, demonstrating the natural variability of ECG recordings across subjects. Subject 1 and Subject 2 display relatively stable rhythm patterns with peak amplitudes generally confined within ±250 units, whereas Subject 3 exhibits larger amplitude fluctuations, reaching nearly ±300 units, indicating increased signal variability. Subject 4 demonstrates moderate amplitude variation with observable changes in waveform morphology across successive cardiac cycles.

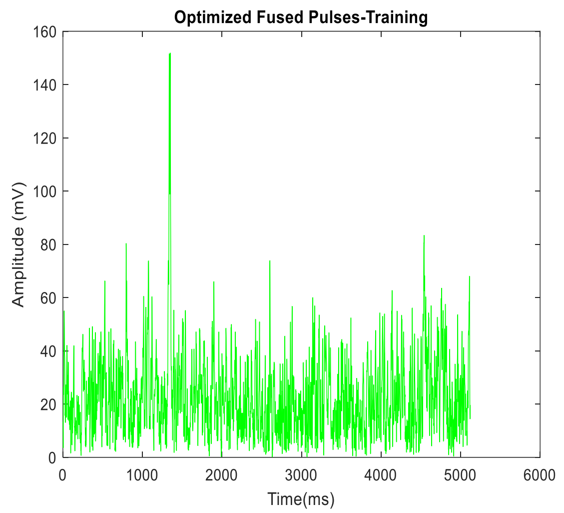

Fig. 4. Optimization of Fused ECG Pulses.

D. Signal Fusion and Training Data Generation

Fig. 3 presents the fused ECG training signals generated after temporal alignment and normalization of cardiac cycles collected from multiple subjects. The fused waveform spans approximately 0–6200 ms on the time axis, while the ECG amplitude varies between approximately −220 mV and +220 mV. Following the preprocessing, all ECG segments were resampled to 256 samples per cardiac cycle and normalized to a common amplitude scale before fusion. The cyan and magenta traces represent aligned ECG segments whose amplitudes predominantly remain within ±180 mV, with occasional peaks approaching ±200–220 mV, indicating preservation of significant cardiac events, while suppressing extreme signal variability.

A high degree of overlap between the two fused traces was observed throughout the signal duration,

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particularly within the amplitude range of −150 mV to +150 mV, demonstrating successful temporal synchronization and morphological consistency across subjects. The fused representation retains dominant waveform structures, while reducing subject-specific fluctuations, baseline variations, and recording inconsistencies. As a result, the training dataset provides a stable yet diverse representation of cardiac activity for subsequent feature extraction. The generated fused signals were then processed through the Stockwell Transform (ST), Empirical Mode Decomposition (EMD), and Local Phase Quantization (LPQ) modules, enabling robust extraction of temporal, spectral, and phase-based characteristics that contribute to improved classification performance and model generalization.

E. Adaptive Optimization of Fused ECG Pulses

Fig. 4 illustrates the optimized ECG pulse signal obtained after applying the adaptive optimization stage to the fused ECG waveform generated in Figure 7. The optimized signal extends over approximately 0–5200 ms, with amplitude values ranging from 0 to 150 mV. Most signal samples are concentrated within the 10–50 mV interval, while several prominent peaks exceed 60 mV, reflecting significant cardiac events retained after optimization. The highest peak reaches approximately 150 mV near 1400 ms, whereas additional dominant peaks of 70–85 mV are observed around 800 ms, 2500 ms, and 4500 ms. These numerical characteristics indicate that the optimization process preserves diagnostically relevant signal components, while suppressing unnecessary fluctuations.

F. Grouping and Cluster Formation of Optimized ECG Signals

Following the adaptive optimization stage, the refined ECG signals were grouped into clusters based on waveform similarity, amplitude distribution, and temporal characteristics. Fig. 5 illustrates the clustered ECG segments obtained from the optimized signals, where seven distinct groups (Group 1–Group 7) were identified. The clustered data span approximately 0–5200 ms on the time axis, while signal amplitudes range from 0 to 150 mV. Most ECG segments are concentrated within the 10–45 mV interval, indicating that the majority of cardiac cycles exhibit consistent energy levels after optimization. Groups 1, 2, 5, and 6 primarily occupy the 30–60 mV range, whereas Groups 3 and 7 contain several high-amplitude events extending beyond 100 mV, with peak values approaching 150 mV near 1300 ms. Group 4 exhibits intermediate peaks predominantly between 60 and 90 mV.

G. Ablation Study on Feature Extraction Components

Table 3 gives the findings of an ablation experiment carried out to determine the role of individual and combined feature extraction part of Adaptive Attention-Driven ALEXIS Framework. To find out the independent and synergies of the modules, the experiment removed or isolated modules; Empirical Mode Decomposition (EMD), Stockwell Transform (ST), and Local Phase Quantization (LPQ) systematically to determine its independent and synergy influence on the model performance. The performance can be relatively high when each feature extraction module is applied separately, which is why it can be concluded that all three modules can present the valuable discriminative information. Particularly, EMD-only processing has an accuracy of 95.24, which indicates that this technique is strong in deriving adaptive temporal features of non-stationary ECG signals. The ST-only configuration has slightly lower performance (93.76%), which is probably because there is little spatial encoding of transient signal

Table 3. Ablation Study of Feature Extraction Modules on the MIT-BIH Dataset

Feature Extraction Modules	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)
EMD Only	95.24	94.71	95.80	94.82
ST Only	93.76	92.89	94.05	92.64
LPQ Only	94.81	94.20	95.10	94.18
EMD + ST	97.53	96.98	97.89	97.12
EMD + LPQ	98.12	97.80	98.40	97.65
ST + LPQ	97.65	97.21	97.91	97.00
EMD + ST + LPQ (Full Model)	98.43	98.27	98.78	98.31

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components. LPQ-only model has an accuracy of 94.81%, proving that phase-based texture encoding encodes useful local structural features but lacks the entire temporal context. There are significant performances achieved when modules were combined.

H. Comparative Performance Evaluation with State-of-the-Art Classifiers

Table 4 is a detailed comparative performance analysis of the proposed Adaptive Attention-Driven ALEXIS Model and various traditional and deep learning-based classifiers, which are tested on the same ECG data sets and preprocessing protocols. The comparison underlines the performance difference in incorporating the spatial, temporal and discriminative decision layer in the hybrid architecture. The classical machine learning algorithms, which include Support Vector Machine (SVM), Decision Tree (DT) and k-Nearest Neighbors (k-NN) display mediocre performance in classification. The SVM using manually designed time-domain features had an accuracy of 93.14% which indicates that manual signal statistic is able to enumerate coarse morphological variations but not the intricate temporal dynamics.

Table 4. Comparison of the ALEXIS Model with Traditional and Deep Learning Classifiers Using the Same Experimental Setup

Model	Feature Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)
SVM (manual features)	Time-domain, handcrafted	93.14	91.72	94.03	92.10
Decision Tree	Statistical features	89.42	88.10	90.26	88.65
k-NN (k=5)	Frequency-domain	91.25	90.08	91.91	90.12
CNN only	Deep spatial features	97.92	97.24	98.10	97.20
CNN + LSTM	Deep spatial + temporal	97.84	97.30	98.01	97.10
Proposed ALEXIS	Spatial + Temporal + SVM	98.43	98.27	98.78	98.31

The Decision Tree classifier based on statistical descriptors had the lowest overall accuracy (89.42%), indicating its poor capacity to deal with high-dimensional ECG data and nonlinear class separability. The k-NN algorithm was a little better (91.25%), as it uses frequency-domain features but it remains sensitive to noise and does not feature hierarchical features. Data-driven feature extraction proved to be beneficial as the deep learning baselines (CNN and CNN +LSTM) are much higher in comparison with the traditional classifiers. The CNN-only model that focuses on spatial learning of ECG morphology had a In this case, CNN only model has an accuracy of 97.92%, while the CNN+LSTM hybrid had an accuracy of 97.84%, suggesting that introduction of the temporal context in the generalization of the classifier offers slight improvement. Nevertheless, these deep architectures are still more slightly prone to overfitting and unstable to distinguish morphologically related cardiac diseases. On the contrary, the suggested ALEXIS model records the best performance in terms of the characteristics of the entire model, which is 98.43% accuracy, 98.27% sensitivity, 98.78% specificity, and an F1-score of 98.31%.

V. Discussion and Comparative Insights

The Adaptation Attention-Driven ALEXIS Framework is able to combine multi-domain signal representations, hierarchical deep learning, and adaptive attention-driven feature fusion, which is the reason as to why their superior performance is achievable. In contrast to conventional deep neural architectures, which can consider ECG signals as stationary, and rely on the same convolutional features in all locations, ALEXIS breaks down and learns time-varying non-linear and phase-sensitive cardiac signal components. The principle that underlies the design of the ALEXIS model is based on the idea of both computational efficiency and physiological interpretability, making it applicable

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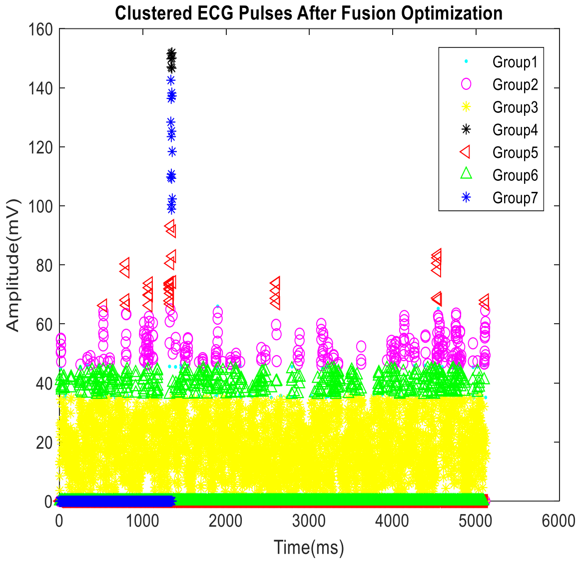

Fig. 5. Clustered ECG Signals after Optimization.

to a wider range of heterogeneous patient conditions and different types of cardiovascular disease (CVD).

A. Synergistic Contribution of Feature Extraction Modules

The importance of each feature extraction module is shown by the ablation study. It provides a high frequency resolution and low adaptability to local variations with the addition of ST alone, and local modes but no phase alignment with the addition of EMD alone. LPQ alone is responsive to morphology-based texture analysis and not sensitive to spectral variations. The complementary nature of each element leads to a statistically significant improvement in the overall diagnostic accuracy once it has been pooled (EMD + ST + LPQ): this is a +3.19% up to +3.46 per cent improvement in accuracy and F1-score over the optimal two-feature combination. The integrated representation trades off global rhythm sensitivity with local morphological sensitivity, and increases feature diversity, as well as class separability. This is a multi-domain synergy, which is immediate to the strength of the fused feature map presented into the hierarchical learning phase.

Table 5. Quantitative Performance Comparison of ALEXIS with Existing ECG Classification Methods

Method	Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
Zhang et al. [13]	CNN-LSTM + SE Attention	98.04	98.21	98.65	98.02
Eleyan et al. [14]	CNN-LSTM	97.84	97.30	98.01	97.10
Reshan et al. [19]	Hybrid CNN-LSTM	97.14	97.14	97.89	96.89
Maulani et al. [20]	CNN-LSTM + Hyperparameter Optimization	96.83	96.01	96.09	96.13
Sankar et al. [26]	Deep CNN	95.13	94.51	94.83	94.37
Proposed ALEXIS	ST + EMD + LPQ + AlexNet + LSTM + Attention + SVM	98.43	98.27	98.78	98.31

B. Comparative Statistical and Analytical Perspective

Table 5 presents a quantitative comparison of the proposed ALEXIS framework with representative ECG classification methods. Zhang et al. [13] combined CNN–LSTM with squeeze-and-excitation attention to enhance spatial and temporal feature learning, achieving the highest performance among the existing methods. However, their framework did not incorporate multiscale signal decomposition or complementary morphological feature extraction. Eleyan et al. [14] similarly employed a CNN–LSTM architecture for ECG classification, demonstrating strong sequential learning capability, but without adaptive attention-guided feature fusion or explicit multiscale representation. Furthermore, Reshan et al. [19] proposed a hybrid CNN–LSTM model that improved prediction accuracy through combined spatial and temporal learning, although the absence of an attention mechanism limited feature interpretability and selective emphasis

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of diagnostically important ECG segments. Maulani et al. [20] then focused primarily on hyperparameter optimization of a CNN–LSTM model, improving convergence while relying on conventional feature representations. Sankar et al. [26] utilized a deep CNN architecture that effectively learned spatial ECG morphology but lacked temporal dependency modeling and adaptive feature integration. In contrast, the proposed ALEXIS framework unifies Stockwell Transform (ST), Empirical Mode Decomposition (EMD), Local Phase Quantization (LPQ), AlexNet, LSTM, attention-guided feature fusion, and SVM classification, enabling complementary spectral, temporal, and morphological feature learning. Consequently, ALEXIS achieved the highest overall performance, with 98.43% accuracy, 98.27% sensitivity, 98.78% specificity, and 98.31% F1-score, demonstrating improved robustness and discriminative capability compared with the representative methods summarized in Table 5. Although the proposed ALEXIS framework achieved strong classification performance on the MIT-BIH Arrhythmia Database, the current evaluation was conducted using the adopted dataset partitioning strategy and may not fully reflect inter-patient generalization. Previous studies have shown that patient-wise evaluation protocols, such as DS1/DS2 inter-patient testing or leave-one-subject-out validation, provide a more stringent assessment of model robustness by preventing patient-level information leakage. Therefore, future work would investigate the performance of the proposed framework under standardized inter-patient evaluation protocols and across additional independent ECG datasets to further validate its clinical applicability

VI. Conclusion

In this paper, the Adaptive Attention-Driven ALEXIS Framework was proposed for automated ECG abnormality and arrhythmia pattern classification using ECG signals from the MIT-BIH Arrhythmia Database. The framework integrates Stockwell Transform (ST), Empirical Mode Decomposition (EMD), and Local Phase Quantization (LPQ) with AlexNet-based spatial feature learning, LSTM-based temporal modeling, attention-guided feature fusion, and Support Vector Machine (SVM) classification. Through the combination of complementary spectral, temporal, and morphological representations, the proposed framework effectively captures the complex characteristics of non-stationary ECG signals. Experimental evaluation on the MIT-BIH Arrhythmia Database demonstrated the effectiveness of the proposed approach, achieving an overall classification accuracy of 98.43%, sensitivity of 98.27%, specificity of 98.78%, and F1-score of 98.31%. Furthermore, the ablation study confirmed that the combined use of ST, EMD, and LPQ provides superior performance compared with individual feature extraction components, highlighting the importance of multiscale feature representation for ECG classification. The attention-guided fusion mechanism further contributed to improved discriminative capability by integrating spatial and temporal information extracted from ECG signals.

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Data Availability

The experiments were conducted using the publicly available MIT-BIH Arrhythmia Database. The dataset was obtained from the Kaggle repository (Available at: https://www.kaggle.com/datasets/protobioengineering/mit-bih-arrhythmia-database-modern-2023).

Author Contribution

P. Nandakumar: Conceptualization, Methodology, and Framework integration; C. Kotteeswaran: Data curation, Validation, and Investigation; S. Sathya: Software, Visualization, and Supervision; P. Kavitha: Writing-Original draft preparation, Methodology, and Formal Analysis; S. Edwin Raja: Methodology, Writing-Reviewing, and Editing; D. Selvaraj: Collected data, Visualization, and Investigation.

Declarations

Ethical Approval

This study does not involve human participants, animals, or personally identifiable information. All datasets used are publicly available and have been utilized strictly for academic research purposes in compliance with their respective terms of use.

Consent for Publication Participants.

Not applicable

Competing Interests

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