

Article

SG-DSN: A Lightweight Network Deep Learning Model for Arrhythmia Classification and Arrhythmia-Induced Cardiomyopathy Risk Alerting Using Multi-Lead ECG

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Abstract

Background: Arrhythmia-induced cardiomyopathy (AIC) is a variation of cardiovascular disease with significant global morbidity and mortality. Arrhythmia is important to detect in time to allow for suitable intervention and clinical management, and this can be accomplished using electrocardiogram (ECG) signals. However, existing approaches face critical challenges to be solved, including (i) similar arrhythmias being hard to distinguish, (ii) misdiagnosis which can lead to life-threatening conditions, and (iii) single-lead ECG possibly missing subtle differences between arrhythmias. **Methods:** The study proposes a lightweight and efficient deep learning framework using selected ECG leads extracted from the PhysioNet large-scale 12-lead ECG arrhythmia database. The signals undergo preprocessing involving baseline wander removal and noise reduction. A Saliency-Guided Depthwise-Separable Dilated Network (SG-DSN) is introduced for feature extraction and classification. The model employs multi-scale dilated convolutions with saliency attention to capture discriminative ECG features, followed by softmax classification. The system not only classifies arrhythmia types but also flags potential AIC risk cases for early clinical intervention. **Results:** Experimental evaluation demonstrates improved arrhythmia classification performance, reduced computational complexity, and enhanced suitability for real-time clinical applications. **Conclusion:** Thus, the proposed framework is an efficient, scalable, and accurate solution for early detection and risk alerting of AIC.

Keywords: 12-lead ECG signal; arrhythmia-induced cardiomyopathy; cardiovascular diseases; electrocardiogram; saliency-guided depthwise-separable dilated network

1. Introduction

Arrhythmia-induced cardiomyopathy (AIC) is a recently recognized and potentially reversible form of cardiomyopathy that develops due to sustained or recurrent cardiac arrhythmias that progressively impair myocardial structure and function [1,2]. Cardiomyopathies are a diverse group of heart muscle disorders associated with structural defects, dysfunction of the ventricles and are a major cause of morbidity and mortality worldwide [3,4]. Early diagnosis is essential to prevent irreversible myocardial damage and, improve the prognosis of the patient, as most myocardial pathologies are irreversible if the underlying arrhythmia is not promptly recognized and treated [5]. Common cardiac arrhythmias such as atrial fibrillation, atrial flutter, supraventricular tachycardia, ventricular tachycardia, and frequent premature ventricular contractions may disrupt normal electrical



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conduction and ventricular synchrony, which can result in decreased cardiac output, ventricular remodeling, heart failure, and progressive cardiac dysfunction [6]. Cardiovascular disease is the most common cause of death globally. Consequently, precise and prompt identification of arrhythmias associated with AIC is crucial to enable effective therapeutic intervention, slow disease progression, and improve long-term clinical results [7].

The primary non-invasive tool for identifying and monitoring cardiac arrhythmias is electrocardiography (ECG), which records the electrical activity of the heart with high temporal resolution [8]. ECG is a crucial tool for detecting abnormalities in cardiac rhythm, conduction pathways and ventricular depolarisation and repolarisation, helping clinicians to diagnose arrhythmias that may lead to AIC [9]. Existing single-lead ECG systems suggest continuous and convenient rhythm monitoring, and can be used in wearable devices and long-term ambulatory monitoring [10]. However, their limited spatial perspective may reduce diagnostic sensitivity for complex arrhythmias [11]. Furthermore, the standard 12-lead ECG records electrical activity of the heart from multiple anatomical views, and can include information about atrial and ventricular activation patterns, conduction abnormalities, and ischemic changes [12]. The multi-perspective representation can aid in the recognition and classification of different types of arrhythmias to enable a more accurate clinical assessment and risk stratification. Figure 1a presents the characteristic components of the single-lead ECG, such as the P wave, QRS complex and T wave, while Figure 1b shows the standard 12-lead ECG electrode configuration for comprehensive cardiac assessment.

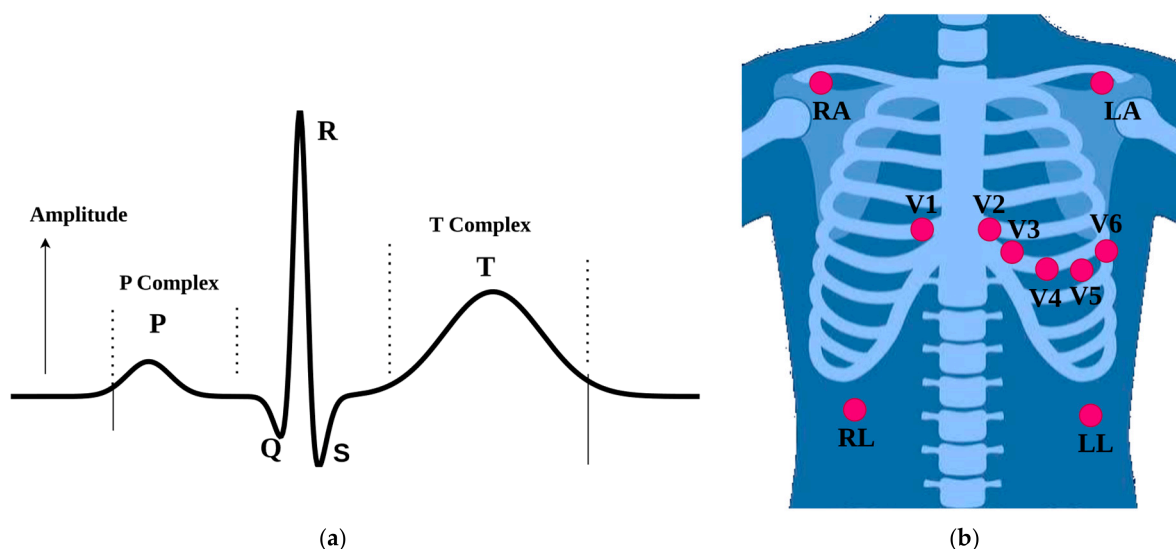


Figure 1. (a). A single-lead ECG signal shows the P complex, QRS, and T complex waves. The P wave represents atrial depolarization, QRS complex denotes ventricular depolarization, and T wave represents ventricular repolarization. (b). Visualization of the 12-lead ECG electrode placement on the human body. The anatomical background image was adapted from Magnific “<https://www.magnific.com/free-photos-vectors/chest-skeleton>” (accessed on 16 July 2026). The 12-lead ECG is divided into limb leads (I, II, III, Right Arm (RA), Left Arm (LA), Right Leg (RL), and Left Leg (LL)) and chest lead (V1–V6).

Artificial Intelligence (AI) has significantly improved automated interpretation of ECG, making the detection of cardiac arrhythmias more accurate and effective. Early machine learning (ML) models were based on handcrafted feature extraction and conventional classifiers, such as gradient boosting, chi-square distance classifiers, support vector machines, decision trees and Particle Swarm Optimization. These methods typically utilize clinically relevant ECG features, including the P wave, the QRS complex, the RR interval, the QT

interval, and heart rate variability [13]. Recently, deep learning (DL) methods have demonstrated better performance by automatically learning hierarchical feature representations directly from raw ECG signals.

The multi-class arrhythmia classification has been widely examined using Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, hybrid CNN–RNN architectures, Transformers, and transfer learning models like ResNet50 and AlexNet [14]. Even more, time–frequency analysis techniques like the Morse Wavelet Transform (MWT) have enabled the conversion of one-dimensional electrocardiograms (ECGs) into a 2D time–frequency domain, which has helped deep neural networks to extract the temporal and spectral information of cardiac activity more effectively [15]. Typically, various preprocessing steps like baseline wander removal, noise suppression, normalization, heartbeat segmentation and signal enhancement are applied before the extraction and classification of features to further enhance the robustness of the model.

Despite significant advances in AI-based ECG analysis, several key challenges still exist that hinder the reliability and practical deployment of automatic arrhythmia detection systems. First, although 12-lead ECG recordings contain rich diagnostic information, the high-dimensional signals require large memory, computational resources, and preprocessing time, which makes real-time implementation difficult, especially in wearable and edge healthcare devices [16]. Second, many cardiac arrhythmias are intermittent or asymptomatic, which results in subtle morphological variations that are difficult to capture consistently, and often lead to delayed or missed diagnosis. Third, there is considerable similarity between different arrhythmia categories such as atrial fibrillation (AFib), supraventricular tachycardia (SVT), atrial flutter, and premature ventricular contractions, which increases the risk of misclassification and decreases diagnostic reliability [17,18]. Furthermore, many existing deep learning models employ computationally intensive architectures with large numbers of parameters, limiting their suitability for resource-constrained clinical environments and continuous patient monitoring [19]. Such limitations affect the performance of existing automated ECG systems for the early detection of arrhythmias associated with AIC. Therefore, there is a need for lightweight, computationally efficient and highly discriminative models that are capable of effectively learning both local morphological features and long-range cardiac patterns, while being suitable for real-time clinical application.

To address these issues, this study proposes the Saliency-Guided Depthwise-Separable Dilated Network (SG-DSN) to accurately and efficiently classify cardiac arrhythmia in multi-lead ECG images through a lightweight network. The proposed framework combines a saliency-guided attention mechanism that highlights the regions in the ECG that contain information that is diagnostic, and suppresses the redundant information, which leads to better discrimination of subtle arrhythmic patterns. In addition, depthwise-separable convolutions minimize the number of trainable parameters and computational cost, making the framework suitable for real-time and resource-constrained healthcare applications. Further, dilated convolutions can include more receptive fields without a corresponding rise in the computational expense, allowing them to learn local morphological features as well as long-range temporal structures, which are essential for accurate heart rhythm analysis—a task that is difficult for dense convolutions. The proposed SG-DSN framework integrates these complementary aspects into a cohesive architecture, providing an accurate, efficient, and robust framework for arrhythmia classification and the early detection of patients at risk of arrhythmia-induced cardiomyopathy (AIC).

Research Contributions

This work presents the following key contributions toward multi-lead ECG-based classification of cardiac arrhythmias and early risk alerting for AIC.

Multi-Lead ECG Feature Extraction: To balance the trade-off between diagnostic and computational efficiency, this work adopts a compact multi-lead configuration (Lead II, V2, V5) instead of a full 12-lead ECG. The proposed saliency-guided attention and multi-scale dilated convolutions exploit complementary lead-wise information to improve discrimination of similar arrhythmias while maintaining a lightweight design.

Early AIC Risk Alerting: The present study proposes a novel clinical decision layer after classification that links the detected arrhythmia type to AIC risk levels for alerting high-risk arrhythmia conditions. Unlike the conventional ECG classification models that merely detect the arrhythmia types, this framework provides actionable clinical insights for timely intervention and prevention of irreversible cardiac damage.

Balanced Preprocessing and Clinical Interpretability: This study uses denoising, normalization and the Synthetic Minority Over-Sampling Technique (SMOTE) to tackle the noise and class imbalance in the ECG data. The novelty is to achieve clinically interpretable outputs by differentiating reversible and non-reversible arrhythmias, thus improving diagnostic reliability and reducing false predictions.

The remaining portion of the manuscript is organized as follows: Section 2 analyzes existing research on cardiac arrhythmias with ECG signals. The proposed SG-DSN methodology is presented in Section 3. Section 4 provides the experimental analysis, and the summarization of the research is covered in Section 5.

2. Related Work

This section reviews recent advances in ECG-based cardiac arrhythmia classification, especially lightweight deep learning models, multi-lead ECG analysis, and their limitations for real-time clinical deployment and risk assessment for AIC.

2.1. Lightweight ECG Models

Lightweight deep learning models have been developed to enable real-time ECG analysis on resource-constrained healthcare devices. Farag et al. [20] proposed the Tiny CNN with Matched Filter (MF) to classify single-lead ECG while maintaining low computational complexity and enabling efficient real-time monitoring. However, single-lead ECG signals present disadvantages such as the lack of comprehensive cardiac information and reduced robustness against the detection of complicated arrhythmias in noisy environments. EP-Moghaddam et al. [21] transformed single-lead ECG signals into visibility graphs, and employed Graph Convolutional Networks (GCN), Multi-Layer Perceptron (MLP) and Random Forest (RF) classifiers for arrhythmia classification. Despite the effectiveness of graph representations in capturing structural ECG characteristics, the study was limited in terms of the number of arrhythmia classes and patients. This also hindered the model from generalizing to various clinical datasets.

2.2. Multi-Lead Deep Learning Models

Multi-lead ECG analysis has significantly improved arrhythmia classification by exploiting complementary cardiac information from multiple leads. Shah et al. [22] proposed ECG-TransCovNet, a unified CNN and Transformer framework for learning spatial and temporal features of ECGs. However, the Transformer part led to a substantial increase in computational burden, preventing the deployment of the model in real-time applications, despite its superior feature representation capacity. Kim et al. [23] proposed a multi-label classifier based on CNN with Global Channel Attention Blocks and Short Residual Blocks to analyze the 12-lead ECGs. Although the model was able to classify correctly multiple arrhythmia categories, its processing of the complete 12-lead ECG recordings required significant computational resources and memory. Moqurrab et al. [24] developed a Hybrid

Residual and Inception-based Deeper Model (HRIDM) that combined the residual module and the inception module to detect heart disease. This model increased the feature extraction, but it was computationally expensive and had a moderate classification performance for multi-class cardiac abnormalities.

2.3. Research Gap and Technical Comparison

The existing studies have achieved promising results; several important limitations remain. Lightweight ECG classification methods mainly improve computational efficiency via simplified CNN architectures or single-lead ECG signals, often sacrificing comprehensive cardiac information and reducing the ability to distinguish morphologically similar arrhythmias. In contrast, multi-lead deep learning models improve diagnostic accuracy by adopting CNN, Transformer, residual, or attention-based architectures but require considerable computational resources and memory, thus making them less suitable for real-time wearable and edge healthcare applications. Moreover, most of the existing methods only focus on arrhythmia classification without clinically meaningful early AIC risk assessment. These limitations highlight the need for a lightweight multi-lead ECG framework that can attain simultaneously high classification accuracy, low computational complexity, efficient feature representation and, and clinically relevant decision support.

Table 1 shows that the existing lightweight ECG classification framework simultaneously provides computational efficiency, effective multi-lead feature learning, and integrated clinical risk assessment. We propose a Saliency-Guided Depthwise-Separable Dilated Network (SG-DSN) in combination with a set of mutually reinforcing technical innovations. First, we introduce a saliency-guided attention mechanism to highlight diagnostically important regions in the ECG waveform for improved discrimination of morphologically similar arrhythmias. Second, we employ depthwise-separable convolutions to reduce the model parameters and computational complexity while maintaining discriminative feature learning to enable efficient real-time deployment. Third, we use dilated convolutions to expand the receptive field to capture both local waveform characteristics and long-range temporal dependencies without incurring additional computational cost. Fourth, the framework utilizes selected multi-lead ECG signals to preserve the complementary diagnostic information and meanwhile reduce computational burden compared to the conventional 12-lead process.

Table 1. Technical comparison between existing lightweight ECG arrhythmia classification methods and the proposed SG-DSN framework.

Ref	Method	ECG Type	Advantages	Limitations
Farag et al. [20]	MF-based Tiny CNN	Single-lead	Lightweight architecture for efficient real-time edge-based ECG monitoring	Limited spatial information reduces robustness for complex arrhythmia detection
Shah et al. [21]	ECG-TransCovNet	Multi-lead	Learns spatial and temporal ECG features for improved arrhythmia detection	High computational complexity limits real-time deployment
Kim et al. [22]	CNN with Global Channel Attention	12-lead	Enables accurate multi-label classification using 12-lead ECG signals	Processing 12-lead ECG increases memory and computational cost
EPMoghaddam et al. [21]	Visibility Graph-Based Method	Single-lead	Graph-based ECG representation for structural feature extraction	Limited dataset diversity reduces model generalization
Moqurrab et al. [24]	HRIDM	12-lead	Employs deep residual-inception learning for robust ECG feature extraction	High model complexity with only moderate classification performance
Proposed SG-DSN	Saliency-Guided Depthwise-Separable Dilated Network	Selected multi-lead	Lightweight multi-lead ECG framework with efficient feature extraction, improved arrhythmia discrimination, and early AIC risk alerting	Validated on a single dataset; requires multi-center clinical validation for broader generalization

Finally, unlike existing lightweight ECG classification methods, the proposed framework incorporates early AIC risk alerting, extending automated arrhythmia classification into clinically meaningful decision support. Collectively, these innovations distinguish SG-DSN from existing lightweight ECG classification models by jointly optimizing classification accuracy, computational efficiency, feature discrimination, multi-scale temporal feature extraction, and clinical applicability, making it suitable for real-time multi-lead ECG analysis and early AIC risk assessment.

3. The Proposed Framework

The proposed framework is illustrated in Figure 2. The illustration shows the overall research workflow, beginning with multi-lead ECG acquisition, preprocessing, feature extraction using SG-DSN, arrhythmia classification, AIC risk assessment, and comprehensive performance evaluation. The study suggests a novel SG-DSN framework for cardiac arrhythmia classification using the PhysioNet database [25], with ECG signals from 45,152 patients. Initially, the raw ECG signal is preprocessed through resampling, band-pass filtering, and normalization. The signals are then segmented into fixed-length windows and fed into the SG-DSN framework. The SG-DSN has two branches: an ECG feature extractor using depthwise dilated convolution and a saliency-guided attention mechanism to highlight relevant regions. The depthwise dilated convolution highlights the local and global temporal dependency, and the saliency attention mechanism draws the attention of the network to the most relevant parts of the ECG waveform. The features from both branches are merged and fed into dense layers with dropout regularization. Finally, a soft classifier performs the classification.

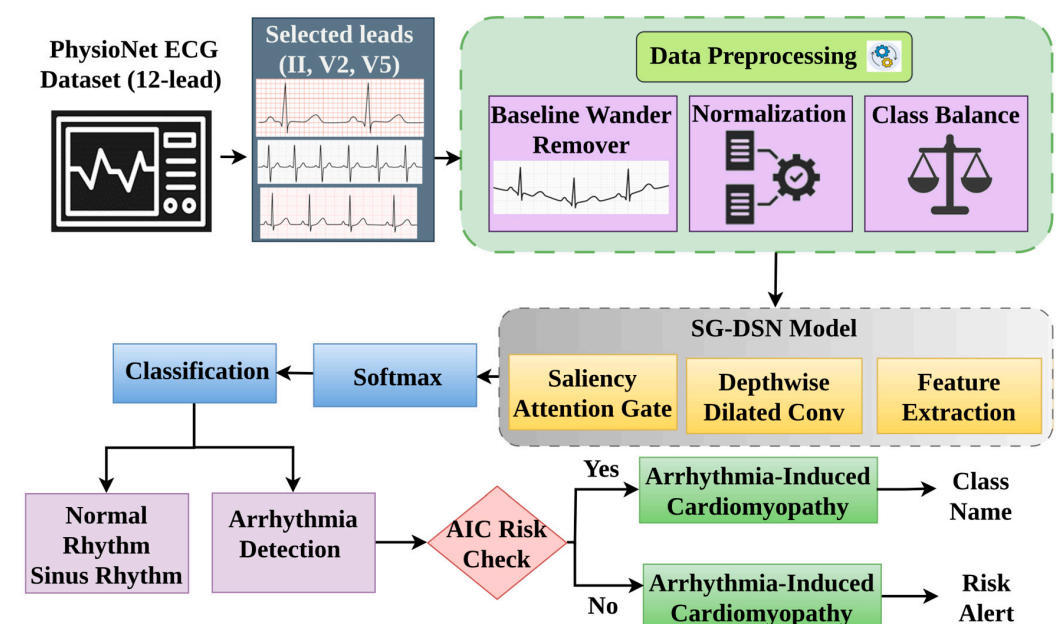


Figure 2. Workflow of the proposed ECG arrhythmia classification and arrhythmia-induced cardiomyopathy (AIC) risk alerting framework, including electrocardiogram (ECG) lead selection, data preprocessing, Saliency-Guided Depthwise-Separable Dilated Network (SG-DSN)-based feature learning, softmax classification and clinical risk assessment. The framework employs selected ECG leads (II, V2, and V5) and a lightweight SG-DSN to accurately classify normal Sinus Rhythm (SR) and multiple cardiac arrhythmia-induced cardiomyopathy (AIC) risk alerts.

3.1. Data Collection

The study was performed on the PhysioNet 12-lead ECG database, which contains ECG recordings of 45,152 patients. A total of 10,646 patients were selected from this

database to develop the model according to the study inclusion criteria. Patients with complete 12-lead ECG recordings, valid rhythm annotations corresponding to the 11 target arrhythmia classes, and sufficient demographic information were included. Duplicate entries, incomplete ECG recordings, missing diagnostic labels, or corrupted ECG signals were excluded. The chosen data include: raw ECG signals, preprocessed ECG signals, cardiac rhythm labels, and patient demographic information.

Each ECG recording is linked to its corresponding diagnosis file, which contains the patient identifier, rhythm annotation, associated cardiac conditions, and demographic details, enabling accurate mapping between ECG signals and their clinical labels. The dataset was split and partitioned into a set of partitions using a patient-wise split, where ECG recordings from a patient were kept in a single partition. The patients were randomly split into training 70%, validation 20% and testing 10% sets. This partitioning by patient helps to evaluate the proposed SG-DSN framework in an unbiased way and enhances the reliability and the generalizability of the classification results reported. Lastly, only three clinically important ECG leads (Leads II, V2 and V5) were chosen from 12-lead ECG recordings to save processing time and retain clinically important information.

To balance clinical relevance and computation efficiency, three clinically relevant leads (Lead II, Lead V2 and Lead V5) were selected from the original 12-lead ECG recordings. Lead selection was based on the complementary physiological information provided by the leads, not just classification accuracy. Lead II visualizes P wave morphology and atrioventricular conduction and is particularly useful for detecting atrial fibrillation, atrial tachycardia and other supraventricular arrhythmias. Lead V2 records the septal and anterior ventricular electrical activity and facilitates identification of ventricular conduction abnormalities, bundle branch blocks and ventricular arrhythmias. Lead V5 represents left ventricular depolarization and repolarization and is useful in diagnosing left ventricular disorders and ischemic changes. The three leads are complementary with recording a left atrial, a septal and a left ventricular electrical activity and considerably less dimensional than the full 12-lead ECG system, maintaining the essential diagnostic information needed for arrhythmia classification. As a result, this compact lead setup allows for the development of a lightweight deep learning framework that can be used in real-time clinical and wearable healthcare applications.

3.2. Data Preprocessing

The preprocessing pipeline involves multiple stages to enhance ECG signal quality and prepare balanced data for model training. A high-pass filter is used to eliminate low-frequency drift and stabilize the signal baseline, which removes baseline wander. Low-pass filtering helps to eliminate artifacts at high frequencies, and notch filtering eliminates power-line interference. The Z-score is normalized to standardize the signal by scaling across samples by shifting it around the zero mean and unit variance. Finally, the class imbalance issue is addressed by using SMOTE [26] to generate synthetic instances for the minority classes to improve the model's performance.

3.3. Saliency-Guided Depthwise-Separable Dilated Network (SG-DSN)

The proposed framework, referred to as the SG-DSN, is designed to efficiently classify cardiac arrhythmias while maintaining low computational complexity $X \in R^{L \times C}$, where X represents the ECG data matrix, R denotes the real-valued space, L denotes the time samples, and C denotes the leads. The depthwise dilated convolution is applied to each lead separately to capture local and global temporal dependencies.

3.3.1. Feature Extraction Using Depthwise Dilated Convolution

The SG-DSN uses depthwise-separable dilated convolutions, where each ECG lead is processed independently to effectively capture local and global temporal dependencies in

the signal [27]. Depth-wise-separable dilated convolutions create spaces between kernel elements, hence enabling an increase in the size of receptive fields with the same computational cost. Thus, this helps capture global ECG patterns and enables the detection of complex arrhythmias. This can be described as shown in Equation (1).

$$f_{dw} = X_{*d}.W_{dw} \quad (1)$$

where f_{dw} is the transformed feature representation produced by convolving the input X with depthwise dilated filters W_{dw} , and $*d$ represents the dilated convolution operation.

3.3.2. Saliency Attention Mechanism

To improve the representation of the features, an attention-based gate [28] is applied within the network. In other words, the proposed architecture learns an attention weight for different sections of the ECG signal and uses this attention vector to highlight clinically important aspects of waveforms. The attention-based feature map is represented as follows in Equation (2).

$$F_* = \sigma(f_{dw} \odot A) \quad (2)$$

where F_* is the saliency weighted feature map, while A denotes the attention weights learnt by the model, $\odot$ is element-wise multiplication, f_{dw} is the transformed feature representation, and σ is a nonlinear activation function. This mechanism improves classification performance by emphasizing relevant features and suppressing irrelevant information.

3.3.3. Classification Layer

The depthwise dilated convolution module enhances ECG feature extraction; dilated convolution is used to enlarge the receptive field without increasing the parameters to capture the long-range temporal dependencies and indirect waveform variations. The output feature maps are $D_h \times D_h \times M$, where D_h denotes the spatial dimension of the feature map and M represents the number of input feature channels. The depthwise convolution with kernel size D_k is then applied independently to each input channel where D_k denotes the depthwise convolution kernel size. This operation reduces the computational complexity while preserving the channel-specific information and results in output feature maps of size $D_1 \times D_1 \times M$ where D_1 is the spatial dimension of the output feature maps. The 1×1 pointwise convolution layer takes the information across all the channels to generate a better feature representation of size $D_1 \times D_1 \times M$ where N is the number of output feature channels.

The Saliency Attention Gate module selectively highlights salient patterns in the ECG from the feature tensor f_{out} ; $(C \times H \times W)$ denotes the number of feature channels, height and width of the feature map. Global Average Pooling (GAP) extracts channel-wise descriptors which are refined through successive 1×1 convolution layers with Rectified Linear Unit (ReLU) and Sigmoid activation functions to generate normalized attention weights. These attention weights are multiplied element-wise with the original feature map to emphasize clinically relevant regions such as abnormal P waves, QRS complexes, and T wave abnormalities while suppressing irrelevant noise as illustrated in Figure 3. After saliency-guided feature enhancement, the refined ECG features are passed into the fully connected softmax classifier [29] represented by interconnected neural nodes as shown in Equations (3) and (4). The classifier calculates probability scores for multiple cardiac rhythm categories, shown on the left side of the figure, including SR, AFIB, AF, SVT, AT, PVC, ST, SB, LBBB, RBBB, and PAC, providing comprehensive and fine-grained arrhythmia detection and classification for effective cardiac diagnosis and risk assessment.

$$\hat{Y}_i = \frac{e^{F_{s,i}}}{\sum_{j=1}^K e^{F_{s,i}}} \quad (3)$$

$$i = 1, 2, \dots, K \quad (4)$$

where k denotes the total number of classes, $e^{F_{s,i}}$ is the exponential transformation of the score, $F_{s,i}$ is the score for the class i before normalization, and $\hat{Y}_i$ denotes the output probability for class i . The softmax layer produces the probability distribution for all arrhythmia classes and identifies the most probable cardiac rhythm category. This enables accurate arrhythmia classification and supports early AIC risk alert generation with reduced computational complexity.

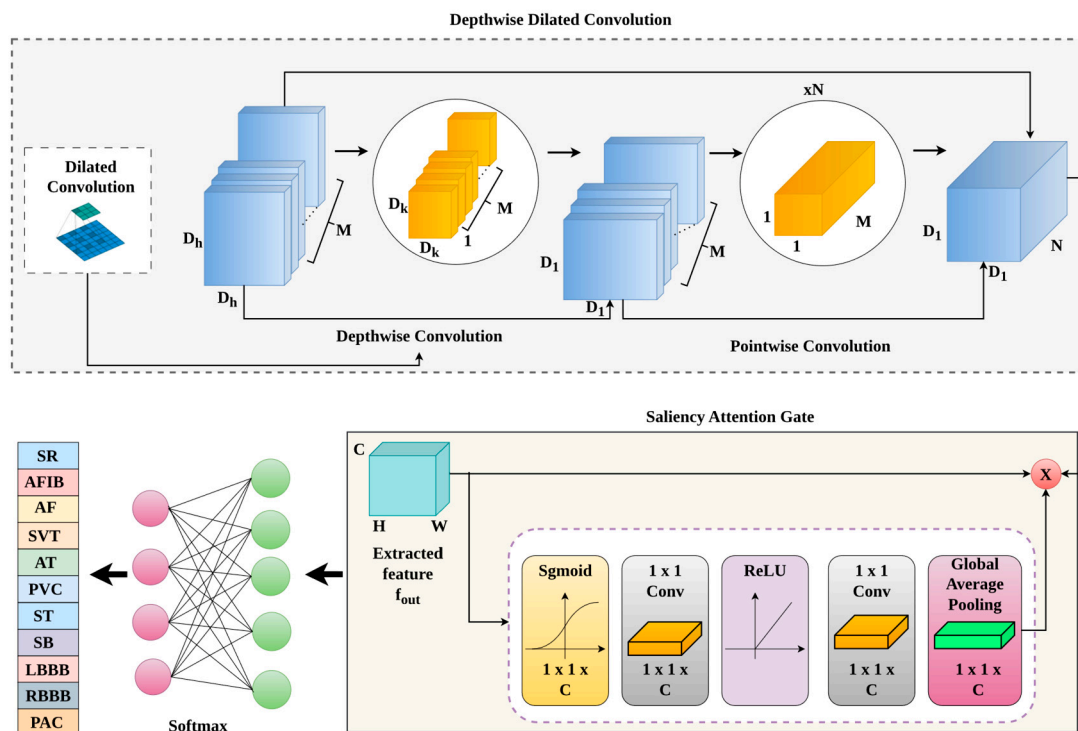


Figure 3. Architecture of the proposed SG-DSN framework for ECG arrhythmia classification, consisting of depthwise dilated convolution, saliency attention gating, feature extraction, and softmax-based multi-class rhythm, which predicted the classes are sinus rhythm (SR), atrial fibrillation (AFIB), atrial flutter (AF), supraventricular tachycardia (SVT), atrial tachycardia (AT), premature ventricular contractions (PVC), Sinus Tachycardia (ST), Sinus Bradycardia (SB), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Premature Atrial Contraction (PAC), and arrhythmia-induced cardiomyopathy (AIC).

3.3.4. Clinical Decision Logic

In addition to arrhythmia classification, a clinical decision-making module is incorporated to improve the interpretability and practical usability of the proposed SG-DSN framework [30], as shown in Figure 4. After the softmax classifier predicts the cardiac rhythm category, the decision logic analyses the predicted output. If the predicted class is identified as SR, the ECG signal is considered a normal heart rhythm. Otherwise, the corresponding arrhythmia type is displayed as the classification result. Furthermore, the system identifies whether the detected arrhythmia is related to AIC. If the predicted arrhythmia can lead to AIC, the model outputs an early risk alert message recommending a medical consultation.

This clinical decision layer enhances the capability of the proposed system to support early diagnosis, risk assessment, and timely clinical intervention for cardiac patients, as

demonstrated in Algorithm 1.

Algorithm 1: Clinical Decision Logic for Arrhythmia and AIC Risk Detection

Input: Predicted ECG class C from the SG-DSN framework

Output: Rhythm diagnosis, AIC risk alert, Clinical recommendation

```

1. Begin
2. Receive predicted class C from Softmax classifier
3. IF C = "SR" THEN
4.     Display "Normal Sinus Rhythm"
5.     Risk Level "Low"
6.     Recommendation "Routine clinical follow-up"
7. ELSE
8.     Display detected arrhythmia type
9.     IF C ∈ {AFIB, AF, SVT, AT} THEN
10.    Risk Level "High"
11.    Recommendation "Immediate cardiology consultation is recommended"
12. ELSE IF C ∈ {PVC, ST} THEN
13.    Risk Level "Medium"
14.    Recommendation "Clinical evaluation and periodic cardiac monitoring
are recommended"
15. ELSE IF C ∈ {PAC, LBBB, RBBB, SB} THEN
16.    Risk Level "Low"
17.    Recommendation "Routine follow-up; additional assessment if clinically
indicated"
18. ELSE
19.    Risk Level "Unknown"
20.    Recommendation "Further clinical assessment required"
21. END IF
22. END IF
23. Display "AIC Risk Level: ", Risk Level
24. Display Recommendation
25. Return rhythm diagnosis, AIC risk level, and recommendation
26. End

```

The proposed three-level AIC risk stratification is established based on previously reported clinical evidence regarding the relationship between sustained arrhythmias and arrhythmia-induced cardiomyopathy. Persistent tachyarrhythmias, particularly AF, AT, and SVT, have been identified as major contributors to tachycardia-induced cardiomyopathy through prolonged ventricular rate elevation, impaired ventricular filling, and adverse myocardial remodeling. Therefore, these arrhythmias are categorized as high-risk conditions requiring early clinical evaluation and intervention [31]. Frequent premature PVCs and persistent ST are considered intermediate-risk conditions because a high arrhythmic burden over an extended period has been associated with ventricular dysfunction and potentially reversible cardiomyopathy. Hence, these conditions are assigned a medium-risk category for continuous monitoring and clinical assessment [32]. Conversely, SR, isolated PACs, bundle branch blocks (LBBB/RBBB), and SB are categorized as low-risk conditions because they are not typically primary causes of AIC unless accompanied by underlying structural heart disease or persistent hemodynamic abnormalities [33].

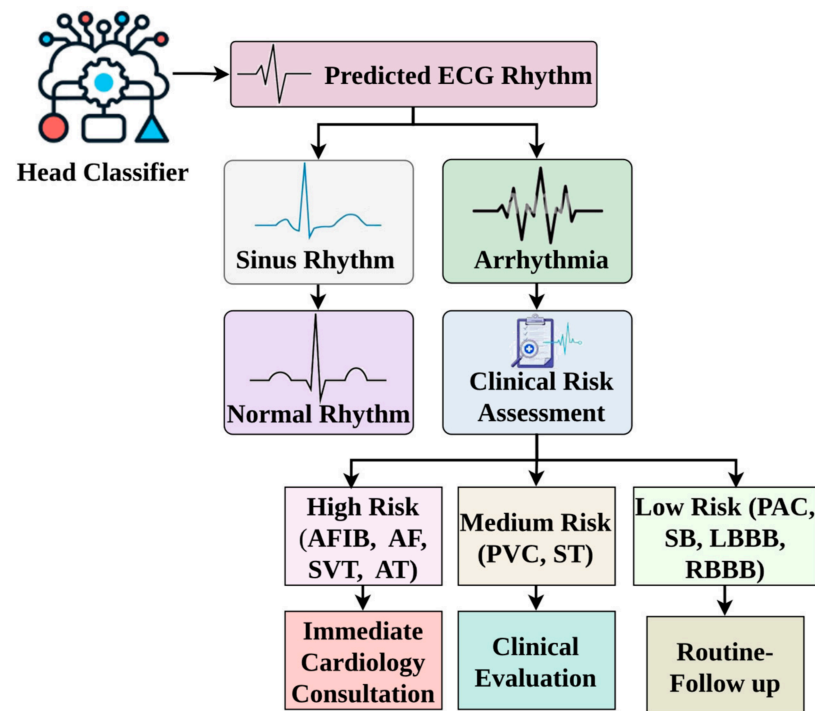


Figure 4. Clinical decision logic for ECG-based arrhythmia and AIC risk detection, where the SG-DSN framework identifies sinus or arrhythmic rhythms and predicts the presence or absence of AIC risk alerting for early clinical intervention.

Based on these clinical observations, the proposed decision layer does not replace clinical diagnosis but provides an automated risk-alerting mechanism to prioritize patients requiring further cardiological assessment. This approach provides more clinically relevant decision support by prioritizing patients for urgent cardiology evaluation and minimizing unnecessary alerts for lower risk rhythm abnormalities.

3.4. Performance Evaluation Metrics

The performance of the proposed SG-DSN framework was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, specificity, Matthews Correlation Coefficient (MCC), Negative Predictive Value (NPV), False Positive Rate (FPR), False Negative Rate (FNR), AIC Risk Prediction Rate (AIC-RPR), Multi-scale Adaptive Deep Arrhythmia (MADA), and Saliency Attention Effectiveness (SAE). These evaluation metrics were used to comprehensively assess the classification performance, clinical risk prediction capability, and saliency-guided feature learning effectiveness of the proposed framework shown in Equation (5).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (5)$$

where true positives (TP) refer to correctly classified positive samples, true negatives (TN) refer to correctly classified negative samples, false positives (FP) refer to incorrectly classified positive samples, and false negatives (FN) refer to incorrectly classified negative samples. The accuracies obtained from these three methods have been provided below in Equations (6)–(8).

$$AIC - RPR = \frac{TP_{AIC} + TN_{nonAIC}}{TP + TN + FP + FN} \quad (6)$$

$$MADA = \frac{1}{N} \sum_{i=1}^N \frac{TP_i}{TP_i + FP_i} \quad (7)$$

$$SAE = \frac{\sum (A_{salient} * G_{ground})}{\sum G_{ground}} \quad (8)$$

where TP_{AIC} represents the true positive counts of correctly alerted AIC cases, TN_{nonAIC} denotes the true negative counts of correctly identified non-AIC cases, TP_i and FP_i are the true positives and false positives for the class i , N is the number of classes, $A_{salient}$ is the predicted saliency map, and G_{ground} is the ground truth mask. These equations indicate the proportion of correctly classified ECG samples over the total number of evaluated samples for each model, reflecting their overall classification performance.

4. Results and Discussion

The proposed SG-DSN framework is evaluated for arrhythmia classification using multi-lead ECG signals. This model uses depthwise dilated convolutions with saliency attention for efficient feature extraction. The training is done using an Adam optimizer, a learning rate of 0.001, a batch size of 64, for 50 epochs, and a ReduceLROnPlateau scheduler to keep stable convergence. The hyperparameters used are given in Table 2.

Table 2. Hyperparameters of the proposed model.

Hyperparameter	Value	Hyperparameter	Value
Optimizer	Adam	Kernel Size	3
Learning Rate	0.001	Activation	Sigmoid
Learning Rate Scheduler	ReduceLROnPlateau	Number of Blocks	4
LR Decay Factor	0.5	Conv1D Filters	32
LR Patience	5 epochs	Kernel Size	3
Batch Size	64	Dilation Rates	[1, 2, 4]
Epochs	50	Depthwise Convolution	Yes
Loss Function	Categorical Cross-Entropy	Pointwise Conv (1 × 1)	Yes
Weight Decay (L2)	1×10^{-5}	Activation	ReLU
Gradient Clipping	1.0	Normalization	BatchNorm
Dilation Rate	2	Kernel Size	3×3
Convolution Blocks	4	Batch Size	32

4.1. Performance Analysis of the Proposed SG-DSN Framework

The proposed SG-DSN framework was evaluated using the performance metrics described in Section 3.4. The experimental results demonstrate that the proposed framework achieves an overall accuracy of 99.87%, precision of 99.82%, recall of 99.79%, F1-score of 99.80%, specificity of 99.92%, Matthews Correlation Coefficient (MCC) of 99.73%, and an AUC of 0.9992 on the PhysioNet dataset. These results indicate the effectiveness of the proposed framework for accurate and reliable arrhythmia classification.

4.2. Confusion Matrix

Figure 5 displays the confusion matrix of the proposed SG-DSN framework for the classification of 11 cardiac rhythm categories consisting of SR, AFIB, AF, SVT, AT, PVC, ST, SB, LBBB, RBBB, and PAC. The diagonal elements indicate the number of instances of correct classification, where each class achieves approximately 498–499 correct per-class predictions, indicating highly accurate classification. On the other hand, the non-diagonal elements denote incorrect classifications, which are exceedingly low. The robust attention

of values along the diagonal matrix reinforces that this framework has learned to extract from the ECGs some of the most highly discriminative features that can be derived from an ECG. Overall, it demonstrates that the proposed framework has performed consistently well across all of the cardiac rhythm classification categories.

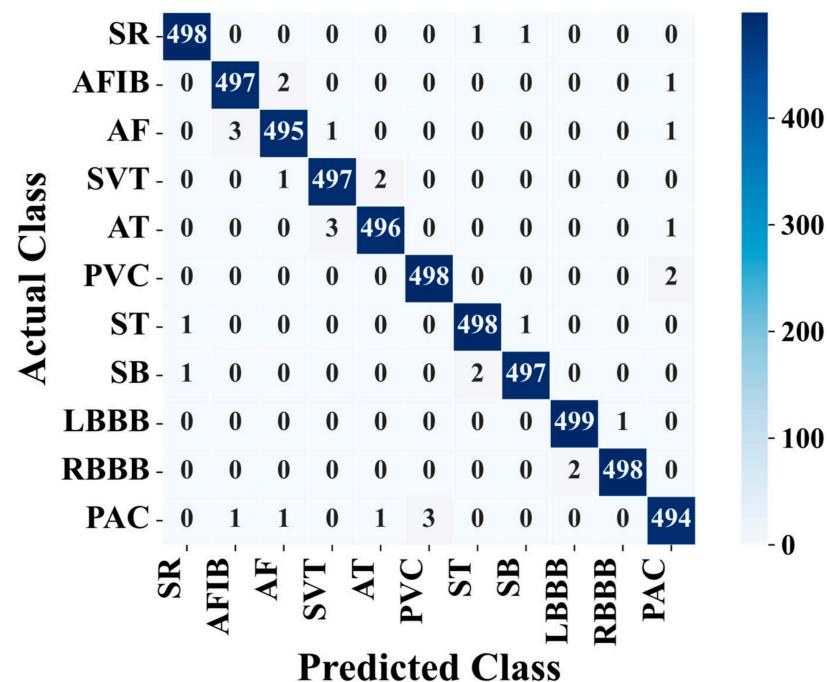


Figure 5. Confusion matrix of the SG-DSN classification model with 11 arrhythmia categories.

4.3. Accuracy of the SG-DSN Framework

Figure 6 demonstrates the classification accuracy of the proposed SG-DSN framework across eleven cardiac arrhythmia classes. The figure categorizes rhythm classes into strong (99.5%), good (99.1 to 99.5%), and comparatively lower (99.1%) accuracy groups. We observe that most classes of arrhythmia have a high accuracy of 99.5%, indicating that they are reliable and consistent. PAC and AF are relatively weak classes with lower accuracy than other classes. The marginal variation in accuracy of 98.8% to 99.8% for all classes indicates that the algorithm does not prefer any class in particular, further substantiating the ability of the multi-scale dilated convolution architecture to capture nuanced variations in ECG signals throughout the spectrum of arrhythmias.

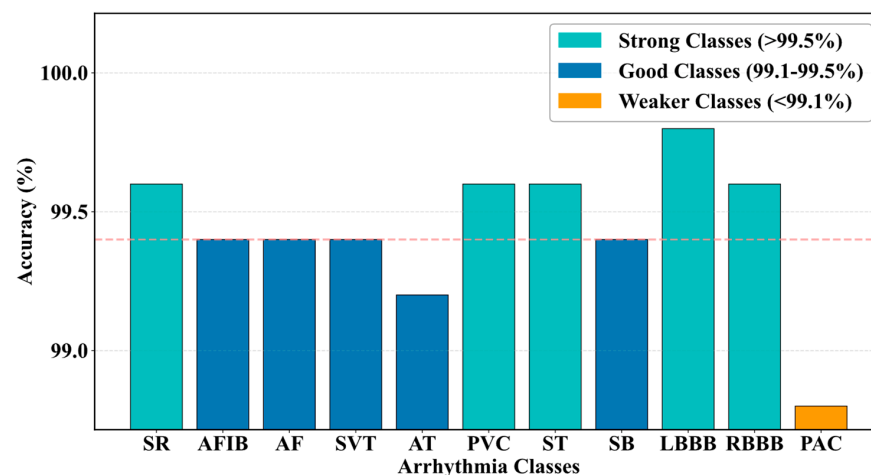


Figure 6. Classification accuracy of the SG-DSN framework across the eleven arrhythmia classes.

4.4. Training and Validation Performance of the SG-DSN Framework

Figure 7 shows that both training and validation accuracy are steadily increasing, and the loss is smoothly decreasing, which means the learning is stable. The good agreement of the curves indicates that the framework does not overfit and generalizes well. It also demonstrates proper convergence during training. This validates the consistency and reliability of the proposed framework. It proves that the SG-DSN architecture learns effectively for arrhythmia classification.

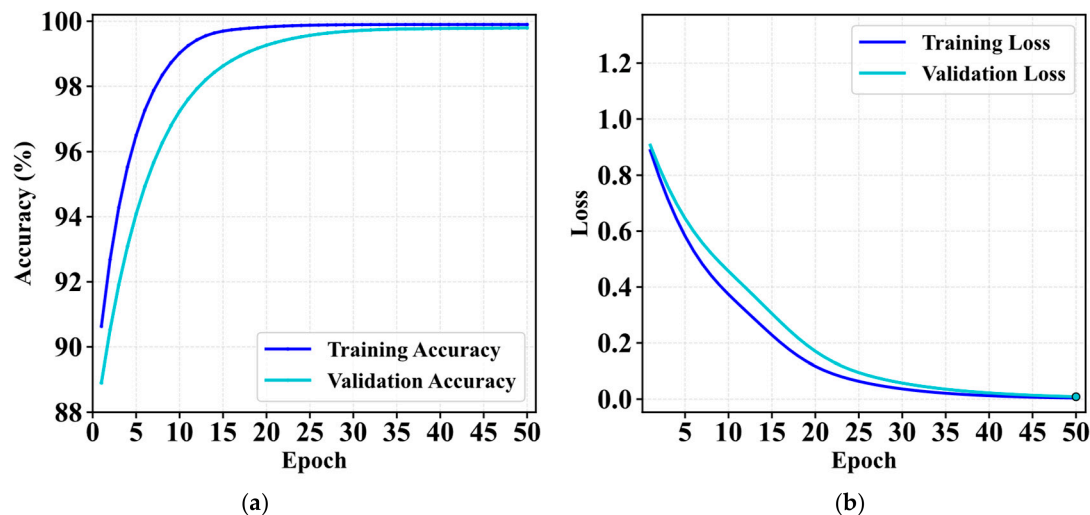


Figure 7. Training and validation (a) accuracy curve and (b) loss curve of the SG-DSN framework.

4.5. Precision–Recall Curve Analysis for Multi-Class ECG Arrhythmia Classification

Figure 8 shows the PR characteristics of each of the 11 arrhythmia classes with respect to the trade-off between precision and recall for the different thresholds used. The PR curve confirms consistent accuracy at higher rates of recall. The average precision (AP) score across all classes ranged between 0.993 and 0.999, showing the system's high accuracy and few, if any, false positive and false negative classifications of arrhythmias. The balanced and tightly clustered PR curves, regardless of the class, show that the SG-DSN framework provides consistent accuracy for all of the arrhythmia classes without any inherent bias against any specific type of arrhythmia. Also, the outstanding PR results with SMOTE demonstrate the effectiveness of this technique in addressing the problem of class imbalance, thus supporting the validity of the SG-DSN framework as an accurate clinical tool for predicting arrhythmias.

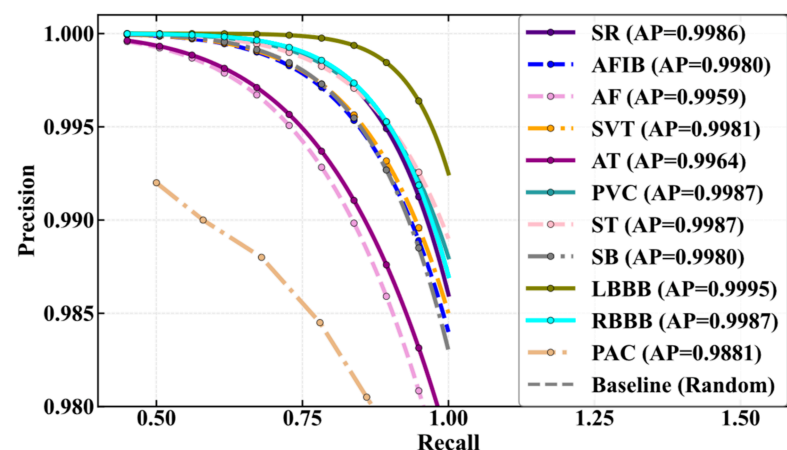


Figure 8. Precision–recall curves showing the classification performance of the SG-DSN framework across all arrhythmia classes.

4.6. Multi-Class ROC Curve Analysis for ECG Arrhythmia Detection Using SG-DSN

Figure 9 shows that ROC curves are concentrated near the top-left corner, indicating the ability to identify true positives is high, while there are also very few false positives. All classes have an AUC greater than 0.996, indicating outstanding performance with respect to distinguishing among them. The AUC for LBBB is slightly lower than that of PAC, but both classes achieved excellent discriminative abilities. The Macro AUC is also very high, showing that the framework is reliable and accurate in the recognition of type of arrhythmia.

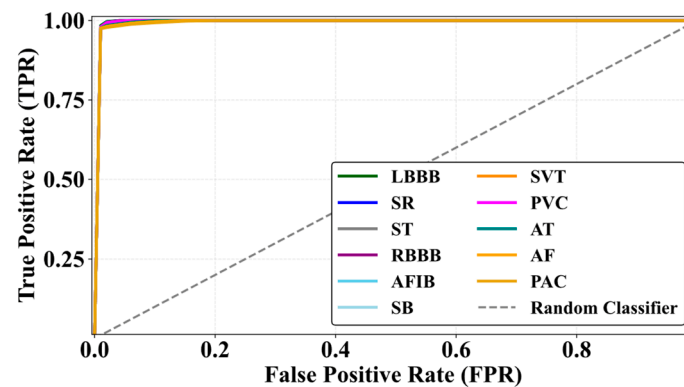


Figure 9. Multi-class ROC curves for cardiac arrhythmia classification using the SG-DSN framework.

4.7. Effect of SMOTE on ECG Class Distribution: Before and After Balancing

Figure 10 presents a comparison of the class distribution before and after SMOTE preprocessing. (a) In the SMOTE section, the SR class dominates with a significantly larger area, while minority classes like PAC occupy very small regions, clearly indicating severe class imbalance. (b) After applying SMOTE, it is clear that there was a balance among all the classes in terms of the amount of space they had, almost evenly distributed with 18,000 instances for each one.

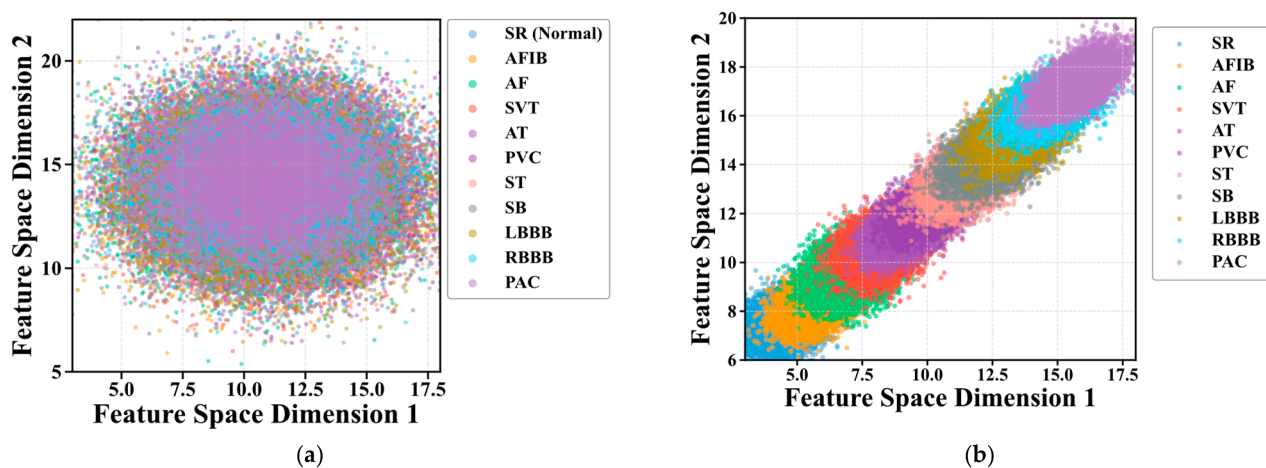


Figure 10. Visualization of ECG class distribution before and after SMOTE balancing (a) ECG class distribution before applying SMOTE, showing the original imbalanced dataset (b) ECG class distribution after applying SMOTE, showing the balanced class distribution.

Table 3 presents the distribution of ECG rhythm classes before and after preprocessing. The original dataset shows a strong class imbalance, where normal SR is the largest class with an excess of 8200 samples; the second largest class is AFIB, which has over 7600 samples. Both PVC and ST have significant numbers of samples in comparison to the

dominant classes, having 7000 and 6800, respectively. Compared to the dominant classes, the minority classes include PAC with only approximately 2052 samples, LBBB with 4300, and RBBB with 4200 total samples. After completing the class-balancing preprocessing step, the total number of samples within each ECG rhythm class was brought into balance. After preprocessing, the dataset was balanced after preprocessing with all classes having close to an equal number of samples, with 4990–5013 samples per class. This balancing step reduces the bias towards the majority classes and ensures equal representation of all ECG rhythm categories. Finally, the model is less likely to overfit to the dominant classes and is expected to have better generalization performance, especially in detecting rare arrhythmias.

Table 3. Class imbalance statistics of the dataset before preprocessing.

Class	Original Samples	After
SR	8200	4986
AFIB	7600	5013
AF	6100	4994
SVT	5200	5008
AT	4800	5003
PVC	7000	4991
ST	6800	5006
SB	5900	5009
LBBB	4300	4993
RBBB	4200	5002
PAC	2052	5006

4.8. Saliency Map Visualization of ECG Signals

Figure 11 shows the ECG signal overlaid with a saliency color map, where different colors represent the intensity of model attention. The brighter color indicates the more salient region of the ECG signal, and the red marker indicates the more salient peak attention point. From the visualization, we observe that the model attends to clinically meaningful regions, QRS complexes, and waveform transitions. It indicates that the SG-DSN framework can extract the important features and pay more attention to them in the classification.

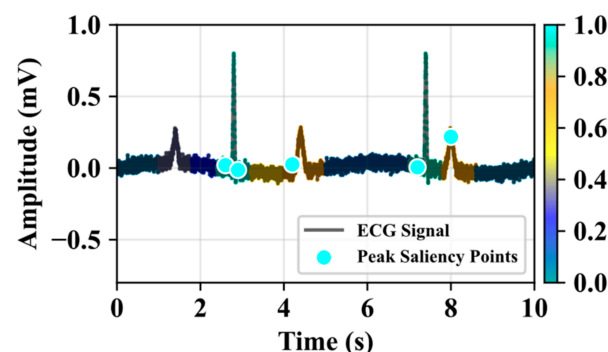


Figure 11. ECG waveform with saliency color map highlighting model attention regions.

4.9. Performance Comparison of Different ECG Lead Combinations for Arrhythmia Classification

Figure 12 compares the classification performance of different ECG lead configurations. Among the evaluated combinations the selected three-lead configuration (Lead II, V2, and

V5) achieved high classification accuracy while using substantially fewer ECG channels than the full 12-lead system. From a clinical perspective, these leads provide complementary information on atrial rhythm (Lead II), septal and ventricular conduction (Lead V2), and left ventricular activity (Lead V5). Combined with the reduced input dimensionality, this configuration provides an effective balance between diagnostic performance and computational efficiency. The quantitative comparison of parameter count, computational complexity, and inference time further confirms the suitability of the proposed three-lead configuration for lightweight real-time ECG analysis.

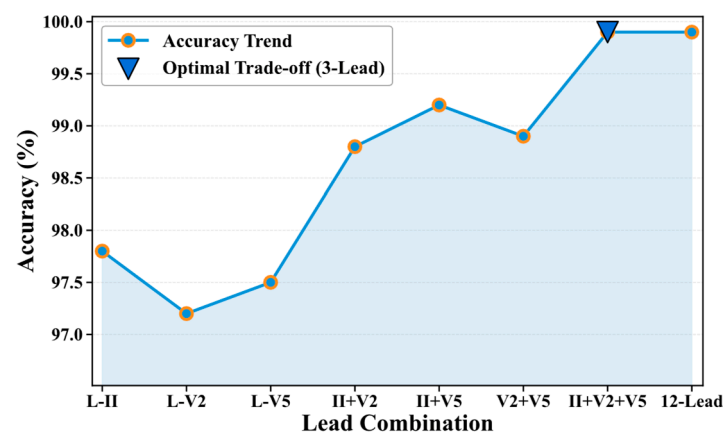


Figure 12. Accuracy trend across different ECG lead combinations.

4.10. Comparison of Different ECG Lead Configurations

To validate the choice of Leads II, V2 and V5, comparative experiments with single-lead, dual-lead, three-lead, six-lead and traditional 12-lead ECG were performed. This comparison considers classification accuracy, number of parameters, computational complexity (FLOPs), model size and inference time to find the best trade-off between diagnostic performance and computational efficiency.

Table 4 shows the trade-off between the computational efficiency and the diagnostic performance of various ECG lead configurations. The conventional 12-lead ECG yields the highest classification accuracy of 99.91%, but at the cost of the highest number of parameters, computational complexity, model size, and inference time. Our proposed three-lead configuration (Lead II, V2, and V5) achieves a competitive accuracy of 99.87% with a decrease of only 0.04% and a significant reduction in the number of parameters, computational complexity, model size, and inference time when compared to the 12-lead configuration. This shows that a selected three-lead scheme offers the best trade-off between classification accuracy and lightweight computational performance, making it particularly well suited for real-time and resource-constrained healthcare applications.

Table 4. Comparison of different ECG lead configurations for accuracy and computational efficiency.

Lead Configuration	Parameters (M)	FLOPs (G)	Model Size (MB)	Inference Time (ms)	Accuracy (%)
Lead II	2.41	0.91	9.8	6.8	98.34
Lead II + V2	3.27	1.36	13.1	8.9	99.05
Lead II + V2 + V5 (Proposed)	4.3	1.82	16.9	11.6	99.87
Six Leads	6.82	3.11	25.7	18.4	99.89
Twelve Leads	10.48	5.94	41.8	30.5	99.91

4.11. Comparative Analysis of Lightweight Deep Learning Models and Proposed SG-DSN

Table 5 compares the proposed SG-DSN framework with some of the existing lightweight deep learning models, such as MobileNetV2, ShuffleNetV2, SqueezeNet, GhostNet and EfficientNet-B0 under identical experimental settings. Some lightweight architectures, like SqueezeNet, have fewer parameters and a smaller model size but result in lower classification accuracy when compared with the proposed architecture. SG-DSN attains a high classification accuracy of 99.87%; SG-DSN uses only 4.30 M parameters, 1.82 GFLOPs, a model size of 16.9 MB and an inference time of 11.6 ms, while maintaining low computational complexity. The findings show that the proposed framework is an effective balance between classification performance and computational efficiency, making it well suited for real-time and resource-constrained ECG applications.

Table 5. Quantitative comparison of the proposed SG-DSN framework with state-of-the-art lightweight deep learning models.

Reference	Model	Parameters (M)	FLOPs (G)	Model Size (MB)	Inference Time (ms)	Accuracy (%)	Lightweight Efficiency
Farag et al. [20] (2023)	Hybrid CNN-LSTM	12.8	5.42	48.6	34.8	96.85	Moderate
Shah et al. [22] (2024)	CNN + LSTM + KNN + XGB Ensemble	18.5	7.93	71.2	52.4	97.92	Low
EPMoghaddam et al. [21] (2024)	DenseNet + ABiLSTM	14.9	6.85	56.4	41.7	98.45	Moderate
Moqurrab et al. [24] (2024)	CNN-BiLSTM + Uncertainty Predictor	16.2	7.14	61.8	46.3	98.96	Moderate
Dhanalaxmi et al. [34] (2025)	MobileNetV2	3.50	2.02	14.1	13.9	98.82	High
Ma et al. [35] (2025)	ShuffleNetV2	2.31	1.46	10.3	10.8	98.46	High
Kumar et al. [36] (2025)	SqueezeNet	1.24	0.89	5.8	9.6	97.93	High
Li et al. [37] (2025)	GhostNet	5.18	2.27	19.5	14.8	99.14	High
Padhy et al. [38] (2025)	EfficientNet-B0	5.29	2.39	20.8	16.7	99.26	High
Proposed	Proposed SG-DSN	4.30	1.82	16.9	11.6	99.87	High

4.12. Cross-Dataset Validation

This section evaluates the generalization capability of the proposed SG-DSN. Cross-dataset validation was performed using the MIT-BIH Arrhythmia Database and PTB-XL in addition to the PhysioNet dataset used in the proposed framework. The MIT-BIH Arrhythmia Database contains 48 annotated half-hour ambulatory ECG recordings acquired from 47 patients using two ECG leads (Modified Lead II and V1/V5), with expert annotations for various supraventricular and ventricular arrhythmias. The PTB-XL dataset is a large-scale publicly available clinical ECG database comprising 21,799 twelve-lead ECG recordings collected from 18,869 patients, with diagnostic annotations based on SCP-ECG statements covering rhythm, conduction, and morphological abnormalities. These datasets provide diverse recording conditions, patient populations, and acquisition protocols, enabling a comprehensive evaluation of the proposed framework under heterogeneous clinical environments.

Table 6 presents the cross-dataset evaluation, which determines that the proposed SG-DSN framework consistently achieves high classification performance across heterogeneous ECG datasets. The model also performed well on the MIT-BIH Arrhythmia Database [39] and PTB-XL [40] with classification accuracies of 97.94% and 98.28%, respectively, where the drops were only 1.93% and 1.59%, respectively. Likewise, across all datasets, high precision, recall, F1-score, specificity, MCC and AUC were consistently preserved, demonstrating a good discriminative ability despite the differences in ECG acquisition devices, patient populations, annotation protocols and recording conditions. These findings determine that

the proposed saliency-guided attention mechanism, depthwise-separable convolutions, and dilated convolutions effectively learn generalized ECG representations rather than dataset-specific features, thereby improving the robustness and transferability of the SG-DSN framework across diverse clinical scenarios.

Table 6. Cross-dataset generalization performance of the proposed SG-DSN framework.

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)	MCC (%)	AUC	Performance Drop (%)
PhysioNet (Internal)	99.87	99.82	99.79	99.8	99.92	99.73	0.9992	-
MIT-BIH Arrhythmia [36]	97.94	97.71	97.42	97.56	98.31	96.83	0.9895	1.93
PTB-XL [37]	98.28	98.11	97.86	97.98	98.64	97.46	0.9928	1.59

4.13. Comparison of Class Imbalance Handling Methods

To evaluate the effectiveness of SMOTE for handling class imbalance in ECG time-series data, comparative experiments were conducted using the original dataset, Random Undersampling, Random Oversampling, ADASYN and SMOTE. The performance of each balancing technique was estimated using the proposed SG-DSN framework under identical training conditions.

Table 7 shows that the choice of balancing technique significantly influences the classification performance of the proposed SG-DSN framework. The lowest performance is attained with Random Undersampling, as it discards informative samples of the majority class, while Random Oversampling improves the performance, but with a risk of introducing redundant samples by simple duplication. ADASYN achieves better results by generating adaptive synthetic samples of the minority class, but the proposed SMOTE-based method always provides the highest accuracy (99.87%), precision (99.82%), recall (99.79%) and F1-score (99.80%). The results suggest that SMOTE efficiently deals with the class imbalance while maintaining the discriminative properties of the ECG signals, making it the most suitable balancing strategy for the proposed framework.

Table 7. Performance comparison of different class imbalance handling methods.

Balancing Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Original Dataset	97.86	97.74	97.58	97.66
Random Undersampling	97.24	97.12	96.95	97.03
Random Oversampling	98.73	98.65	98.57	98.61
ADASYN	99.31	99.24	99.18	99.21
SMOTE	99.87	99.82	99.79	99.8

4.14. Ablation Study

Table 8 shows the performance comparison between the different model configurations in the proposed SG-DSN architecture. The baseline CNN performs the worst, indicating its limitation in handling complicated ECG patterns.

Depthwise convolution helps in improving the efficiency of feature extraction, and dilated convolution helps in extracting temporal features. The combination of depthwise and dilated convolutions results in a better performance across all performance measures. Finally, the overall SG-DSN framework that integrates saliency attention achieves the highest accuracy, precision, recall, F1-score, and specificity. This shows that each parameter individually improves, and their combined effect leads to superior and reliable arrhythmia classification performance. Furthermore, this demonstrates that the proposed AIC risk alert

module achieves a high AIC Risk Prediction Rate (AIC-RPR), confirming its effectiveness in providing reliable early AIC risk assessment.

Table 8. Performance comparison of various configurations of the proposed framework.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)	AIC-RPR (%)	MADA (%)	SAE (%)
Baseline CNN	96.42	96.38	96.31	96.34	97.12	95.74	96.08	95.63
Depthwise Only	97.68	97.71	97.62	97.66	98.04	96.83	97.21	97.08
Dilated Only	98.21	98.27	98.18	98.22	98.53	97.74	98.02	98.11
Depthwise + Dilated	99.12	99.08	99.03	99.05	99.24	98.36	98.79	98.64
With Multi-Scale Fusion	99.46	99.41	99.36	99.38	99.59	99.02	99.08	99.01
With Channel Attention	99.63	99.58	99.54	99.56	99.74	99.18	99.21	99.15
With AIC Risk Alert Module	99.76	99.72	99.69	99.7	99.86	99.33	99.31	99.24
Without AIC risk alert	99.34	99.28	99.17	99.22	99.53	99.16	99.19	99.21
SG-DSN (Full)	99.87	99.82	99.79	99.80	99.92	99.41	99.36	99.28

4.15. Comparative Analysis with State-of-the-Art Approaches

Table 9 compares the proposed SG-DSN with state-of-the-art lightweight deep learning models under identical evaluation settings. The proposed SG-DSN achieves the highest performance across all evaluation metrics including accuracy (99.87%), precision (99.82%), recall (99.79%), F1-score (99.80%), AIC-RPR (99.41%), MADA (99.36%), and SAE (99.28%). These results demonstrate that the integration of saliency-guided attention, depthwise-separable convolution, and dilated convolution provides an architecture that can be kept lightweight, is suitable for real-time ECG analysis, and can achieve better diagnostic performance.

Table 9. Performance analysis of the proposed SG-DSN framework with existing arrhythmia classification models.

Reference	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AIC-RPR (%)	MADA (%)	SAE (%)
Farag et al. [20] (2023)	Hybrid CNN-LSTM	96.85	96.7	96.5	96.6	95.4	96.7	95.6
Shah et al. [22] (2024)	CNN + LSTM + KNN + XGB Ensemble	97.92	97.9	97.8	97.8	97.7	96.9	97.2
EPMoghaddam et al. [21] (2024)	DenseNet + ABiLSTM	98.45	98.5	98.4	98.4	98.2	98.3	97.5
Moqurrah et al. [24] (2024)	CNN BiLSTM + Uncertainty Predictor	98.96	98.9	98.9	98.9	98.2	98.5	97.7
Dhanalaxmi et al. [31] (2025)	MobileNetV2	98.82	98.76	98.68	98.72	98.41	98.37	98.24
Ma et al. [35] (2025)	ShuffleNetV2	98.46	98.39	98.31	98.35	98.12	98.08	97.95
Kumar et al. [36] (2025)	SqueezeNet	97.93	97.86	97.74	97.8	97.58	97.46	97.33
Li et al. [34] (2025)	GhostNet	99.14	99.08	99.02	99.05	98.86	98.81	98.73
Padhy et al. [35] (2025)	EfficientNet-B0	99.26	99.19	99.13	99.16	98.98	98.94	98.87
Proposed	SG-DSN (Full)	99.87	99.82	99.79	99.80	99.41	99.36	99.28

4.16. Discussion

The suggested SG-DSN network represents a significant improvement in the automated detection and classification of heart arrhythmia using multi-lead ECG data. Heart disease is one of the primary causes of death worldwide. Arrhythmia is among those conditions that cause many sudden deaths and other deadly conditions. Therefore, it is vital to create highly accurate and efficient yet lightweight diagnostic systems that can help in the early diagnosis of heart arrhythmia and other diseases. The SG-DSN will address many of the limitations of current arrhythmia detectors, especially with respect

to processing techniques, computational resources, and the ability to work in a real-time environment. The major challenges in arrhythmia classification are the large amount of ECG data generated by traditional 12-lead ECG systems. For example, the volume of ECG data produced by standard 12-lead systems creates a significant storage requirement and preprocessing amount before analysis. For this reason, previous work tried to reduce this complexity by using single-lead systems. However, due to differences among waveform shapes and the ability to identify similar arrhythmias, the accuracy of these methods has typically been low. In this study, the use of selected leads Lead II, Lead V2, and Lead V5 provides an effective balance between data reduction and diagnostic accuracy, while retaining an appropriate level of accuracy when performing an analysis on only a few leads.

The preprocessing step is vital to generate such data and to ensure the quality and validity of the ECG signals used to train the model. High-pass filters are used to remove baseline drift; low-pass and notch filters are used to remove noise and power-line interference. It provides feature extraction from ECG signals to develop a model. Moreover, Z-score normalization was used on the amplitudes of the ECG signals in order to normalize the distribution of the input data among the different patients. In order to solve the class imbalance problems in medical datasets, SMOTE was used to generate new samples of a specific class with different frequencies. Although SMOTE generates synthetic samples that may introduce artificial dependencies, comparative experiments with Random Undersampling, Random Oversampling, and ADASYN demonstrated that SMOTE achieved the best overall performance while maintaining robust generalization. This approach increased the overall generalizability of the model with little classification bias. The contribution of the work lies in the construction of the SG-DSN framework architecture. Specifically, this model integrates saliency-based attention-type processing with depthwise-separated dilation convolutional layers to capture both local and global curricular-type features from ECG data. By using depthwise-separable convolution, the number of tunable parameters required by the SG-DSN will significantly decrease compared to a traditional CNN architecture, resulting in lower complex computing requirements and faster computational speed.

The experimental results demonstrate that the proposed framework is effective with the overall classification accuracy of 99.87%, precision of 99.82%, recall of 99.79%, F1-score of 99.80%, specificity of 99.92%, Matthews Correlation Coefficient (MCC) of 99.73 and AUC of 0.9992 on the PhysioNet dataset. Moreover, the cross-dataset validation results demonstrate excellent generalization capabilities, with accuracies of 97.94% on the MIT-BIH Arrhythmia Database and 98.28% on PTB-XL, which are only 1.93% and 1.59% lower, respectively. These results establish that SG-DSN has constantly high diagnostic performance across various ECG datasets regardless of the variations in acquisition devices, patient demographics and recording protocols. The AIC risk alert module is able to identify patients with arrhythmia who are at risk of developing AIC and alert the clinician at the appropriate time for timely intervention and proactive cardiac care.

From a clinical perspective, the proposed SG-DSN framework is intended to function as a clinical decision support tool by assisting cardiologists in the early identification of arrhythmias associated with AIC risk. The generated risk alerts should be interpreted alongside the patient's clinical history, physical examination, and other diagnostic findings rather than being used as a standalone diagnosis. Although the proposed framework demonstrates promising performance, further validation in collaboration with experienced cardiologists and prospective multi-center clinical studies is required before routine clinical deployment. In addition, future work will involve the validation of the proposed SG-DSN framework with real-world ECG data gathered from various hospitals around the globe and different population areas of patients to further demonstrate its clinical applicability and generalizability.

Early detection of any arrhythmia contributing to AIC is essential since it can usually be reversed with timely treatment. The SG-DSN framework both classifies the types of arrhythmias and provides an early indication of overall risk for the potential development of AIC. This added clinical benefit will aid in the prevention of AIC through early detection of arrhythmia and help reduce the risk of permanent heart damage. The proposed framework achieves reliable classification performance while maintaining low computational requirements. The use of the Adam optimizer allowed the system to achieve efficient training and increased speed of convergence to demonstrate stable performance during the testing phases. The SG-DSN was designed to minimize memory and processing scale compared to standard deep neural networks. Therefore, the system is particularly appropriate for deployment via wearables, remote monitoring systems and designated low-resource healthcare situations. Furthermore, the cross-dataset validation on the MIT-BIH Arrhythmia Database and PTB-XL showed that the proposed SG-DSN framework consistently attains high classification performance across different patient populations, acquisition devices, and recording conditions, thus confirming its robustness and generalization ability beyond the PhysioNet dataset.

Despite its promising performance, the proposed SG-DSN framework has several limitations that warrant further investigation. Although the model demonstrates promising generalization performance on multiple public ECG datasets, future work will focus on validating the framework using real-world ECG data collected from multiple hospitals and geographically diverse patient populations to further establish its clinical applicability and generalizability. To further improve classification performance, advanced data augmentation techniques beyond SMOTE, such as generative adversarial networks (GANs) and diffusion-based augmentation methods, will be explored to address class imbalance and enhance the representation of rare arrhythmia classes. Future research will also investigate architectural enhancements for improved recognition of complex and clinically challenging arrhythmias, particularly those with subtle morphological variations. In addition, explainable AI (XAI) techniques, such as SHAP and Grad-CAM, will be integrated to provide interpretable predictions and increase clinicians' confidence in the model's decision-making process. Finally, the proposed framework will be optimized and validated for deployment on real-time wearable devices and edge healthcare platforms to assess its feasibility for continuous ECG monitoring and point-of-care diagnosis under practical clinical conditions.

5. Conclusions

The study proposed a SG-DSN was developed as a new approach to classifying cardiac arrhythmias and detecting them early in patients at risk of developing AIC. Using the multi-lead ECG signals, the SG-DSN overcame some of the limitations of the existing heterogeneous systems to achieve lower computational costs and storage requirements with high levels of classification performance, and to improve data quality and provide more reliable models. The SG-DSN used three chosen ECG leads and enhanced the corresponding format using advanced methods for improved data quality and more robust models, incorporating filtering, normalization, and SMOTE. The SG-DSN's lightweight architecture allows it to be used for real-time applications such as health monitoring devices and delivering remote patient care. The experimental results strongly support the effectiveness of the proposed SG-DSN framework for lightweight ECG-based arrhythmia classification and early AIC risk alerting. The framework achieved an overall classification accuracy of 99.87%, precision of 99.82%, recall of 99.79%, F1-score of 99.80%, specificity of 99.92%, MCC of 99.73%, and an AUC of 0.9992 on the PhysioNet dataset. Overall, the SG-DSN framework shows great promise in reliably detecting arrhythmias

and alerting to higher levels of clinical risk at an earlier stage than previous methods, thus improving patient outcomes, reducing costs, and improving management strategies for cardiac diseases.

Author Contributions: Conceptualization, D.C.; Methodology, D.C.; Validation, A.D.; Formal Analysis, A.D.; Writing—Original Draft Preparation, A.D.; Writing—Review and Editing, D.C. and A.D.; Visualization, D.C. and A.D. All authors contributed to the conception of the problem setting and overall design of the work. This version was revised and improved by all authors, who also read and approved the final manuscript. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The study was implemented using the PhysioNet ECG Arrhythmia Dataset, which is publicly available at <https://physionet.org/content/ecg-arrhythmia/1.0.0/> (accessed on 16 March 2026). The MIT-BIH Database (<https://www.kaggle.com/datasets/mondejar/mitbih-database>) (accessed on 16 March 2026) and the PTB-XL ECG Dataset (<https://www.kaggle.com/datasets/khyeh0719/ptb-xl-dataset/code>) (accessed on 16 March 2026) were used for cross-dataset validation to assess the generalizability of the proposed model.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

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