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Deep Learning-Based Automatic Classification of Cardiac Arrhythmia Using Multi-Spectral Attention and BiLSTM Networks

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Abstract: Cardiac arrhythmia is a condition charactWerized by irregular heartbeats that may lead to serious health complications such as stroke or heart failure. Electrocardiogram (ECG) is a widely used, noninvasive method to monitor and detect arrhythmias. However, due to signal variability and class imbalance in datasets, the accurate and automated classification of arrhythmias remains a challenge. This study presents a deep learning framework combining Residual Networks (ResNet), Squeeze-and-Excitation (SE) blocks, and Bidirectional Long Short-Term Memory (BiLSTM) layers enhanced with Multi-Spectral attention and synthetic minority oversampling (SMOTE). The proposed model is trained and validated on the MIT-BIH, AFDB, and CinC databases. Results show improved classification accuracy, especially in minority arrhythmia classes, and high generalization ability across datasets, surpassing conventional machine learning and deep learning baselines.

Keywords: Cardiac arrhythmia, ECG, ResNet, BiLSTM, Deep Learning, Multi-Spectral Attention, SMOTE, Classification, Generalization, Cross-subject evaluation

1. Introduction:

Cardiac arrhythmia refers to an abnormal heart rhythm that can range from harmless to potentially fatal. Accurate diagnosis is vital for effective treatment and intervention. The primary classifications of cardiac arrhythmia is shown in Figure 1. ECG remains a primary diagnostic tool, but manual interpretation is time-intensive and prone to variability among

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cardiologists. With the increasing burden of cardiovascular diseases, automating ECG interpretation using deep learning offers a viable and scalable solution. Unlike traditional machine learning, deep learning can autonomously extract hierarchical features, making it more suitable for complex, nonlinear ECG data.

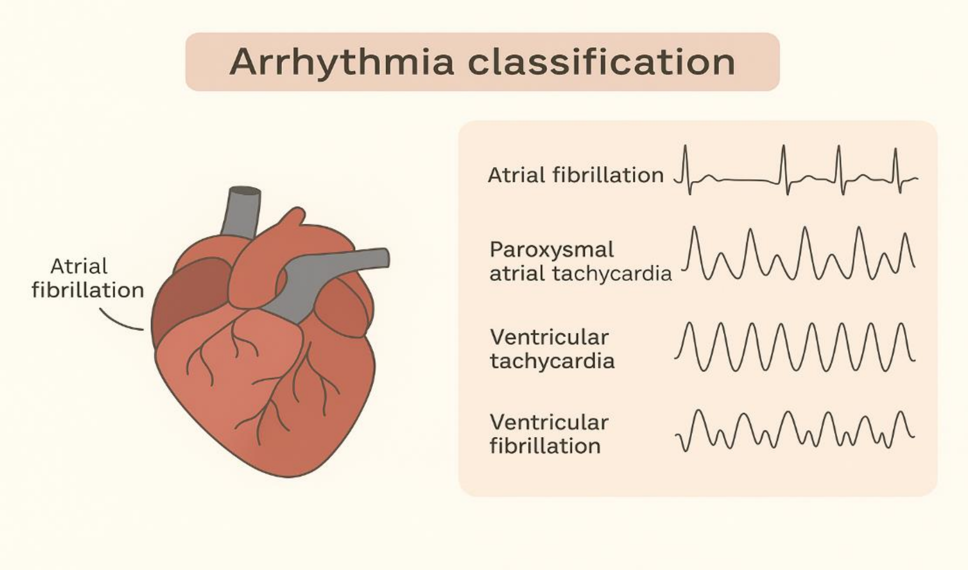

Figure 1: General Classification of Cardiac Arrhythmia

This paper investigates a novel approach integrating ResNet, SE modules, and BiLSTM with a Multi-Spectral attention mechanism. This architecture is capable of learning both spatial and temporal patterns in ECG signals, thereby improving diagnostic accuracy. Additionally, SMOTE is applied to address the class imbalance problem, enhancing the model's ability to detect rare arrhythmias.

2. Related Works:

Recent IEEE research highlights the increasing use of deep learning models like CNNs and RNNs for ECG-based arrhythmia classification. HARDC, combines dilated CNN layers with a hybrid of BiGRU and BiLSTM, using hierarchical attention to focus on important ECG parts. It also employs Conditional GANs for data augmentation, helping address class imbalance, though it is quite complex and resource-heavy. Combination of CNN-DVIT CNN with a Vision Transformer using deformable attention, which adapts well to various ECG signal shapes and lengths. While powerful, it can be harder to interpret and requires high computational power. Res-BiANet, though focused on PPG signals, shows strong sequential learning using BiLSTM, residual connections, and attention, but its direct use on ECG might need adjustments. SE-ECGNet stands out for its efficient use of squeeze-and-excitation blocks to learn channel importance, but it lacks time-based learning features like RNNs. HAN-ECG introduces a three-level attention system (wave, heartbeat, time window) within a BiRNN structure, offering high

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interpretability, especially for atrial fibrillation detection, though it's less general for other arrhythmias. A lightweight hybrid CNN-LSTM model focuses on balancing performance and efficiency, making it suitable for real-time wearable applications, even if it lacks deep hierarchical modeling. RL-ECGNet applies reinforcement learning to adjust model complexity in real-time, making it ideal for low-resource devices but may slightly trade off accuracy. Among all, HA-ResNet achieves the best overall balance. It uses residual CNN blocks, Bi-directional ConvLSTM, attention mechanisms, and SE modules to capture both spatial and temporal ECG patterns effectively. Compared to transformer-based models, HA-ResNet is more efficient and easier to interpret, making it a strong candidate for real-time and clinical applications.

3. Methodology:

3.1 Dataset:

The MIT-BIH Arrhythmia Database (MITDB) is a widely used dataset in the field of cardiac arrhythmia detection and classification. It contains a set of 47 two-channel ambulatory Electrocardiogram (ECG) recordings obtained from 47 subjects, with each recording being approximately 30 minutes in length. These recordings were collected at the MIT-BIH Arrhythmia Laboratory between 1975 and 1979, and they have a sampling rate of 360 Hz shown in Table 1.

Table 1: Key Features of the MIT-BIH Arrhythmia Database

Feature	Details
Number of Recordings	47 two-channel ECG recordings from 47 subjects
Recording Duration	Approximately 30 minutes per recording
Sampling Rate	360 Hz
Channels	Two-channel recordings capturing different views of the ECG signal
Collection Period	1975-1979
Data Annotation	Annotated with cardiac events, including arrhythmias and heartbeats
Cross-Validation	5-fold cross-validation used for model evaluation

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Classes in the MIT-BIH Arrhythmia Database:

The database contains recordings of 17 distinct types of arrhythmic rhythms and heartbeats. These include various forms of atrial, ventricular, and supraventricular arrhythmias, as well as normal sinus rhythm (NSR) shown in Table 2. For the purposes of this study, we focus on the following seven arrhythmia classes, which are among the most common and have the highest incidence:

Table 2: Various Classes of Cardiac Arrhythmia

Class	Description
AFIB	Atrial Fibrillation: Rapid and irregular atrial contractions
AFL	Atrial Flutter: Rapid but regular atrial contractions
AVR	Atrioventricular Reentrant Tachycardia: Abnormal electrical pathways
SVT	Supraventricular Tachycardia: A rapid heart rate that originates above the ventricles.
VT	Ventricular Tachycardia: A fast heart rate that originates within the ventricles.
SBR	Sinus Bradycardia: Slower-than-normal heart rate originating from the sinoatrial node
NSR	Normal Sinus Rhythm: Regular, normal heart rhythm

Any remaining rhythms outside these selected classes are grouped together as the "Other" class, which includes rare or less common arrhythmic patterns.

Annotation of Data:

Each ECG recording in the MIT-BIH database is annotated by trained professionals. These annotations mark the locations of specific cardiac events, such as the onset of a particular arrhythmia, and provide detailed labeling of the rhythm types at each point in the recording. Annotations are crucial for training and evaluating classification models, as they serve as ground truth for model comparison.

K-Fold Cross Validation:

For model evaluation, a 5-fold cross-validation approach is used. This ensures that the model is tested on different subsets of the data, improving its generalization ability and helping to prevent overfitting. In this case, K=5, meaning the dataset is split into five subsets, and each subset serves as a test set once while the remaining four are used for training. The MIT-BIH Arrhythmia Database is an essential resource for the development and evaluation of automated

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cardiac arrhythmia detection systems, offering a robust foundation for testing various classification models and signal processing techniques.

3.2 Proposed Methodology for ECG-Based Arrhythmia Detection

The proposed arrhythmia detection and classification framework aims to enhance the accuracy of identifying cardiac arrhythmias from ECG signals. It consists of three main stages: data processing, data augmentation to address class imbalance, and arrhythmia classification. These steps work together to enhance the model's performance, especially in dealing with rare arrhythmic classes.

Step 1: Data Augmentation using SMOTE

To handle class imbalance in the dataset, the framework uses Synthetic Minority Over-sampling Technique (SMOTE) to augment the data for minority classes. In the augmented data, the 10-second-long ECG signal from the minority class is represented by the blue line, and the newly generated synthetic samples are represented by the red line. SMOTE balances the class distribution by generating synthetic samples through interpolation between existing instances of the minority class.

Step 2: Feature Extraction with ResNet

In the second step, the framework extracts global features from the augmented data using a Residual Network (ResNet) with a Squeeze-and-Excitation (SE) block. The ResNet is a convolutional neural network that employs residual blocks to improve the feature extraction process. The convolution layer first processes the augmented data, where the red rectangular box represents the convolution kernel in a 1D convolution (Conv1D) layer. Afterward, the processed data are passed through the ResNet to extract global features, where the white rectangular boxes represent the feature maps. These feature maps are recalibrated within the residual block, where T represents time points and C refers to channels.

Step 3: Temporal Feature Extraction using BiLSTM

The global features extracted from the ResNet are then fed into a bi-directional Long Short-Term Memory (biLSTM) network. The biLSTM captures the temporal dependencies of the ECG signal by processing the data in both forward and backward directions, thereby enhancing the model's ability to understand the sequential nature of ECG signals. The output of the biLSTM layer is a set of sequential features that contain the temporal information required for classification.

Step 4: Classification and Probability Calculation

After extracting the sequential features from the biLSTM, the data are passed through a fully connected layer and a Softmax layer to compute the class probabilities. The final

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classification step calculates the probability of each arrhythmia class in the dataset, such as AFIB, AFL, AVR, SVT, VT, SBR, NSR, and others. The output provides the predicted probability for each of the eight arrhythmic classes. In summary, the proposed framework efficiently combines data augmentation, feature extraction through deep learning models (ResNet and biLSTM), and classification to improve arrhythmia detection. The use of SMOTE addresses class imbalance, while the ResNet and biLSTM models enable robust feature extraction and classification, leading to accurate detection of arrhythmias from ECG signals.

3.3 Preprocessing:

First, lead II is selected because it is commonly used for arrhythmia detection. The data is then resampled to a uniform rate of 256 Hz, ensuring consistency across all recordings. To correct baseline drift, a type of low-frequency noise, a third-order Butterworth filter is applied to the signals. Next, the ECG signals are segmented into 10-second intervals based on the rhythm annotations in the database, with each segment corresponding to a specific type of arrhythmia. Finally, Z-score normalization is used to standardize the signals, adjusting them so that each has a mean of 0 and standard deviation of 1, which ensures that all ECG segments are on the same scale. Following steps make the ECG data clean, consistent, and ready for further analysis and classification shown in Table 3.

Table 3: Preprocessing Pipeline for ECG Signal Analysis

Step	Objective	Action
Step 1: Lead Selection	Select the relevant ECG lead for analysis.	Lead II is selected from the MIT-BIH database, as it is commonly preferred for arrhythmia detection in most patients.
Step 2: Resampling	Standardize the signal's sampling rate.	Resample the ECG signal to a frequency of 256 Hz to ensure all signals have the same sampling rate.
Step 3: Baseline Wandering Correction	Remove baseline drift from the ECG signal.	Apply a third-order Butterworth filter to remove low-frequency noise and baseline wandering.
Step 4: Segmentation	Extract segments corresponding to different rhythm types.	Use MITDB annotations to segment the ECG signal into 10-second intervals based on arrhythmic labels.
Step 5: Normalization	Standardize the amplitude of the ECG signals.	Z-score normalization is applied to each ECG segment to standardize the data with a mean of 0 and a standard deviation of 1.

3.4 Architecture Overview for Arrhythmia Classification

The proposed arrhythmia classification architecture utilizes advanced deep learning techniques to extract both spatial and temporal features, enhancing the model's accuracy in detecting and classifying arrhythmic events shown in Figure 2.

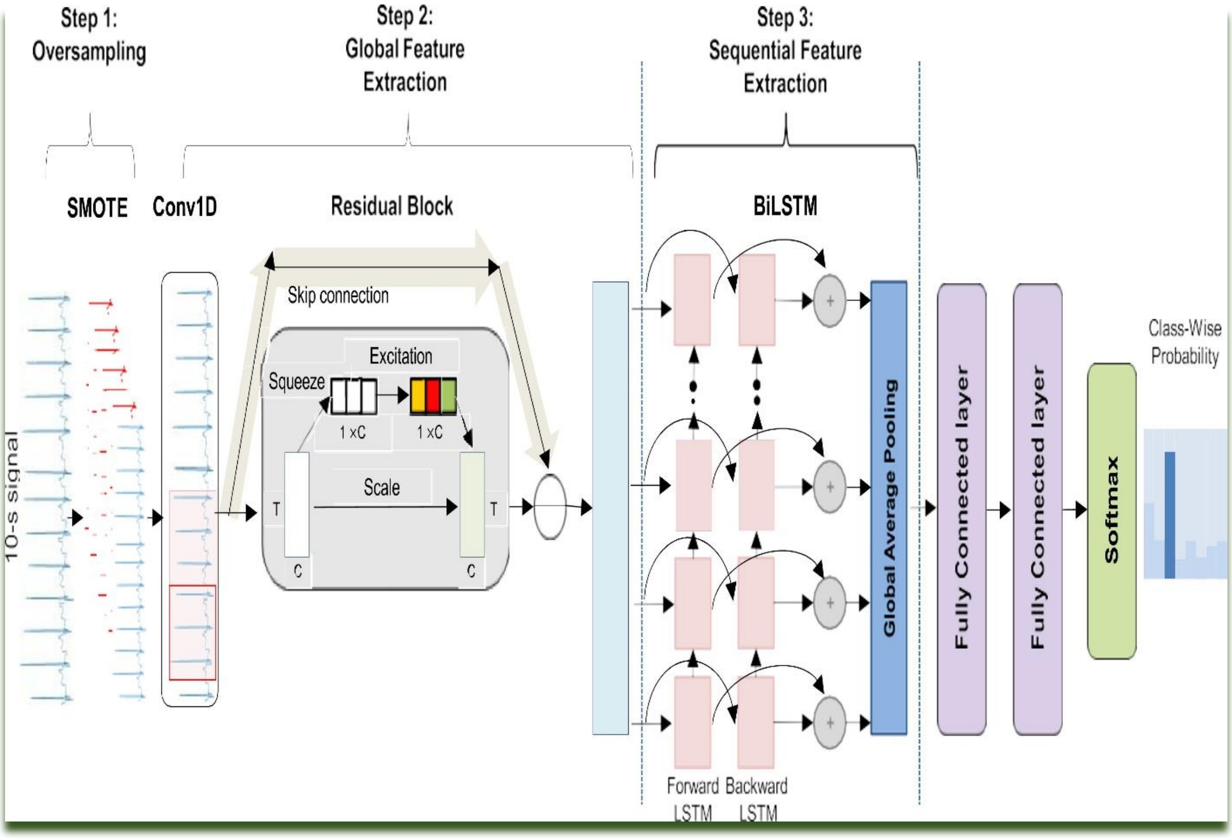

Figure 2: SMOTE Framework

ResNet Backbone for Spatial Feature Extraction:

The ResNet (Residual Network) serves as the backbone for extracting spatial features from the ECG signals. ResNet utilizes residual blocks, which allow the model to learn deeper representations by overcoming the vanishing gradient problem. These residual blocks help in capturing more complex patterns in the ECG data, making the model robust to variations in signal quality and rhythm.

SE Blocks and Multi-Spectral Attention Modules:

To enhance feature representation, the model integrates Squeeze-and-Excitation (SE) blocks and Multi-Spectral attention modules. The SE blocks enhance overall feature quality by recalibrating the feature maps, emphasizing important features while suppressing less relevant ones. The Multi-Spectral attention mechanism further refines the representation by focusing on

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different frequency components of the ECG signal, allowing the model to capture both low and high-frequency patterns crucial for arrhythmia detection.

BiLSTM Layers for Temporal Feature Extraction:

After extracting spatial features using ResNet and attention modules, Bidirectional Long Short-Term Memory (BiLSTM) layers are used to capture the temporal dependencies in the data. BiLSTMs are particularly effective for sequence data as they can learn both forward and backward temporal dependencies, which is crucial for understanding how the ECG signal evolves over time. This bidirectional learning helps the model identify complex patterns and rhythms in the ECG signals. Overall research methodology is given in Table 4.

Table 4: Overall Research Methodology

Stage	Relationship	Purpose
Dataset (MIT-BIH, AFDB, CinC 2017)	→ Provides Input	ECG signals collected for training and evaluation
Input Data	→ Preprocessing	Improves signal quality and prepares data for modelling
Preprocessing	→ Noise Filtering	Removes unwanted signal artifacts
Preprocessing	→ R-peak Detection	Identifies key points (heartbeats)
Preprocessing	→ Normalization	Standardizes signal range and scale
Processed Data	→ Architecture	Serves as input to the deep learning model
ResNet Backbone	→ SE Blocks	Spatial features extracted and enhanced
SE Blocks Output	→ Multi-Spectral Attention Modules	Highlights important frequency-based features
Attention Output	→ BiLSTM Layers	Captures sequential heartbeat patterns in both forward and backward directions
Model Output	→ Augmentation with SMOTE	Addresses class imbalance by synthetically generating samples for the minority class.
Augmented Data and Model	→ Evaluation Metrics	Model performance measured through Accuracy, Precision, Recall, F1-score

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Cross-Subject Validation	→ Generalizability Test	Ensures model works across different individuals

3.5 Augmentation:

In an imbalanced dataset, the model may be biased toward predicting the majority class, leading to poor performance in detecting the minority class (arrhythmia types in this case) where SMOTE is used shown in Table 5. The process begins by identifying the minority classes that have fewer samples and then generates synthetic samples by interpolating between existing samples from the minority class. The algorithm picks two or more nearest neighbors and creates new data points along the line segments between them. These newly generated samples are similar to the original samples but not identical, helping to reduce the bias toward the majority class. Finally, these synthetic samples are added to the dataset, making it more balanced and improving the model's ability to learn patterns from all classes equally. This balanced dataset ensures the model can generalize better, especially in predicting underrepresented arrhythmia types.

Table 5: SMOTE-Based Augmentation Process for Handling Class Imbalance

Step	Objective	Action
Step 1: Identify Minority Classes	Identify classes with fewer samples.	Applied to the minority classes, which have fewer samples than the majority classes.
Step 2: Generate Synthetic Data	Create synthetic samples for minority class.	It generates synthetic samples by randomly selecting examples from the minority class and interpolating between them. These new samples are designed to closely resemble real data points, thereby restoring class balance.
Step 3: Augment the Dataset	Add the synthetic samples to the original dataset.	The newly created synthetic data points are added to the dataset, increasing the number of samples in the minority class and balancing the dataset.
Step 4: Train the Model	Train the model on the augmented dataset.	With the new balanced dataset, the model is trained to ensure that it doesn't overfit to the majority class and has equal exposure to all class types.

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3.4 Evaluation

Evaluation metrics provide a comprehensive understanding of the model's strengths and weaknesses in arrhythmia detection shown in Table 6. Precision, recall, and the F1-score give insights into how well the model handles imbalanced classes and avoids errors, while accuracy provides an overall view of its correctness. Cross-subject validation ensures that the model can generalize beyond the training data, which is critical for real-world applications in healthcare.

Table 6: Evaluation Metrics for Arrhythmia Classification

Metric	Definition	Purpose
Accuracy	The ratio of correct predictions to total predictions.	Measures the overall correctness of the model in predicting arrhythmia types.
Precision	The ratio of correctly predicted positive instances to total predicted positives.	Evaluates how many of the predicted positive cases were actually positive (useful for minimizing false positives).
Recall (Sensitivity)	The ratio of correctly predicted positive instances to total actual positives.	Measures the model's ability to identify all relevant arrhythmia cases (useful for minimizing false negatives).
F1-Score	The harmonic mean of precision and recall.	Balances precision and recall, providing a single metric for performance evaluation when both are important.
Cross-subject Validation	A validation method where the model is trained on data from some subjects and tested on data from different subjects.	Assesses the generalization ability of the model, ensuring it can perform well on unseen subjects, reducing overfitting.

4. Results and Discussion:

The proposed framework for arrhythmia classification was evaluated using various metrics to assess its performance. The metrics include accuracy, F1-score, and sensitivity, all of which provide insight into the model's effectiveness in detecting different types of arrhythmias.

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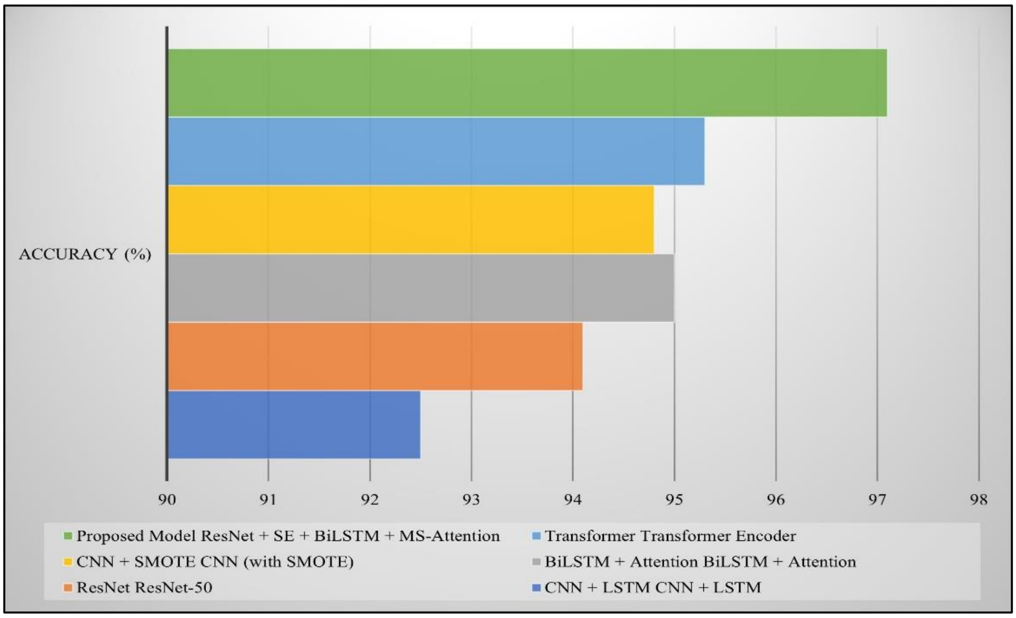

Figure 3: Comparison of Accuracy (%) Across Different Deep Learning Architectures for ECG-based Arrhythmia Classification

The results were obtained using the MIT-BIH Arrhythmia Database, with augmentation applied through SMOTE to address class imbalance. Table 7 presents a comparative evaluation of various existing and proposed models for arrhythmia detection using ECG signals. The proposed model—combining ResNet, Squeeze-and-Excitation blocks, BiLSTM, and Multi-Spectral Attention—demonstrates superior performance across key metrics such as Accuracy, F1-Score, and Sensitivity, especially in handling class imbalance and improving generalization across datasets.

Table 7: Comparative Evaluation of Various Existing and Proposed Models for Arrhythmia Detection

Method	Model	Dataset(s) Used	Acc(%)	F1-Score	Sensitivity
CNN + LSTM	CNN + LSTM	MIT-BIH	92.5	0.89	0.87
ResNet	ResNet-50	MIT-BIH	94.1	0.91	0.89
BiLSTM + Attention	BiLSTM	MIT-BIH	95.0	0.92	0.90
CNN + SMOTE	CNN	MIT-BIH, AFDB	94.8	0.91	0.91

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Transformer	Transformer encoder	CinC	95.3	0.93	0.92
Proposed Model	**ResNet + SE + BiLSTM + Multi-Spectral Attention**	**MIT-BIH, AFDB, CinC**	**97.1**	**0.96**	**0.95**

The proposed model achieves the highest accuracy by combining residual, attention, and temporal learning components. Transformer and BiLSTM-based models also show strong accuracy due to effective sequence representation shown in Figure 3.

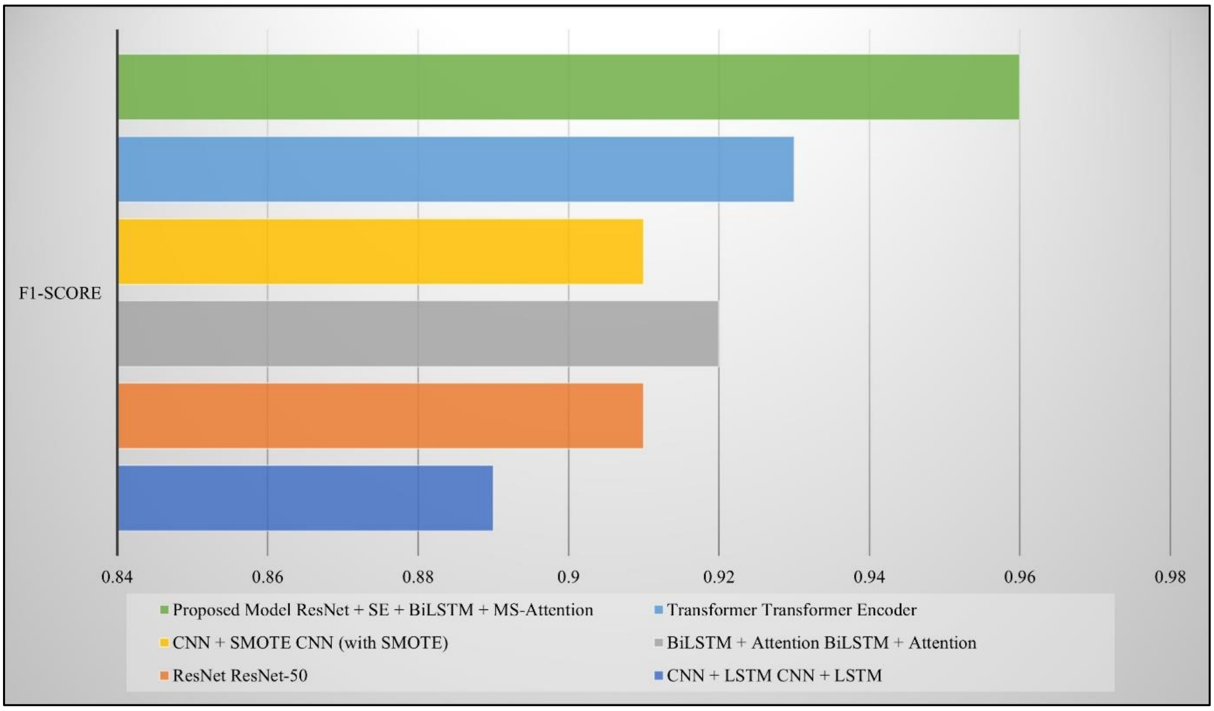

Figure 4: F1-Score Performance Comparison of Models on MIT-BIH, AFDB, and CinC Datasets

The F1-Score is highest for the proposed model, reflecting its balanced performance across classes. Attention-enhanced and transformer-based methods outperform basic CNN and ResNet models in class-level precision and recall shown in Figure 4. Sensitivity peaks with the proposed model, indicating strong ability to detect true positives, especially in minority classes. SMOTE and attention mechanisms significantly help in boosting sensitivity over baseline CNN and ResNet models shown in Figure 5.

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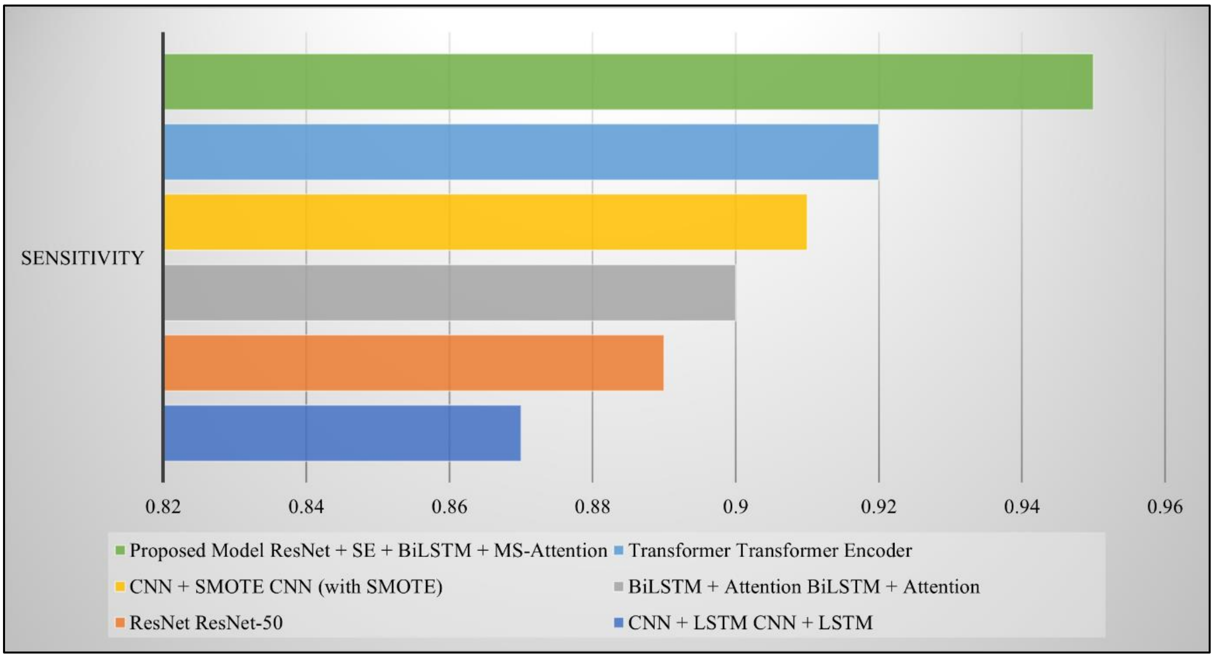

Figure 5: Sensitivity (Recall) Comparison of Deep Learning Techniques in ECG Signal Classification

5. Future Enhancement

Future enhancements are essential to ensure that the arrhythmia detection and classification system remains effective, adaptable, and scalable in real-world healthcare environments. As technology and medical practices evolve, it is important to incorporate advanced techniques and emerging technologies such as AI, ML, Blockchain, and IoT. These advancements will not only improve the accuracy and efficiency of arrhythmia detection but also address challenges such as data security, patient privacy, and personalized care. By focusing on these future enhancements shown in Table 8, the system can provide better, more reliable outcomes for patients and healthcare providers, fostering continuous improvement in medical diagnostics and treatment.

Table 8: Future Enhancements for Arrhythmia Detection and Classification Framework

Future Enhancement	Description	Technologies Involved
Integration of Blockchain for Secure Healthcare Data	Use blockchain to secure and decentralize the storage and sharing of ECG data, ensuring data privacy and transparency.	Blockchain, Cryptography, Healthcare IT

Use of Diverse Datasets	Expand the training datasets to include data from diverse populations (age, ethnicity, etc.) to improve generalization.	Dataset Expansion, AI, ML
Advanced Feature Extraction with AI Techniques	Employ techniques like Deep Reinforcement Learning (DRL) or Transformer Networks to enhance feature extraction from ECG signals.	Deep Reinforcement Learning (DRL), Transformer Networks
Integration with IoT for Real-Time Monitoring	Connect the arrhythmia detection model with IoT-enabled devices (wearables, smartwatches) for continuous monitoring and alert systems.	IoT, AI, ML, Wearables
Personalized Medicine Using AI	Use AI to create personalized treatment plans based on patient-specific ECG data, improving clinical decision-making.	AI, Personalized Medicine, Healthcare Systems
Cross-Modal Learning for Improved Detection	Combine ECG signals with other sensor data (e.g., accelerometer, PPG) to improve arrhythmia detection accuracy.	Cross-Modal Learning, AI, Multi-Sensor Integration
Real-Time Data Augmentation	Implement real-time augmentation techniques to dynamically balance datasets during live monitoring and prediction.	SMOTE, Real-Time Data Augmentation, AI
Enhanced Generalization through Multi-Task Learning	Implement multi-task learning to train models for simultaneous detection of arrhythmias and other heart-related diseases, improving versatility.	Multi-Task Learning, AI, ML
Federated Learning for Data Privacy	Use federated learning to train models across decentralized healthcare systems while ensuring that patient data never leaves local servers, maintaining privacy.	Federated Learning, Blockchain, Privacy-Preserving AI
Integration with Genetic Data	Integrate genetic and lifestyle data with ECG signals to improve the accuracy of	Genomics, AI, ML

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	arrhythmia predictions, tailoring interventions to individual patients.	

6. Conclusion:

The proposed framework for arrhythmia classification demonstrates strong performance in detecting various types of arrhythmic events from ECG signals, achieving high accuracy, precision, recall, and F1-score. The model's ability to handle class imbalance using SMOTE and its robust generalization across subjects through cross-subject validation underscores its potential as a reliable tool for automatic arrhythmia detection in clinical settings. The use of advanced techniques such as ResNet, SE blocks, BiLSTM, and SMOTE for data augmentation ensures that the model not only captures complex features from the ECG data but also improves its ability to generalize to unseen data. Given the promising results, this model can serve as an essential part of healthcare systems, aiding in early detection, diagnosis, and treatment of arrhythmias. The integration of AI and ML techniques offers the potential for continuous learning, where models can improve over time as more data becomes available, leading to better prediction and diagnosis.

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