RESEARCH PAPER

Patient-Independent Arrhythmia Classification Through Adaptive ECG Segmentation and Deep Convolutional Learning

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ABSTRACT

Cardiac arrhythmia is one of the critical conditions of the heart. One of the key reasons for this condition is abnormal heart rhythm. If it is not detected during the initial stage, it may lead to other dangerous heart diseases or may be a cause of death. Electrocardiogram signals are frequently utilized to detect abnormal heart activity and diagnose arrhythmia. In this work, an adaptive ECG segmentation and deep learning model is presented for automatic arrhythmia classification. The model was implemented using the MIT-BIH Arrhythmia Dataset. This dataset contains different heartbeat groups, i.e., Normal, Supraventricular, Ventricular, Fusion, and Unknown beats.

The presented method uses adaptive ECG segmentation to preserve important heartbeat patterns in a better way than traditional segmentation methods. A deep one-dimensional Convolutional Neural Network (CNN) was utilized for arrhythmia classification. Focal loss optimization was included to improve the learning of minority heartbeat classes and reduce the impact of class imbalance. Both intra-patient and patient-independent experiments were implemented to measure the effectiveness of the presented model.

Experimental results showed that the presented adaptive segmentation method gained better performance than fixed-window and standard R-peak segmentation methods under patient-independent evaluation. The presented model achieved 99.67% accuracy and 99.63% F1-score for intra-patient evaluation, while patient-independent evaluation achieved 94.67% accuracy and 95.70% F1-score. The achieved results show that adaptive ECG segmentation increases heartbeat representation and improves arrhythmia classification performance across different patients.

Keywords: Electrocardiogram, Arrhythmia classification, adaptive ECG segmentation, deep learning, Convolutional Neural Network, patient-independent evaluation

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1. Introduction

Cardiovascular diseases are the main reason of death in the world [1]. One of the main cardiovascular disorders is cardiac arrhythmia. It is identified by abnormal heart rhythm and may cause heart problems. If it is not diagnosed at a primary stage, the patient may die. Since electrocardiogram (ECG) signals provide key details about the electrical functioning of the heart, they are generally used to observe the cardiac activity and find arrhythmias.

In biomedical signal processing, automatic ECG arrhythmia classification has become an essential research area. Traditional ECG analysis generally contains several steps [3], i.e., signal preprocessing, heartbeat segmentation, feature extraction, and classification. During the preprocessing step, filtering methods are applied to eliminate noise and artifacts from ECG signals. After preprocessing, meaningful features are extracted from heartbeat patterns, and classification methods are used to detect different arrhythmia categories.

For ECG arrhythmia classification, deep learning methods can be used because these methods are capable of learning discriminative features from biomedical signals. Convolutional Neural Networks (CNNs) are widely utilized for ECG analysis because they are effective in capturing local morphological patterns from heartbeat signals. However, to classify arrhythmia accurately is a challenging task because ECG signals vary considerably among different individuals. Variations in amplitude, waveform morphology, heart rate, age, physical activity, and noise can significantly affect classification performance. Since ECG signals are non-stationary in nature [2], they may show inter-patient variability. This variability makes patient-independent arrhythmia classification particularly difficult.

An ECG signal has many waves, i.e., P, QRS, and T waves, along with important intervals such as RR, PR, ST, and QT segments. Proper segmentation of these heartbeat regions is a critical task in preserving clinically important morphological information for arrhythmia analysis. Conventional fixed-window and standard R-peak segmentation techniques may not always preserve heartbeat morphology efficiently under varying patient conditions. Figure 1 shows the diagram of the ECG with different waves and segments.

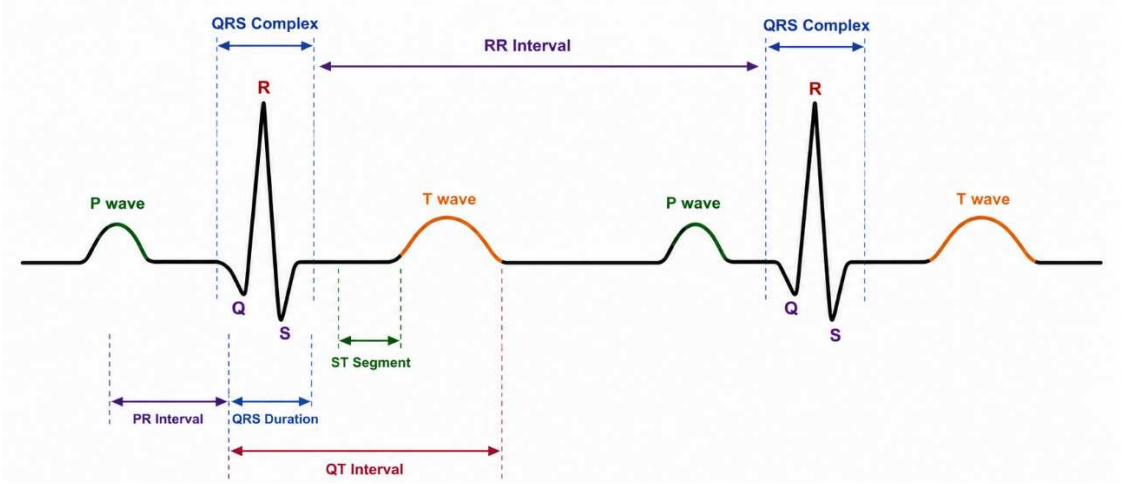


Figure 1. Basic structure of an ECG signal.

This research presents an adaptive ECG segmentation to address these limitations. The model has a deep focal-learning framework for robust arrhythmia classification. In the presented method, an adaptive heartbeat-centered segmentation is used to better preserve ECG morphology variations. A deep one-dimensional CNN is integrated with focal loss optimization for improved minority-class learning. In this work, patient-independent evaluation is performed to analyze the robustness and generalization capability of the presented model across unseen subjects.

2. Related Work

Many deep learning approaches have been presented for automatic ECG arrhythmia classification. Oh et al. presented a model of an auto-encoder for ECG signal diagnosis [1]. Their model can detect normal sinus beats, premature ventricular contractions, atrial premature beats, left bundle branch block (lBBB) and right bundle branch block (rBBB). They improved the U-net technique that can analyze beat-wise on heterogeneously segmented ECGs of different lengths. They used the MIT-BIH arrhythmia dataset. Ullah et al. [4] suggested deep learning methods on freely available standard databases, e.g., the PTB Diagnostic ECG dataset and the MIT-BIH arrhythmia dataset. They used a Convolutional Neural Network (CNN) based deep learning model, a CNN with Long Short Term Memory (LSTM), and a CNN with a combination of LSTM & Attention Model. According to Khan et al. [5], the deep learning-based methods can automatically classify arrhythmia effectively, but these methods are not considered as a generalized method by expert cardiologists. The major causes that influence the fame of the arrhythmia diagnosis techniques are selecting features manually, feature extraction and classification methods, and the use of imbalanced data for classification. They suggested classification methods to overcome the drawbacks in the present methodologies.

Rahman et al. [6] worked on the CAA-TL model, which has the multi-classification of the ECG database. It is available on Kaggle. They improved some of the healthy and unhealthy databases with the Kaggle dataset, i.e., the MIT-BIH dataset, which was obtained in real time. They used deep learning methods like ResNet50, AlexNet, and SqueezeNet. Wu et al. [7] proposed a powerful and systematic 12-layer deep one-dimensional CNN. They worked on a dataset of the MIT-BIH Arrhythmia database, having five types of heartbeats. For classification, they used a wavelet self-adaptive threshold de-noising method. Li [8] proposed a common method which is depended on ECG (two-dimensional) and Residual Neural Network (ResNet) with detached squeeze and excitation modules. By this, they can classify normal and eight arrhythmia beats. They used the China Physiological Signal Challenge 2018 for this work.

Islam et al. [9] also discussed many different classification techniques for ECG, like Deep CNNs, Long Short Term Memory, Support Vector Machine, Neural Network classifier, TQWT, and Wavelet. Singh et al. [10] worked on Recurrent Neural Networks (RNN) for categorizing the different beats in an ECG. They used the MIT-BIH dataset for their work. Rexy et al. [11] applied a technique in which they used the Bi-Directional Long Term Memory method for the classification of heartbeats. The beats were dependent on the AAMI standard classes. Rajkumar et al. [12] worked on categorizing ECG using deep learning. They compared their model with many activation functions by

altering the number of epochs.

Xiao et al. 2023 [13] worked on a review paper for ECG classification. They focused on the ECG dataset, preprocessing techniques, deep learning techniques, assessment criteria, performance measurements, and code availability to recognize research tendencies, dares, prospect for the classification of ECG Arrhythmia established on deep learning. Madan et al. [14] suggested their model, in which one-dimensional ECG signals are transformed into two-dimensional Scalogram images for noise cleaning and mining of features automatically. They joined two learning techniques, namely a 2-D convolutional neural network and an LSTM network. Ullah et al. [15] suggested a model in which a 2-D Convolutional Neural Network method is used for categorizing the ECG beats into 8 groups. They utilized the MIT-BIH dataset for their model.

Maximum existing methods only focus on classification architectures and perform well, but they give limited attention to heartbeat segmentation techniques and inter-patient generalization. Conventional fixed-window and standard R-peak segmentation methods may fail to preserve clinically important ECG waveform patterns under varying patient conditions. To remove these limitations, this work proposes an adaptive ECG segmentation and deep focal-learning framework for robust patient-independent arrhythmia classification.

Table 1. Comparison of Existing ECG Arrhythmia Classification Methods

Author(s)	Method / Model	Performance	Limitation
Oh et al. [1]	Modified U-Net	Achieved 97.32% classification accuracy and 99.3% R-peak detection accuracy	Limited patient-independent evaluation
Ullah et al. [4]	CNN, CNN-LSTM, CNN-LSTM + Attention	Attained 99.12%, 99.30%, and 99.29% accuracy respectively	Used random train-test split
Rahman et al. [6]	ResNet50, AlexNet, SqueezeNet	Achieved 98.8%, 90.08%, and 91% accuracy respectively	Higher computational complexity
Wu et al. [7]	1D CNN	Achieved 97.41% accuracy, 97.05% sensitivity, and 99.35% specificity	Lower minority class performance
Li et al. [8]	DSE-ResNet	Attained an average F1-score of 0.817 for classifying normal rhythm and eight arrhythmia classes	Evaluated on CPSC2018 dataset
Singh et al. [10]	RNN, GRU, LSTM	LSTM achieved 88.1% accuracy, outperforming RNN (85.4%) and GRU (82.5%)	Lower performance compared to recent deep CNN models
Rajkumar et al. [12]	Deep Learning with ELU Activation	Achieved 93.6% accuracy with ELU activation function	Limited evaluation under varying patient conditions
Xiao et al. [13]	Systematic Review of Deep Learning Methods	Reported that most deep learning models achieved classification accuracy above 95%	F1-score and other metrics remained comparatively lower
Madan et al. [14]	CNN-LSTM with 2D Scalogram ECG Images	Achieved 98.7%, 99%, and 99% accuracy for ARR, CHF, and NSR classification respectively	Increased computational complexity due to image transformation

Ullah et al. [15]	2D CNN Spectral Image Representation	Achieved 99.11% average classification accuracy on MIT-BIH dataset	Dependence on ECG image transformation
Proposed Framework	Adaptive ECG Segmentation + 1D-CNN + Focal Loss	Achieved 94.67% accuracy and 95.70% F1-score under patient-independent evaluation	Minority heartbeat classes remain challenging

In Table 1, many existing methods reported very high classification accuracy. Many researchers implemented intra-patient or random train-test split approaches, in which heartbeat samples from the same patient may appear in both the training and testing datasets. In contrast, the proposed model was evaluated using a patient-independent protocol. This evaluation approach provides a more realistic and challenging assessment of the model's generalization capability across previously unseen patients.

3. MIT-BIH Dataset

The MIT-BIH Arrhythmia Dataset is publicly available [16]. It includes forty-eight half-hour fragments of 2-channel ambulant ECG recordings. These recordings are acquired from forty seven points, which were learned in the BIH Arrhythmia lab from the year 1975 to 1979. Only twenty-three records were selected arbitrarily from a group of four thousand 24-hour ambulant ECG records. At Boston's Beth-Israel-Hospital, the recordings were gathered from an assorted population of inpatients and outpatients; the ratio of inpatients and outpatients was 60:40. The last twenty-five records were chosen from a similar group to involve fewer usual but clinically notable arrhythmias, which could not be fine-tuned in a minor random sample.

Table 2 presents the general details of the Arrhythmia dataset, while Table 3 describes the heartbeat categories used in this work. The source of the dataset is Physionet. The number of samples (training +testing) in the database is 109446 with 360 Hz sampling frequency. These samples are categorized into 5 different classes. The classes are ('S', 'N', 'V', 'F', and 'Q'), i.e., (Supraventricular ectopic, Normal, Ventricular Ectopic, Fusion, and Unknown) beats respectively. The diagrams of all classes' beats are shown in Figures 4 to 8.

Table 2. Arrhythmia Dataset

Arrhythmia Dataset	
Samples Numbers:	109446
Total Categories:	5
Sampling Frequency:	360 Hz
Source of data:	MIT-BIH Arrhythmia Database from Physionet
Classes:	['N', 'S', 'V', 'F', 'Q']

Table 3. Beat Abbreviation and Name

Beat Type	**Beat Name**
'N'	Normal-Beat
'S'	Supraventricular- Ectopic-Beats
'V'	Ventricular- Ectopic-Beats
'F'	Fusion-Beats
'Q'	Unknown-Beats

The distribution of different heartbeat categories in the MIT-BIH Arrhythmia Database is presented in Table 4.

Table 4. Distribution of heartbeat categories in the training dataset

Beat Type	Counts in the training dataset
'N'	72471
'S'	2223
'V'	5788
'F'	641
'Q'	6431

The class imbalance among different heartbeat categories in the complete MIT-BIH Arrhythmia Database is shown in Figure 2. Figure 3 shows representative waveform patterns of different heartbeat categories used in this work.

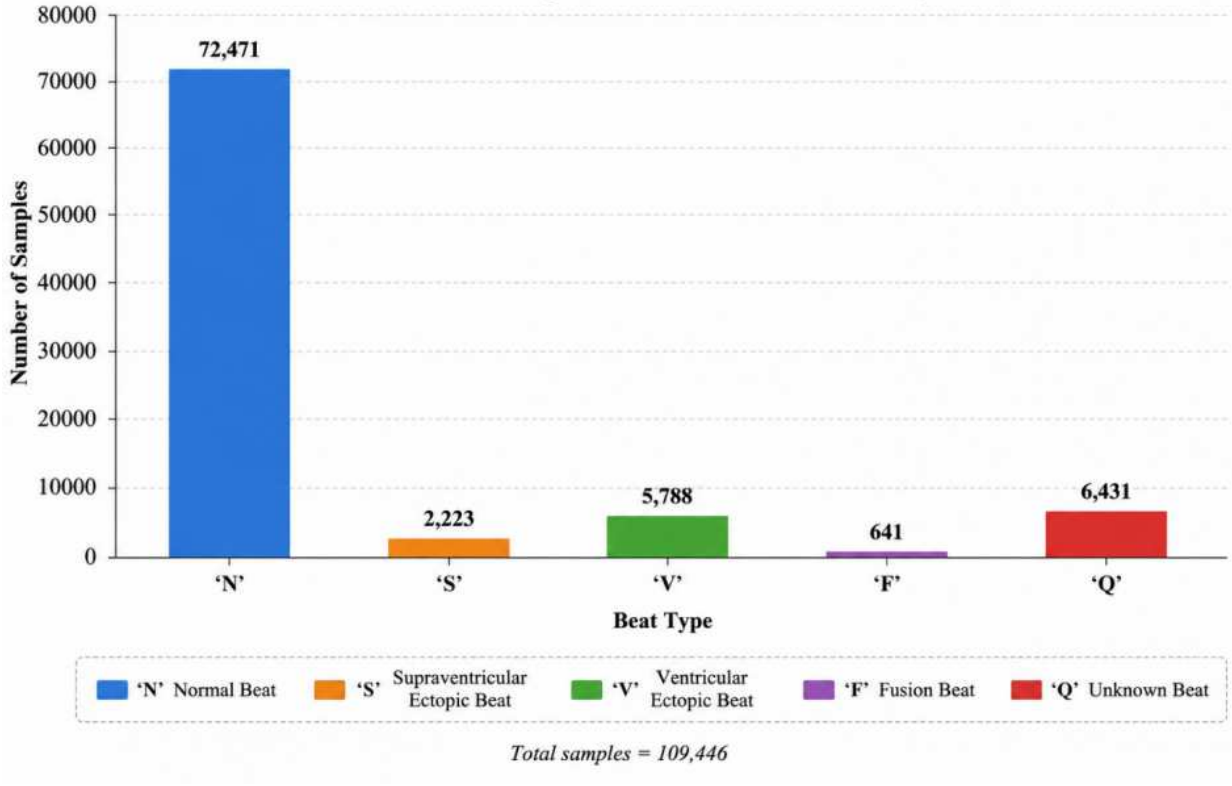


Figure 2. Distribution of heartbeat categories in the complete MIT-BIH Arrhythmia Full Database

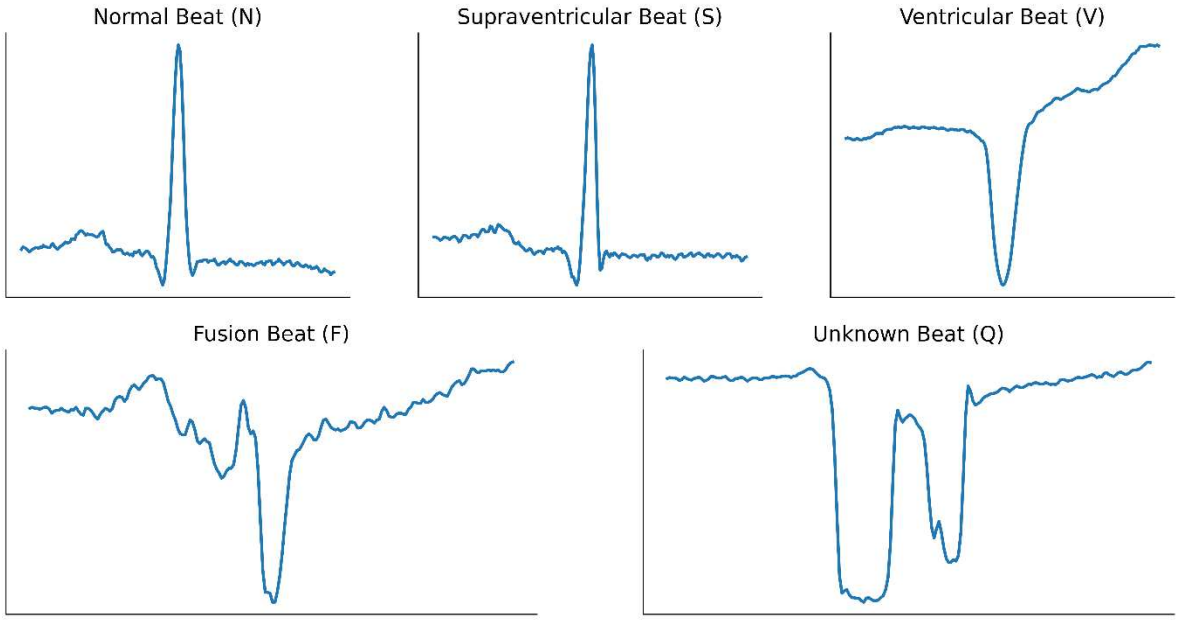


Figure 3. ECG heartbeats from the MIT-BIH Arrhythmia Database

4. Methodology

The workflow of the proposed adaptive ECG-based arrhythmia classification framework is shown in Figure 4. The model consists of ECG signal preprocessing, adaptive heartbeat segmentation, signal normalization, feature learning using a one-dimensional Convolutional Neural Network (1D-CNN), focal loss optimization, arrhythmia classification, and patient-independent evaluation.

Figure 4 shows the complete pipeline of the proposed model. Each stage of the model is described in detail in the following subsections.

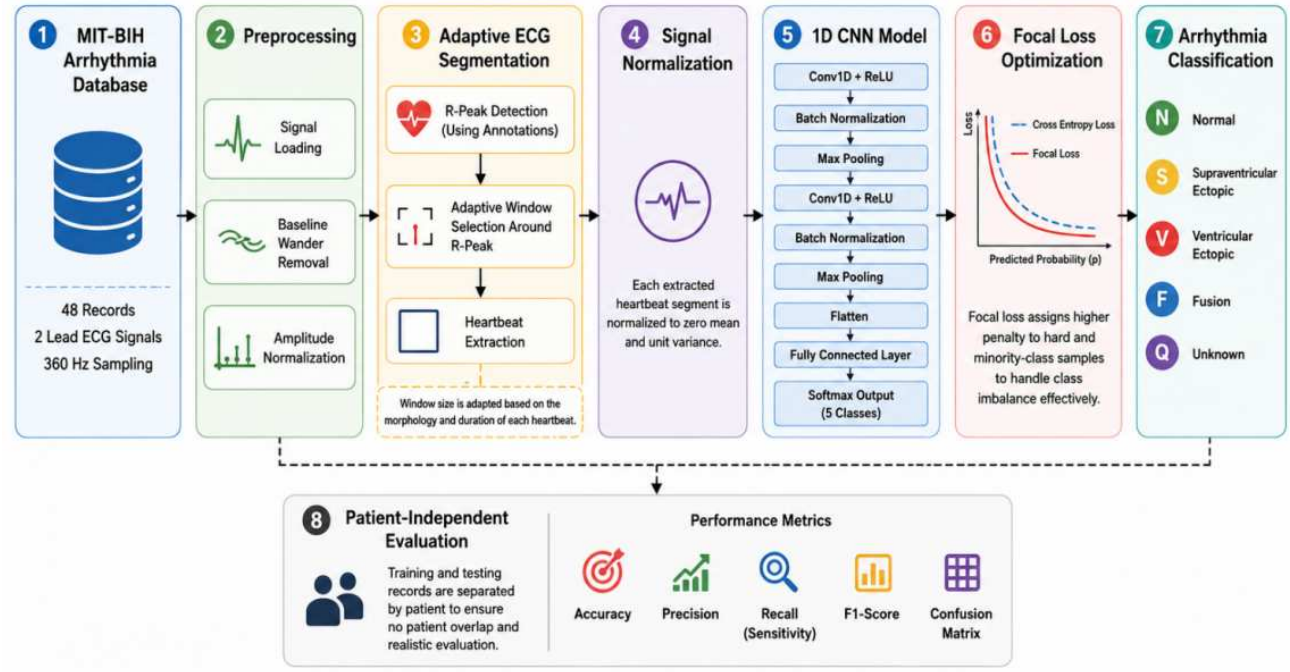


Figure 4. Proposed Adaptive ECG-Based Arrhythmia Classification Model

4.1 ECG Signal Preprocessing

The Preprocessing techniques were applied to the ECG signals to increase the quality of heartbeat extraction and classification. Normalization techniques were implemented on the ECG recordings to reduce amplitude variations among different patients and recordings. The MIT-BIH dataset contains the annotation files, which were utilized to recognize the R-peak locations of ECG signals. The use of these R-peaks is to segment the heartbeat.

4.2 Proposed Adaptive ECG Segmentation

Fixed-window heartbeat extraction is a conventional ECG segmentation technique. Due to variations in heartbeat duration among different patients, this technique may fail to preserve important waveform characteristics. To handle this situation, an adaptive ECG segmentation strategy was proposed in this work. The proposed method dynamically extracted heartbeat segments around the detected R-peaks. This method considers variable ECG waveform features in place of rigid segmentation boundaries.

Annotation files of the MITBIH dataset are used to identify the R-peak positions in this model. After identifying the R-peaks, heartbeat segments were extracted using the R-peak positions provided in the MIT-BIH annotation files. An initial window of 250 samples was extracted for each R-peak, consisting of 100 samples before the peak and 150 samples starting at R-peak onward. The (i)-th heartbeat segment can be expressed as:

$$x_i[n] = x[r_i - 100 + n] \qquad (1)$$

where (x) represents the original ECG signal, (r_i) denotes the position of the i^{th} R-peak, n is the position of a sample inside the heartbeat segment, and ($x_i[n]$) represents the extracted heartbeat segment. This window provides a consistent input length for subsequent feature learning and arrhythmia classification.

To determine whether the initial heartbeat segment requires adjustment, three signal characteristics are calculated: signal energy, variance, and mean absolute amplitude. These characteristics are defined as follows:

$$E_i = \sum_{n=0}^{249} x_i[n]^2 \quad (2)$$

$$V_i = Var(x_i) \quad (3)$$

$$D_i = \frac{1}{250}\sum_{n=0}^{249}|x_i[n]| \quad (4)$$

where E_i, V_i, and D_i represent the energy, variance, and mean absolute amplitude of the i^{th} heartbeat segment, respectively.

The three signal characteristics are compared with predefined thresholds to determine whether the initial heartbeat window requires adjustment. If the signal energy is below 0.05, the variance is below 0.01, or the mean absolute amplitude is below 0.15, the conditional adjustment is triggered. Otherwise, the initial window is retained. After segmentation, each heartbeat segment is normalized using its mean and standard deviation. The segment is then truncated or padded to maintain a fixed length of 250 samples. This consistent input length allows the segmented ECG signals to be processed by the same one-dimensional convolutional neural network (1D CNN).

Figure 4 shows the presented adaptive ECG segmentation model.

4.3 Data Balancing Strategy

The MIT-BIH Arrhythmia Dataset has imbalanced heartbeat sets. The number of normal beats is very high than the abnormal heartbeat classes. Such an imbalance may negatively affect the learning capability of deep learning models. The models can reduce classification performance for minority classes. To address this situation, focal loss optimization was used during model training. The focal loss function assigns larger weights to difficult and minority-class samples. This loss function enables the model to learn discriminative features more effectively. This technique upgraded the classification performance of minority heartbeat sets such as S, F, and Q beats.

4.4 Proposed One-Dimensional CNN Architecture

For automatic arrhythmia classification, a deep one-dimensional Convolutional Neural Network (1D-CNN) was developed. The proposed model consisted of multiple convolutional layers followed by batch normalization, Rectified Linear Unit (ReLU) activation, and max-pooling operations [17]. The convolutional layers automatically extract the discriminative ECG waveform features from segmented heartbeat signals.

After feature extraction, the task of the fully connected layers is to classify the heartbeats. At the last stage, a softmax activation layer was used to classify ECG beats into five groups, i.e., N, S, V, F, and Q beats. The proposed model automatically learned ECG waveform representations without manual feature engineering.

4.5 Focal Loss Optimization

The focal loss function is mathematically expressed as:

$$L_{FL} = \frac{1}{N}\sum_{i=1}^{N} \alpha\left(1 - p_{t,i}\right)^{\gamma} \left(-\ln p_{t,i}\right)$$

where N represents the number of samples in a batch, $p_{t,i}$ denotes the predicted probability of the correct class for the i^{th} sample, α is the weighting factor, and γ is the focusing parameter. In this study, (α =1) and (γ =2) were used. The focusing parameter reduces the relative contribution of easily classified samples while emphasizing difficult-to-classify samples during model training.

Focal loss optimization was integrated into the proposed model to enhance minority heartbeat classification. During the training process, focal loss decreases the contribution of easily classified samples and focuses more on minority-class samples during training. This optimization approach improved the sensitivity of the model for abnormal heartbeat detection and enhanced overall classification robustness [18].

4.6 Patient-Independent Evaluation

In this research, patient-independent evaluation was performed to assess the generalization capability of the proposed model. In this approach, ECG recordings from training patients were completely separated from testing patients to avoid patient overlap between training and testing datasets. This evaluation approach provides a more realistic clinical assessment compared to conventional random train-test splitting methods. The patient-independent protocol ensured that the presented model was assessed on unseen patient data. Overall, this model improved the reliability and robustness of the experimental results.

4.7 Performance Evaluation Metrics

The performance of the proposed arrhythmia classification method was evaluated using many standard performance metrics, i.e., accuracy, precision, recall, and F1-score. To analyze class-wise classification performance, a confusion matrix was generated. These metrics showed how effectively the proposed model identified and classified ECG arrhythmias.

5. Results and Discussion

5.1 Experimental Setup

Python and TensorFlow were utilized in this work. Experiments were implemented on the MIT-BIH Arrhythmia Dataset. The heartbeat signals were segmented using the proposed adaptive segmentation approach and classified into five heartbeat categories, i.e., N, S, V, F, and Q. In the model, patient-independent evaluation was utilized to evaluate the generalization efficiency.

5.2 Performance of Different Segmentation Methods

Table 5. Comparison of ECG Segmentation Methods

Segmentation Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Fixed Window	77.40	95.66	77.40	84.51
R-Peak	69.79	95.87	69.79	79.63
Adaptive (Proposed)	81.74	95.97	81.74	87.16

Table 5 presents the classification performance of different heartbeat segmentation methods. The proposed adaptive ECG segmentation method achieved the highest accuracy of 81.74% and F1-score of 87.16%. The adaptive method preserved heartbeat morphology more effectively and improved classification performance compared to fixed-window and conventional R-peak segmentation methods. These results demonstrate the significance of appropriate heartbeat segmentation for arrhythmia classification. It should be noted that Table 5 evaluates only the impact of different segmentation methods, whereas the overall performance of the complete proposed framework under patient-independent evaluation is presented in Table 7.

Figure 5 shows the comparative performance of different ECG heartbeat segmentation methods using multiple evaluation metrics. The proposed adaptive segmentation method achieved the best overall performance in terms of accuracy, recall, and F1-score. This demonstrates its effectiveness in preserving heartbeat characteristics for arrhythmia classification.

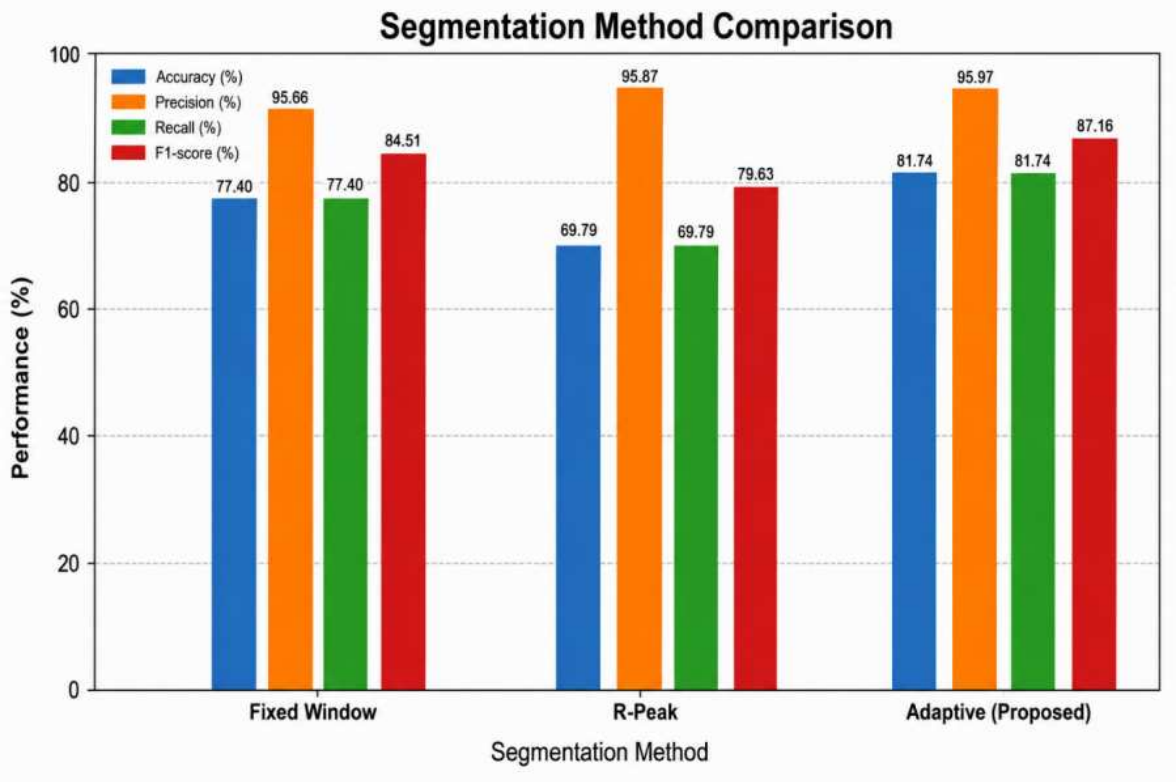


Figure 5. Comparison of ECG heartbeat segmentation methods

5.3 Classification Performance under Patient-Independent Evaluation

Table 6. Classification Report under Patient-Independent Evaluation

Class	Precision	Recall	F1-score	Support
N	0.99	0.96	0.97	20485
S	0.03	0.01	0.02	148
V	0.54	0.90	0.67	663
F	0.00	0.00	0.00	9

Table 6 shows the class-wise classification performance of the proposed framework under patient-independent evaluation. The model achieved excellent performance for Normal (N) beats, with a precision of 0.99 and an F1-score of 0.97. Ventricular Ectopic (V) beats were also effectively identified, achieving a recall of 0.90 and an F1-score of 0.67. Lower performance was observed for Supraventricular Ectopic (S) and Fusion (F) beats due to class imbalance and the limited number of available training samples. The patient-independent evaluation protocol is more challenging than random train-test splitting because the model is tested on previously unseen patients. The Q heartbeat group was not included in the evaluation because no Q samples were present in the test set.

5.4 Overall Performance Evaluation

Table 7. Overall Classification Performance

Metric	Value (%)
Accuracy	94.67
Precision	97.07
Recall	94.67
F1-score	95.70

Table 7 summarizes the overall classification performance of the proposed model. The model achieved an accuracy of 94.67% and an F1-score of 95.70% under patient-independent evaluation. These results show that the proposed adaptive segmentation method and focal loss optimization performed well.

Table 8. Comparison of intra-patient and patient-independent evaluation.

Evaluation Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Intra-Patient	99.67	99.66	99.67	99.63
Patient-Independent	94.67	97.07	94.67	95.70

Table 8 shows the comparison between intra-patient and patient-independent evaluation methods performance used in this model. Intra-patient evaluation performance is better because heartbeat samples from the same patients may appear in both training and testing datasets. In contrast, patient-independent evaluation is more challenging because the model is tested on previously unseen patients. Therefore, patient-independent provides a more realistic assessment of the model's generalization capability.

5.5 Confusion Matrix Analysis

Figure 6 presents the confusion matrix of the proposed model. Maximum Normal (N) and Ventricular Ectopic (V) beats were correctly classified. Misclassifications occurred among minority heartbeat classes because of class imbalance and morphological similarities between certain arrhythmia groups.

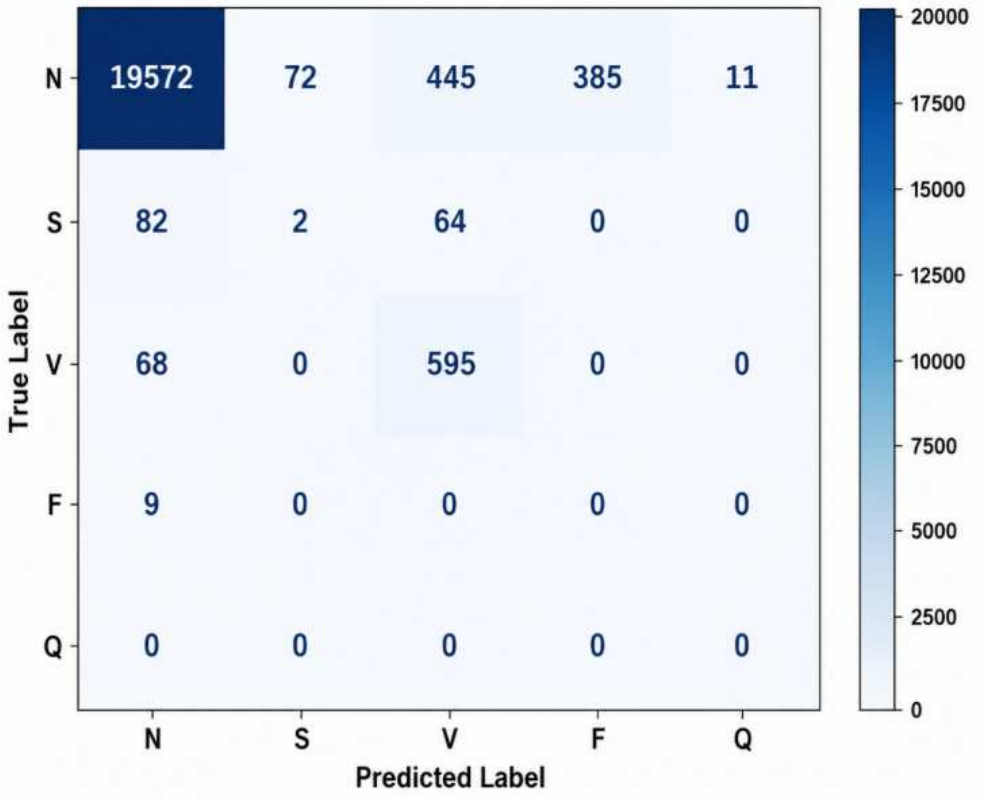


Figure 6. Confusion matrix of the proposed model under patient-independent evaluation

5.6 Training Analysis

Figure 7 shows the training loss curve of the presented 1D-CNN model. The loss value continuously decreased with increasing epochs. This suggests that the model trained successfully and reliably recognized ECG heartbeat patterns.

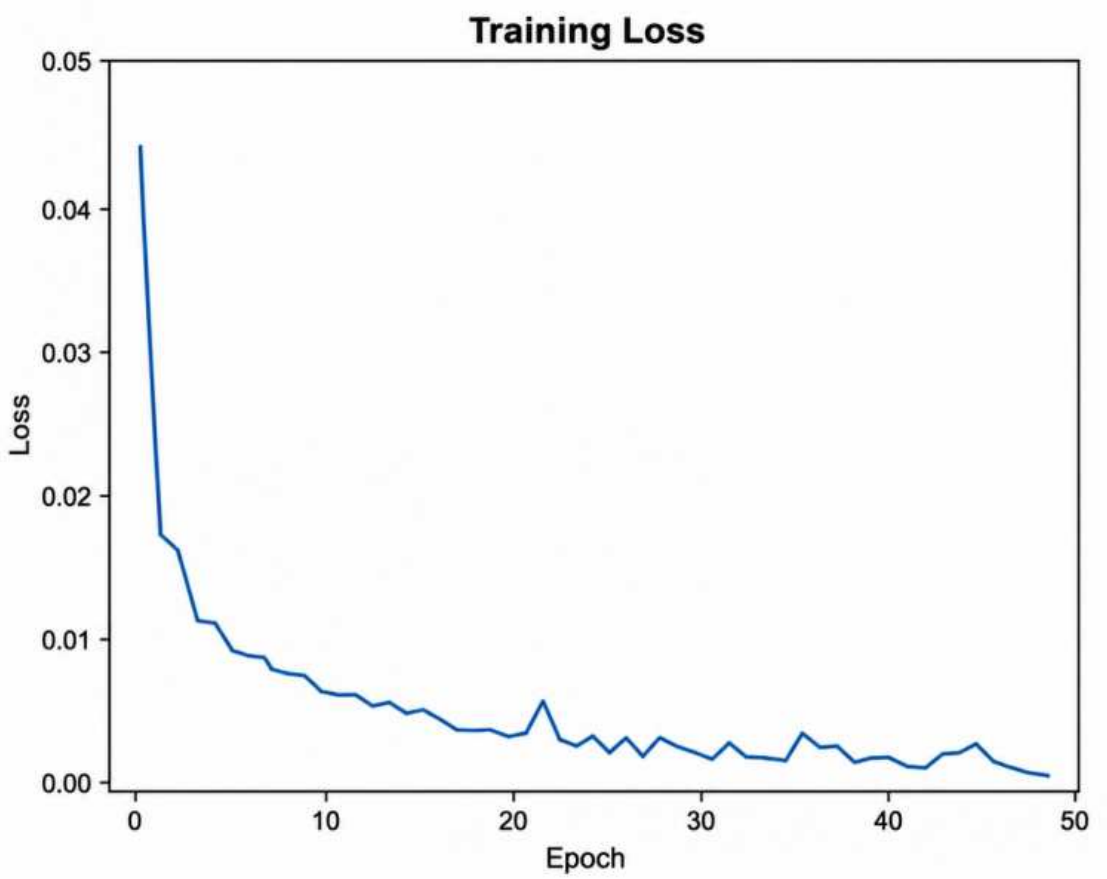


Figure 7. Training loss curve of the proposed 1D-CNN model

5.7 Discussion

The experimental results demonstrate that adaptive ECG segmentation performs better than traditional segmentation methods. Patient-independent evaluation provides a realistic assessment of model generalization. Although the proposed model got good results, classification performance for minority heartbeat classes remains challenging due to the highly imbalanced MIT-BIH dataset. In future, researchers may explore advanced data augmentation and transformer-based architectures to improve minority-class recognition.

6. Conclusion

This study presented an adaptive ECG segmentation-based arrhythmia classification model by using a deep one-dimensional Convolutional Neural Network (1D-CNN) and focal loss optimization. The proposed method was evaluated on the MIT-BIH Arrhythmia Dataset. An adaptive segmentation technique was utilized to extract heartbeat segments around the annotated R-peak. This approach can preserve of heartbeat features in a better way than conventional segmentation methods.

Experimental results demonstrated that the proposed adaptive segmentation approach outperformed than fixed-window and conventional R-peak-based segmentation methods. Under patient-independent evaluation, the framework achieved an overall accuracy of 94.67%, precision of 97.07%, recall of 94.67%, and F1-score of 95.70%. These outputs indicate that the combination of adaptive ECG segmentation, 1D-CNN classification, and focal loss optimization can effectively classify heart disease.

Future work will focus on improving the recognition of minority heartbeat classes, exploring advanced deep learning architectures such as transformer-based models, and validating the proposed framework on larger and more diverse ECG datasets.

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Competing Interests

The authors declare that they have no competing interests as defined by Springer, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

Data Availability

The datasets used in this study are publicly available from online repositories.
G. B. Moody and R. G. Mark, "The MIT-BIH arrhythmia database," PhysioNet, 2005. [Online]. Available: https://physionet.org/content/mitdb/1.0.0/

Ethics, Consent to Participate, and Consent to Publish: Not applicable.

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