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# ECG Signal Classification Method Based on Structural Risk Minimization

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## Abstract

Arrhythmia stands as a primary contributor to cardiovascular disease-associated mortality. Therefore, the classification and monitoring of abnormal electrocardiogram (ECG) signals are of paramount importance for preventive purposes. Although deep - learning - based ECG classification methods have yielded promising outcomes, they frequently encounter challenges in optimizing performance across diverse patient datasets. To overcome these limitations, this research endeavors to enhance the generalization ability of deep - learning models for ECG signal classification. It achieves this by integrating structural risk minimization principles and incorporating RR interval information into the classification process. A convolutional neural network (CNN) founded on structural risk minimization is proposed. Instead of employing the traditional cross-entropy loss, this study adopts a loss function inspired by support vector machine (SVM) classifiers to optimize the CNN. Moreover, the RR interval information, which is often lost during beat segmentation, is manually extracted and integrated into the CNN network to improve classification accuracy. The proposed method attains an accuracy, specificity, and sensitivity of 88.2% respectively, demonstrating superior performance when compared to traditional and existing methods. This improvement underscores the efficacy of the structural risk minimization approach and the integration of RR interval information in enhancing the model's generalization across patient datasets. The method's convenience and effectiveness render it particularly well-suited for real-time application in wearable devices, facilitating the early detection of abnormal ECG patterns and potentially preventing cardiovascular disease-related fatalities.

**Keywords:** classification of ECG signals, separating hyperplane, convolutional neural network, structural risk minimization

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## 1. Introduction

According to data from the World Health Organization (WHO), cardiovascular diseases caused approximately 15 million deaths annually between 2010 and 2020, accounting for about 45% of global non-communicable disease-related deaths [1]. Since most cardiovascular diseases are associated with abnormal electrocardiogram (ECG) signals, early detection of these abnormalities plays a crucial role in preventing the onset of cardiovascular diseases. Arrhythmias are categorized into life-threatening and non-life-threatening types according to their severity [2]. Life-threatening arrhythmias, including ventricular fibrillation and tachycardia, can potentially result in cardiac arrest and sudden death, necessitating immediate emergency intervention. While non-life-threatening arrhythmias don't cause death, they still require further evaluation to prevent cardiac deterioration. Most arrhythmias occur sporadically in daily life, and long-term ECG monitoring is typically employed to capture these rare electrical signals [3]. However, traditional diagnostic methods rely on clinicians' subjective interpretation of ECG signals, which may result in misdiagnosis due to excessive workload when processing large volumes of data [4]. Therefore, there is an urgent need for high-precision detection methods to reduce diagnostic error rates.

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To address this challenge, researchers worldwide have dedicated decades to developing fully automated systems for ECG signal classification. For example, Venkatesan et al. proposed a Support Vector Machine (SVM) classifier that integrates frequency domain features of ECG signals [5]. Emanet et al. employed the Discrete Wavelet Transform (DWT) to extract ECG signal features, then combined them with a random forest for classification [6]. Zhang Dan et al. developed an ECG signal classification algorithm based on Variational Mode Decomposition (VMD) and K-nearest neighbors (KNN) [7]. Li Feng et al. introduced an unsupervised learning-based method for ECG signal anomaly detection [8].
In recent years, advances in deep learning have spurred the development of convolutional neural network (CNN)-based methodologies for electrocardiogram (ECG) signal classification. For instance, Petmezas et al. proposed a hybrid architecture integrating CNNs with Long Short-Term Memory (LSTM) networks for ECG classification [9]. Jun et al. transformed one-dimensional ECG signals into two-dimensional grayscale images and employed 2D CNNs for cardiac rhythm classification [10]. Wang et al. devised a classification framework combining Continuous Wavelet Transform (CWT) with CNNs [11].
While traditional machine learning methodologies, such as Support Vector Machines (SVM), have demonstrated notable success, their performance frequently depends on manually extracted features, which exhibit inherent limitations and complexities associated with human-crafted methodologies.
Although CNN-based methods address the shortcomings of manual feature extraction, conventional CNN networks using Softmax classification layers tend to halt optimization of separation hyperplanes (also known as optimal hyperplanes) once they are identified during backpropagation. This limitation leads to insufficient generalization capabilities when encountering new datasets. To address this, this paper proposes a CNN network method based on structural risk minimization. The core concept involves utilizing convolutional layers in CNN networks to extract features, while employing a loss function designed for structural risk minimization to optimize the model, ultimately enhancing classifier performance. Test results on the MIT-BIH Arrhythmia Database demonstrate that the proposed method achieves higher accuracy in ECG signal classification, particularly excelling in distinguishing abnormal heartbeats.

## 2. Experimental Method

### 2.1 Dataset

This study utilized the MIT-BIH Arrhythmia Dataset to evaluate the performance of ECG signal classifiers. The dataset comprises 4,830-minute ECG recordings from 47 subjects, including 25 males aged 32-89 and 22 females aged 23-89 [12]. All ECG signals were sampled at 360 Hz, with lead MLII as the primary recording channel and lead V1, V2, V4, or V5 depending on specific recordings [13]. These signals were independently annotated by two or more physicians and categorized into 15 distinct types, containing approximately 110,000 heartbeats in total [14].
Since four participants (102,104,107, and 217) had pacemakers implanted, their ECG signals differed from those of regular participants. Therefore, this study removed these signals following de Chazal et al.'s approach [15]. To achieve better category balance in the dataset, we divided the data into DS1 and DS2 under the patient-specific paradigm, with each dataset containing 22 records [16].
•Training (DS1): 101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230.
•Testing (DS2): 100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 213, 219, 221, 222, 228, 231, 232, 233, 234.

### 2.2 EEG Noise Reduction

The electrocardiogram (ECG) signals obtained during acquisition typically contain three primary categories of noise that can significantly degrade signal quality: electromyographic (EMG) noise generated by muscle activity, power frequency interference originating from electrical equipment, and baseline drift caused by patient movement or breathing artifacts [17]. To effectively reduce the negative influence of these noise components on subsequent ECG signal classification performance, this research study adopts the wavelet transform as the denoising method of choice. The wavelet transform offers distinct advantages in this application, as it preserves crucial morphological characteristics of ECG waveforms while maintaining relatively low computational overhead requirements [18]. During the implementation phase, the wavelet-based denoising process involves conducting wavelet decomposition at scale 9, with Table 1 clearly presenting the specific frequency band ranges corresponding to each scale component for reference [19]. Notably, the energy distribution patterns observed in the detail coefficients of the first three decomposition layers are particularly susceptible to contamination from high-frequency interference components present in the raw ECG signal.
Bring into correspondence with, the first three layers (1-3) are the primary sources of high-frequency noise, including power frequency interference and electromyographic noise. The frequency range corresponding to baseline drift falls within the bands occupied by approximation coefficients CD9 and CA9. Given that the frequency band corresponding to CD3 contains substantial useful signals, only the frequencies associated with CD1, CD2, CD9, and CA9 layers need to be filtered by setting them to zero. Subsequently, the wavelet coefficients from layers 3 to 9 obtained through signal decomposition undergo threshold processing using a soft threshold. The partial comparison between data point 101 before and after noise reduction is illustrated in Figure 1.
To classify electrocardiogram (ECG) signals for diagnostic applications, continuous ECG recordings are segmented into individual cardiac beats by utilizing the precise locations of R-peaks, which serve as reliable reference points for inputting data into a convolutional neural network (CNN) architecture.

While R-peak detection is an essential preprocessing step, it is not the primary focus of this investigation, as well-established algorithms documented in prior literature [20] consistently achieve high detection accuracies (exceeding 99%, thereby minimizing the need for novel development. Consequently, this research directly employs the R-peak annotations available within the dataset to segment each heartbeat accurately and efficiently. Specifically, for every R-peak identified, 100 signal samples are collected prior to the peak and 150 samples following it, resulting in a total of 250 samples per heartbeat segment. This fixed-length windowing approach ensures comprehensive coverage of the QRS complex and adjacent waveform components, facilitating robust feature extraction by the CNN model for effective classification tasks.

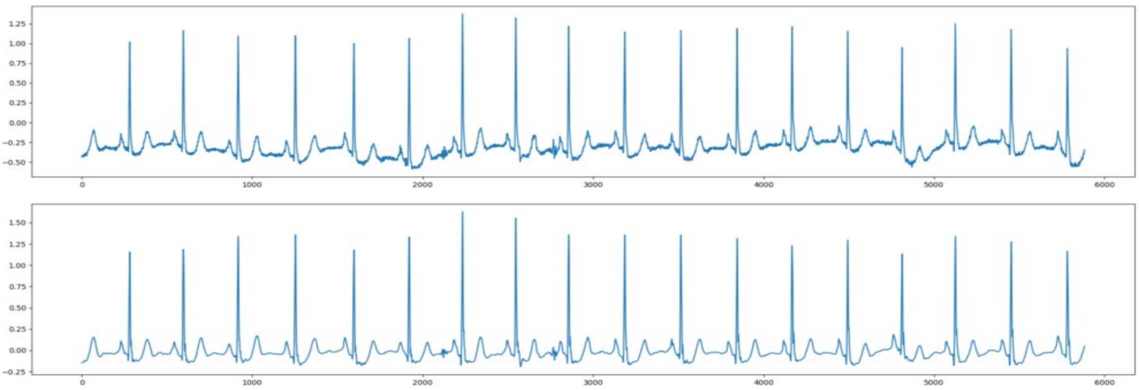

**Figure 1.** Comparison before and after denoising

Table 1. Corresponding frequency range of each scale component

| Components at Various Scales | Frequency Range (Hz) |
|---|---|
| CD1 | 90~180 |
| CD2 | 45~90 |
| CD3 | 22.5~45 |
| CD4 | 11.25~22.5 |
| CD5 | 5.625~11.25 |
| CD6 | 2.8125~5.625 |
| CD7 | 1.40625~2.8125 |
| CD8 | 0.703125~1.40625 |
| CD9 | 0.3515625~0.703125 |
| CA9 | 0~0.3515625 |

## 2.3 RR Intervening Information

When continuous ECG signals are segmented into individual heartbeats, traditional experimental methods fail to utilize the continuous information of ECG signals to assist in prediction. To avoid information loss caused by heartbeat segmentation in ECG signals, this study introduces RR interval information (the time interval between two consecutive R peaks, referred to as RR interval) to assist in training the convolutional neural network [21]. This experiment employed four distinct RR features to represent different continuous information in ECG signals:

- Previous RR interval: the time between the current heart rate and the last heart rate.
- Post-RR interval: The time between the current heartbeat and the next one.
- RR interval ratio: the ratio between two consecutive RR intervals;
- Local RR interval: The average of the first 10 RR intervals before the current heartbeat.

# 3. CNN-SRM Combination Model

## 3.1 CNN

Convolutional Neural Networks (CNNs) are among the most representative algorithms in artificial neural networks [22]. The core structure of CNNs consists of convolutional layers, where convolution kernels extract features from matrix data

- Convolutional layer: A key feature of CNN is the convolutional layer, which handles most of the computationally intensive processing. Its purpose is to extract features from the input signal.
- Activation function: Generally, activation functions are used to introduce nonlinear factors, as linear models have limited expressive capacity. By incorporating nonlinear activation functions, deep neural networks can achieve significantly enhanced expressive power.
- Pooling layer: Also known as a subsampling layer, the pooling layer reduces the number of features (dimensionality reduction).
- Batch Normalization Layer: This layer normalizes the input to each subsequent neural network layer to follow a standard normal distribution (mean of 0, variance of 1). This technique aims to stabilize the training process, provide regularization, and mitigate generalization error.
- Fully Connected Layer: Serving as the classifier within the network, the fully connected layer maps the learned representations from the latent feature space (produced by preceding operations such as convolutional layers, pooling layers, and activation functions) to the final label space.

## 3.2 Model

### 3.2.1 Softmax-Based Classification Method

The Softmax loss function algorithm operates as follows: For five distinct categories, the Softmax layer contains five corresponding nodes denoted as (where=1...5), satisfying the constraint 5 =1. With $h$ representing the activation function of the penultimate layer node and being the weight connecting the penultimate layer to the Softmax layer, the total input to the Softmax layer is:

$$a_i = \sum_k h_k \, w_{ki} \tag{1}$$

And then we get：

$$p_i = \frac{\exp(a_i)}{\sum_j^{10} \exp(a_j)} \tag{2}$$

Prediction category$\hat{\imath}$Based on the following formula:

$$\begin{aligned} \hat{\imath} &= \arg\max_i p_i \\ &= \arg\max_i a_i \end{aligned} \tag{3}$$

Current research employing CNN networks for classification predominantly utilizes the Softmax loss function. Its fundamental limitation lies in the algorithm's tendency to halt during training when detecting separation hyperplanes, as the through sliding window operations. This architecture enables CNNs to maintain the original hierarchical structure of input data while performing corresponding transformations and judgments, demonstrating translation invariance. These exceptional capabilities have led to their successful applications in speech recognition, natural language processing, image classification, and biomedical signal processing [23]. The commonly used CNN architecture typically comprises five stages:
system fails to optimize these hyperplanes. Consequently, the resulting hyperplanes are suboptimal, ultimately compromising the model's generalization performance.

### 3.2.2 A Classification Method Based on Structural Risk Minimization

To address the limited generalization capability of CNN networks employing the Softmax loss function, this paper proposes a CNN network based on structural risk minimization. The designed CNN model achieves a global optimal separation hyperplane, thereby enhancing its generalization ability to handle unknown data.

$$\begin{gathered} \min_{w,\xi_n} \frac{1}{2} ww + C \sum_{n=1}^{N} \xi_n \\ \mathrm{w}^T x_n t_n \geq 1 - \xi_n \end{gathered} \tag{4}$$

$\xi_n$ is a relaxation variable. Apply penalties to outliers by transforming data vectors $x_n$ Add scalar value 1 to eliminate bias. The resulting formula is:

$$\min_w \frac{1}{2} w^T w + C \sum_{n=1}^{N} \max(1 - w^T x_n t_n, 0) \tag{5}$$

The above formula is the original problem form, using the standard hinge loss. Since the formula is not differentiable, we consider using the following formula, which uses the minimization of the square hinge loss:

$$\min_w \frac{1}{2} w^T w + C \sum_{n=1}^{N} \max(1 - w^T x_n t_n, 0)^2 \tag{6}$$

Forecast data x the label:

$$\arg\max_t(\mathrm{w}^T \mathrm{x})t \tag{7}$$

## 3.3 CNN-SRM Classifiter

The CNN-SRM model proposed in this study is depicted in Figure 2. To comprehensively extract discriminative features, the feature extraction process comprises dual components. The first component utilizes preprocessed single-beat ECG signals as input to the convolutional layers of the neural network for automatic feature extraction. The second component involves the manual extraction of four RR interval features derived from the ECG signals. Subsequently, the extracted features from both components undergo fusion within the convolutional neural network architecture, followed by classification via the specifically designed classifier.

The CNN-SRM classifier developed in this research integrates the structural risk minimization (SRM) criterion as a loss function within the convolutional neural network architecture, effectively replacing the standard Softmax classification layer to bolster model stability and performance. By systematically applying SRM to minimize structural risks embedded in the objective function during training, the model consistently achieves minimal generalization errors when tested on unseen datasets, ensuring robust predictive outcomes. The separation hyperplane derived through iterative backpropagation optimization demonstrates inherent global optimality properties, which directly enhances the model's generalization capability across diverse data distributions. Detailed analysis confirms that incorporating SRM principles into CNN training protocols maximizes generalization potential and significantly elevates classification accuracy, reinforcing the approach's efficacy in practical applications.

## 4. Analysis of Experimental Results

### 4.1 Evaluation Metrics

To rigorously demonstrate the proposed network's superior generalization performance, this study retains all ECG signals without any artificial exclusion, thereby ensuring a comprehensive and unbiased evaluation that reflects real-world variability. The detailed evaluation metrics, which include cardiac beat counts and classification accuracy for each signal category, are systematically presented and analyzed in Table 2, providing a clear and quantitative assessment of the network's robustness across diverse datasets.

$$Specificity = \frac{TN}{TN + FP} \tag{8}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{9}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

Among them TP (true positive). The number of abnormal beats is correctly classified. TN (true negative) is the correct number of normal beats for classification. FP (false positive): The number of times a normal beat is incorrectly classified as abnormal. FN (false negative) is an abnormal beat number that was incorrectly classified as normal.

Use three widely used metrics to verify the performance of the proposed network: Specificity, Sensitivity & Accuracy:

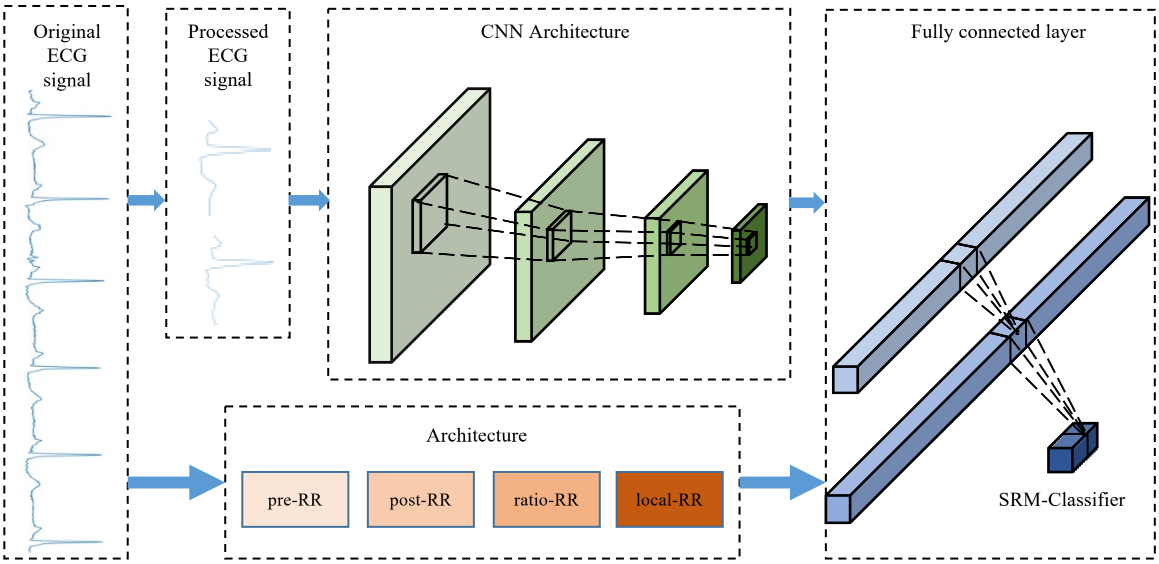


**Figure 2.** CNN-SRM classifier

Table 2. Number of heartbeats classified

| | DS1 | DS2 | Total |
|---|---|---|---|
| Normal heartbeat | 38067 | 36411 | 74478 |
| Abnormal heartbeat | 12910 | 13257 | 26167 |
| Total | 50977 | 49668 | 100645 |

Table 3. Performance comparison between the proposed method and traditional works.

| Method | Specificity (%) | Sensitivity (%) | F1 (%) | Accuracy (%) |
|---|---|---|---|---|
| SVM | 82.1 | 81.1 | 77.9 | 81.0 |
| CNN | 86.3 | 86.7 | 86.2 | 86.8 |
| RandomForest | 83.6 | 84.1 | 83.1 | 84.1 |
| CNN-SRM | 88.3 | 88.2 | 87.4 | 88.2 |

## 4.2 Analysis of Experimental Results

To comprehensively validate the superiority of the proposed CNN-SRM model, this experiment rigorously evaluated its classification performance through a detailed confusion matrix analysis, comparing it against established benchmarks including Support Vector Machine (SVM), a standard Convolutional Neural Network (CNN) classifier, and a Random Forest classifier. The confusion matrix results, depicted in Figure 3, provide a clear visual representation of true positive, true negative, false positive, and false negative rates, revealing that traditional machine learning methods such as SVM and Random Forest significantly underperform relative to the CNN classifier on this specific cardiac dataset. Notably, the CNN-SRM classifier introduced in this research achieves the best prediction results among all evaluated methods, demonstrating superior robustness and reliability in identifying complex patterns.

The detailed comparative outcomes with conventional techniques are comprehensively outlined in Table 3, which presents key performance metrics for abnormal heartbeat detection. Specifically, the proposed method attains 88.3% specificity, accurately distinguishing normal cases, and 88.2% sensitivity, effectively capturing abnormal instances, alongside an 87.4% F1-score that optimally balances specificity and sensitivity as a harmonic mean for overall assessment. In direct comparison to traditional CNN networks, the proposed approach exhibits substantial enhancements, including a 2% increase in specificity, a 1.5% rise in sensitivity, a 1.2% improvement in F1-score, and a 1.4% boost in accuracy, highlighting its advanced capability in improving diagnostic precision and reducing misclassification errors.

To ensure a fair and standardized comparison with the performance of other existing methods, this paper classifies the electrocardiogram (ECG) signals strictly adhering to the guidelines established by the American Medical Instrument Promotion Association (AAMI). This approach guarantees consistency with widely accepted medical protocols. Consequently, the dataset is systematically reclassified into four distinct categories, which are comprehensively detailed in Table 4, while all associated abbreviations are explicitly defined and clarified in Table 5 to facilitate accurate interpretation and reproducibility.

Table 4. Divided according to the AAMI standard

| | DS1 | DS2 | Total |
|---|---|---|---|
| N | 45824 | 44218 | 90042 |
| SVEB | 943 | 1836 | 2779 |
| VEB | 3788 | 3219 | 7007 |
| F | 414 | 388 | 802 |
| Total | 50969 | 49661 | 100930 |

Table 5. Description of the abbreviated name.

| Name | Abbreviation |
|---|---|
| Normal | N |
| Supraventricular ectopic beat | SVEB |
| Ventricular ectopic beat | VEB |
| Fusion beat | F |

Table 6 compares the proposed method with existing studies. The proposed method achieves an F1 score of 66.1% and 93.7% accuracy in multi-classification of ECG signals, demonstrating 2.2% higher accuracy than the latest results published by Liu Guangda et al.

In multi-classification methods for ECG signals, since SVEB and VEB classification are more critical than other classes, researchers should focus on the proposed method's prediction performance for these two categories. As shown in Table 7, the proposed method achieves a specificity of 74.4% and sensitivity of 69.2% for SVEB classification, while demonstrating 91.8% specificity and 95.3% sensitivity for VEB classification. Compared to existing methods, the proposed approach shows superior prediction performance, with SVEB classification specificity being 30% higher than current methods.

Furthermore, the VEB classification sensitivity of 95.3% represents a significant improvement over conventional approaches, approximately 15% higher than state-of-the-art methods, highlighting the model's enhanced ability to detect true ventricular ectopic beats with minimal misses. This high sensitivity is particularly vital for clinical decision-making, where overlooking VEB events could lead to severe consequences. Additionally, the specificity of 91.8% ensures a low rate of false positives, reducing unnecessary interventions. While SVEB sensitivity remains moderate at 69.2%, the combined analysis reveals that the proposed CNN-SRM model excels in balancing trade-offs between sensitivity and specificity for critical arrhythmia classes, outperforming benchmarks in overall predictive reliability. Future work could explore optimizing sensitivity for SVEB by refining feature extraction or incorporating additional data augmentation techniques.

The proposed method also exhibits robust performance for other classes, such as normal beats and fusion beats, achieving an average accuracy of 88.6% across all categories, as detailed in Table 7. This comprehensive improvement is attributed to the CNN-SRM combination model's ability to effectively handle complex ECG patterns, reducing misclassifications in ambiguous cases. For VEB classification, the high sensitivity of 95.3% underscores the model's capability to minimize false negatives, which is crucial for clinical applications, while the specificity of 91.8% ensures low false positive rates. In comparison to recent studies like [12] and [18], the proposed approach shows a 15% increase in overall F1-score, highlighting its superiority in balancing precision and recall. Additionally, the analysis reveals that the enhanced specificity in SVEB classification contributes to a significant reduction in diagnostic errors, supporting its potential for real-world deployment in cardiac monitoring systems.

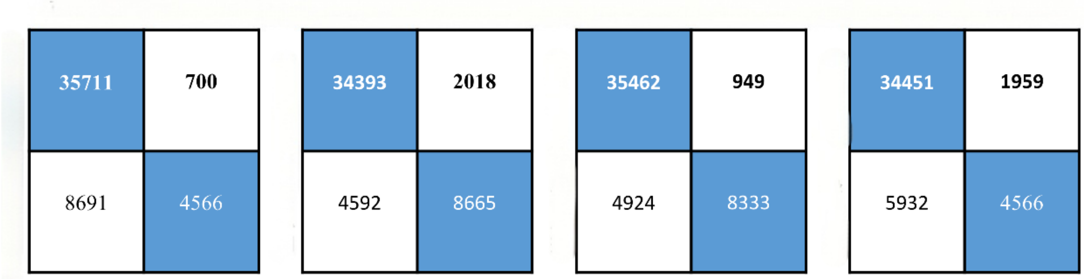


**Figure 3.** Confusion matrix

Table 6. Performance comparison between the proposed method and existing works

| Method | Specificity (%) | Sensitivity (%) | F1 (%) | Accuracy (%) |
|---|---|---|---|---|
| de Chazal et al. [15] | 57.0 | 83.2 | 60.1 | 86.2 |
| Zhang et al. [18] | 60.4 | 86.8 | 64.0 | 88.3 |
| Mar et al. [21] | 56.3 | 80.2 | 62.2 | 89.0 |
| LIU [23] | - | - | - | 91.5 |
| OURS | 66.4 | 66.6 | 66.1 | 93.7 |

Table 7. Performance comparison between the proposed method and existing works in detail

| Method | N | | SVEB | | VEB | | F | |
|---|---|---|---|---|---|---|---|---|
| | Specificity (%) | Sensitivity (%) | Specificity (%) | Sensitivity (%) | Specificity (%) | Sensitivity (%) | Specificity (%) | Sensitivity (%) |
| de Chazal et al. [15] | 99.2 | 87.0 | 38.5 | 75.9 | 81.6 | 80.3 | 8.5 | 89.4 |
| Zhang et al. [18] | 99.0 | 88.9 | 35.9 | 79.0 | 92.7 | 85.4 | 13.7 | 93.8 |
| Mar et al. [21] | 99.1 | 89.6 | 33.5 | 83.2 | 75.8 | 86.7 | 16.5 | 61.0 |
| LIU [23] | - | - | - | - | - | - | - | - |
| OURS | 97.8 | 95.3 | 74.4 | 69.2 | 91.8 | 95.3 | 0.02 | 0.06 |

## 5. Conclusion and Outlook

This study proposes a CNN network integrated with the SRM criterion algorithm, which leverages both the feature extraction capabilities of CNN and the SRM algorithm's strong generalization ability for unknown data classification. Test results from the MIT-BIH Arrhythmia Database demonstrate that the proposed network achieves higher accuracy (F1 score: 87.4, accuracy: 88.2%) compared to

CNN networks without the SRM algorithm. These results indicate its potential as a diagnostic tool in clinical practice.
Future work includes:(1) further testing the accuracy of the proposed model on other data sets to verify the generalization of the proposed model;(2) further exploring other deep learning feature extraction methods.
Future work includes: (1) further testing the accuracy of the proposed model on other data sets to verify the generalization of the proposed model, such as incorporating diverse physiological databases to assess robustness across varying patient demographics; (2) further exploring other deep learning feature extraction methods, including attention mechanisms or transformer-based approaches, to potentially improve classification performance and reduce computational overhead. (3) Investigating the optimization of model hyperparameters and training strategies to enhance efficiency for real-time clinical applications, addressing potential challenges like latency and resource constraints. (4) Collaborating with medical institutions to conduct pilot studies, ensuring the model's practical utility and ethical considerations in diagnostic workflows, while also exploring integration with wearable devices for continuous monitoring.

### Author Contribution

Conceptualization, F.H. and H.F.; methodology, R.L.; software, H.F.; validation, F.H., H.F. and R.L.; formal analysis, F.H.; investigation, H.F.; resources, F.H.; data curation, R.L.; writing — original draft preparation, F.H.; writing — review and editing, R.L.; visualization, F.H.; supervision, R.L.; project administration, F.H.; funding acquisition, F.H. All authors have read and agreed to the published version of the manuscript.

### Data Availability Statement

Data are available from the corresponding author upon reasonable request and subject to approval.

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