International Journal of Innovative Computing, Information and Control
Volume **19**, Number **4**, August **2023**
ICIC International ©2023 ISSN 1349-4198
pp. 1153–1163

DEEP SHRINKAGE NETWORK FOR ARRHYTHMIA DETECTION

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Received December 2022; revised March 2023

Abstract. *Cardiovascular diseases are serious threats to human health. Electrocardiogram (ECG) is of great significance for clinical diagnosis and follow-up treatment of arrhythmias. However, the ECG signal is inevitably contaminated by a large amount of noise during ECG acquisition and transmission, which affects the results of arrhythmia detection. Noise reduction was often applied before classification in previous studies, which may cause the loss of some heart beats. Therefore, the preprocessing of noise reduction is omitted and noisy signals are directly classified in this paper. A novel deep learning model, deep shrinkage network, is developed in this paper to improve feature extraction ability and arrhythmia detection accuracy of noisy ECG recordings. Soft thresholding is introduced into deep fully convolutional neural network (DFCNN) to eliminate noise. ECG spectrograms are used as the input of the proposed network, and the Focal Loss function is employed to solve the problem of data imbalance. By training the original data from the MIT-BIH Arrhythmia Database, an overall accuracy of 99.74% is achieved. Significant advantages are also shown in the detection task of noisy ECG signals with different SNRs, demonstrating the effectiveness of the proposed network.*

Keywords: Electrocardiogram, Arrhythmia, Convolutional neural network, Soft thresholding, Focal Loss, Deep learning

1. Introduction.

Most cardiovascular diseases (CVDs) are accompanied by arrhythmias and other phenomena in the early stage. Some dangerous arrhythmias may lead to sudden cardiac death, putting human life at risk [1]. The present diagnosis of arrhythmia mainly relies on electrocardiogram (ECG). However, a large number of consecutive ECG recordings require manual interpretation by fully trained cardiologists, which is time-consuming, laborious, and even inevitably leads to diagnostic errors in the clinical process. Therefore, automatic arrhythmia detection by ECG signal has become an effective measure to improve the efficiency of diagnosis and treatment.

In the early stage of arrhythmia detection research, ECG signal detection relied heavily on manually extracted features [2]. The extracted features are usually applied to machine learning algorithms such as support vector machine (SVM) [3, 4] and K-nearest neighbor (KNN) [5] for classification tasks. Nevertheless, due to the high computational complexity and limited feature extraction ability of traditional machine learning algorithms, the accuracy of arrhythmia detection is far lower than that of cardiologists. In recent years, deep learning has discovered the inherent hierarchical structure of training data through its multi-level nonlinear transformation, thus showing sustained good results in visual or speech recognition [6, 7], image processing [8], and other fields. Deep learning has also been introduced to biomedical signal processing, which improves classification accuracy.

DOI: 10.24507/ijicic.19.04.1153

Among them, convolutional neural network (CNN) [9], recurrent neural network (RNN) [10, 11], and residual network (ResNet) [12] are widely used in ECG signal automatic classification tasks.

ECG signal classification studies based on deep learning are always the focus of many researchers, most of which are based on one-dimensional (1-D) ECG signals. Simple 1-D CNN models have been employed to detect arrhythmias [13] from both noise and denoised ECG signals, but the noise in this study is extremely weak and cannot simulate real scenarios. Based on the 6-layer CNN, long short-term memory (LSTM) is combined to improve the classification performance of variable length heart beats [14]. Hannun et al. developed a 34-layer 1-D deep neural network (DNN) with single-lead ECGs, which reached the level of cardiologists in classifying 12 rhythm classes [15]. Chen et al. applied the ensemble classifier of CNN and LSTM to the 10-second ECG signal segment, while using the corresponding RR interval as input, to achieve high-precision automatic classification of arrhythmias [16]. Yao et al. proposed an integrated classifier of CNN and gated recurrent unit (GRU) to classify the data after wavelet denoising, realizing high-precision ECG monitoring [17]. Zhu et al. integrated SE-ResNet with a rule-based model, and also introduced sign loss to solve the problem of class imbalance, improving the classification performance and generalizability [18]. Compared with the 1-D convolution calculation only used for processing time series signals, the two-dimensional (2-D) convolution is more general. Features can be extracted in different dimensions using 2-D convolution kernels. Therefore, better performance can be achieved in the ECG classification task by 2-D convolutional models. The plotted heartbeat image is the most convenient and feasible method [19]. Frequency-domain feature maps of ECG signals can be generated using wavelet transform [20] and Fourier transform [21]. To obtain 2-D spectral images containing information in both frequency and time domains, the short-time Fourier transform (STFT) method can also be introduced, followed by CNN for classification [22, 23].

However, as a weak body surface signal, the ECG signal is inevitably contaminated by a large amount of noise during ECG acquisition and transmission [24, 25]. Most classification algorithms adopt filters to denoise and then classify signals [26, 27, 28]. Some researchers have also applied deep learning algorithms such as DNN [29], fully convolutional network (FCN) [30], and generative adversarial networks (GAN) [31] to the study of ECG signal noise reduction, laying a foundation for subsequent feature extraction and classification. However, most noise reduction processes increase the workload of data processing and may also cause the loss of some ECG beats. When dealing with noisy ECG signals, the convolution kernel, as a local feature extractor, may not be able to effectively detect ECG rhythm-related features, thus affecting the final classification accuracy. Moreover, the ECG signal waveform collected in the real scene is more complex and contains more noise than the ECG signal in the datasets. It is of practical significance to develop an arrhythmia detection algorithm that is robust to noise. Therefore, this work aims to improve the accuracy and efficiency of arrhythmia detection under noise conditions, so as to provide convenience and guarantee for clinical treatment.

A novel deep shrinking network, namely DS-ECGNet, is proposed in this paper. The network is composed of a deep fully convolutional neural network (DFCNN) and soft thresholding modules. Training and evaluation of the model are performed on ECG spectrograms generated from the MIT-BIH arrhythmia recordings. To solve the problem of unbalanced heart rhythm classes, Focal Loss, an improved cross-entropy loss, is introduced as the loss function of the proposed model. Compared with several published classification methods, the sensitivity and precision of the proposed method are significantly improved. The classification accuracy and efficiency are higher than those of DFCNN without embedded soft thresholding modules. In addition, with the increase of noise intensity, the performance advantage of the DS-ECGNet becomes more significant, which proves that the soft thresholding modules can improve the feature extraction ability of the convolutional network from noisy ECG signals and ultimately achieve higher classification accuracy.

The rest of this paper is organized as follows. Section 2 explains the proposed arrhythmia detection algorithm in detail, including data preprocessing and the DS-ECGNet. The datasets, experimental setup, and evaluation metric are presented in Section 3. Section 4 demonstrates the experimental results and analysis, and the conclusion is given in Section 5.

2. **Proposed Methodology.** The arrhythmia detection method based on DS-ECGNet is presented in Figure 1, which consists of three steps: segmentation, spectrogram generation, and classification.

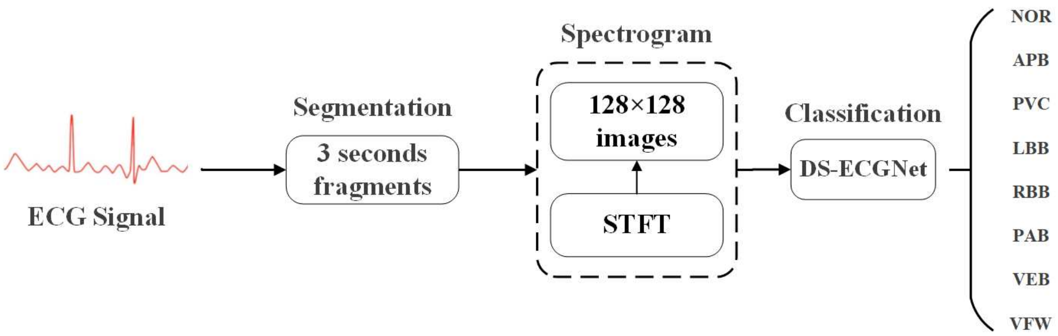

FIGURE 1. Arrhythmia detection flowchart

2.1. **Data preprocessing.** The steps of segmentation and spectrogram generation are collectively referred to as data preprocessing. Firstly, 1-D ECG signals are segmented into sequences of 3-second ECG recording fragments. Secondly, 128 × 128 pixel time-frequency spectrograms are generated through STFT. The instantaneous frequency of the ECG signal varies with time. Although the signal characteristics in the frequency domain can be reflected by the Fourier transform, the time domain signal characteristics cannot be analyzed. To combine the time and frequency domain information, the short-time Fourier transform is applied. It is a windowed Fourier transform, which moves on the time axis through the window function, and applies Fourier transform on the recording fragments. The formula is shown in Equation (1).

$$\mathrm{STFT}(t,f) = \int_{-\infty}^{+\infty} x(u)h(u-t)e^{-j2\pi fu}du \tag{1}$$

where $\mathrm{STFT}(t,f)$ is the spectrum at time t, $x(u)$ is the input signal, and $h(u-t)$ is the window function. The Hamming window function with window size = 64 samples and stride length = 32 is adopted in the experiments.

2.2. **Deep shrinking network: DS-ECGNet.** The overall architecture of the developed DS-ECGNet is shown in Figure 2(a). The soft thresholding module is inserted into the convolutional layers to form the DS-ECG block, which is shown in Figure 2(b). As the building unit of DS-ECGNet, DS-ECG blocks are stacked. The superimposed convolutional layers can learn discriminative features. In addition, soft thresholding as a shrinking function can eliminate noise and improve the classification accuracy of noisy ECG signals.

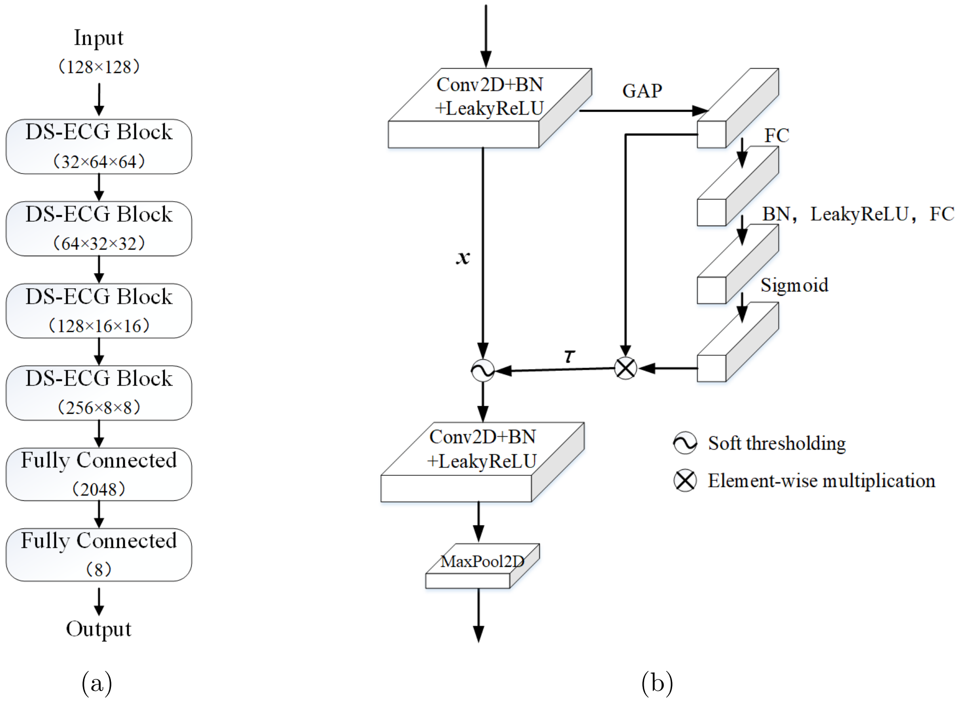

FIGURE 2. The architecture of the DS-ECGNet: (a) The overall network structure; (b) DS-ECG block

Our model refers to the network architecture of VGGNet [32], a classical network model in the field of image recognition. Two 3×3 convolutional layers and a 2×2 max pooling layer are employed in the convolutional part to form a feature extraction block. Batch normalization (BN) is applied after each activation function to ensuring that the transformations of different batches are kept within a certain range and to speeding up model convergence. The nonlinear activation function is widely used in CNN models, which makes the network a better fitting ability. In this paper, we adopt the LeakyReLU activation function, which is an extension of ReLU. LeakyReLU assigns a non-zero slope to all negative values so that some of the negative axis values are retained and information is not completely lost. The function expression of LeakyReLU is shown in Equation (2), and θ is generally set to 0.01.

$$y = \max(0, x) + \theta \min(0, x) \tag{2}$$

Recently, soft thresholding has been commonly used in signal denoising tasks [33, 34]. The filter can be learned automatically by the gradient descent algorithm, which avoids the requirement for much signal processing expertise to design the filter manually. Through the filter, useful information is transformed into extremely positive or negative features, while noise information is transformed into features close to zero. Then the near-zero features will be converted to zeros by soft thresholding, achieving the purpose of eliminating noise-related features. The function of soft thresholding can be expressed as

$$y = \begin{cases} x - \tau & x > \tau \\ 0 & -\tau \le x \le \tau \\ x + \tau & x < -\tau \end{cases} \tag{3}$$

where y is the output feature, x is the input feature, and τ is the threshold.

In this paper, the modified SE block is applied to learning the threshold adaptively, which automatically sets thresholds without professional knowledge. SENet [35], a typical channel attention mechanism, is composed mainly of squeeze and excitation. SE blocks can update the weights of each channel to suppress negative features and enhance positive features. They are often integrated into standard architectures such as ResNet and Inception networks, which can improve the ability of feature extraction and achieve better performance. The squeeze operation is the global average pooling for each channel. The excitation operation automatically generates the importance, or weight, of each feature channel. Finally, these weights are multiplied by the original feature map to generate the output of the SE block which serves as the input of the next layer.

The structure of DS-ECG block is shown in Figure 2(b), which is a modified SE block to calculate the threshold. The global average pooling (GAP) is an operation of calculating the average value from each channel of the feature map, which is the same as the squeeze operation of the SE block. Then feature maps are passed to two fully connected (FC) layers in turn and activated using the Sigmoid function finally. These operations are similar to the excitation operation of the SE block. The scale parameter in the range of $(0, 1)$ is multiplied element-wise with the value of GAP, and the threshold τ is obtained finally.

3. **Experiment.**

3.1. **Datasets.** The MIT-BIH Arrhythmia Database [36] from the PhysioNet website is adopted as the experimental data. It contains 48 half-hour two-channel ambulatory electrocardiogram recordings from patients ranging in age from 23 to 89. Most recordings consisted of the modified limb lead II and modified lead V1 (occasionally V2 or V5), so only lead II is used in the experiment. We select normal beat (NOR) and seven types of ECG arrhythmias including atrial premature beat (APB), premature ventricular contraction (PVC), left bundle branch block beat (LBB), right bundle branch block beat (RBB), paced beat (PAB), ventricular escape beat (VEB) and ventricular flutter wave (VFW).

The MIT-BIH Noise Stress Test Database [37] is applied as additional noise in the experiment. The database includes 3 half-hour typical noise recordings in ambulatory ECG recordings: baseline wander (BW), muscle artifact (MA), and electrode motion artifact (EM). By setting different signal-to-noise ratios (SNRs), the mixed noise recording is added to the clean recordings for training and testing. The calculation formula of SNR is shown in Equation (4).

$$\mathrm{SNR(dB)} = 10 \log_{10} \frac{P_{signal}}{P_{noise}} \tag{4}$$

where dB is the unit of SNR, P_{signal} and P_{noise} are the power of signal and noise, respectively.

3.2. **Experimental setup.** The DS-ECGNet and other models in this experiment are implemented with the deep learning framework PyTorch. The graphics card NVIDIA RTX 2080Ti (11G) is used for model training. During the training phase, Xavier initialization is adopted to initialize the weights. Adam optimizer with an initial learning rate of 0.001 is applied to accelerating the training process. To avoid over-fitting, a dropout rate of 0.5 is introduced in the fully connected layer. It can ignore certain neurons randomly to reduce the dependence between layers and improve the performance of the model.

In the field of medical data analysis, the datasets are seriously imbalanced. To solve this problem, the α-balanced variant of Focal Loss [38] is employed as the loss function for model training, and the calculation formula is shown in Equation (5). Based on the cross-entropy loss, the class weighting factor α and modulation factor $(1 - p_t)^{\gamma}$ are added to reduce the proportion of sample loss with a large amount of data in the overall loss, thereby solving the problem of severe class imbalance and difficulty in training samples from the minority classes. The tunable focus parameter is represented by γ ($\gamma \geq 0$). When $\gamma = 0$, the Focal Loss is equivalent to α-balanced cross-entropy loss.

$$\mathrm{FL}(p_t) = -\alpha_t(1 - p_t)^\gamma \log(p_t) \tag{5}$$

3.3. **Evaluation metric.** The confusion matrix visualizes the detailed data of the model classification results, with each row representing the true label and each column representing the predicted label. To evaluate the performance of networks, we can calculate the following common evaluation metrics. These are accuracy (Acc), specificity (Spe), sensitivity (Sen), and precision (Pre). The TP, FP, TN, and FN denote true positives, false positives, true negatives, and false negatives, respectively. These metrics evaluate the classification performance of the model from different perspectives, and can be calculated as

$$\mathrm{Acc} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \times 100\% \tag{6}$$

$$\mathrm{Spe} = \frac{\mathrm{TN}}{\mathrm{FP} + \mathrm{TN}} \times 100\% \tag{7}$$

$$\mathrm{Sen} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \times 100\% \tag{8}$$

$$\mathrm{Pre} = \frac{\mathrm{TP}}{\mathrm{FP} + \mathrm{TP}} \times 100\% \tag{9}$$

4. **Results.** This section provides the classification results based on the same datasets. In addition, comparisons are described with the results of some published algorithms. The confusion matrix of the ECG classification results when SNR = 5 is illustrated in Figure 3. It can be seen that DS-ECGNet performs better in NOR, LBB, and PAB classes.

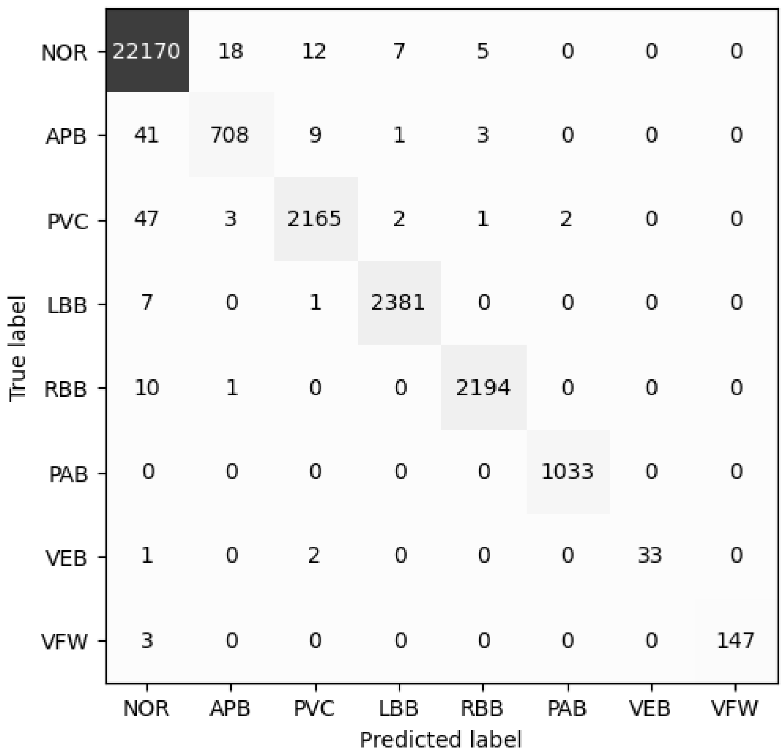

FIGURE 3. Confusion matrix when SNR = 5

Table 1. Experimental results

Class	Acc/%	Spe/%	Sen/%	Pre/%
NOR	99.51	98.76	99.81	99.51
APB	99.75	99.93	92.91	96.99
PVC	99.75	99.92	97.52	98.90
LBB	99.94	99.97	99.67	99.58
RBB	99.94	99.97	99.50	99.59
PAB	99.99	99.99	100	99.81
VEB	99.99	100	91.67	100
VFW	99.99	100	98.00	100
Average	99.86	99.82	97.39	99.30

There are a large number of misclassification of NOR in APB and PVC classes, which is largely related to the similarity of the spectrograms. And Table 1 shows the index evaluation results for each class. As can be seen, the average accuracy of all classes is above 99.8%, which has an outstanding classification performance. The sensitivity of APB and VEB is lower than that of other classes, while VEB has the lowest sensitivity. This is due to the lowest number of samples in this class. Although a special loss function is employed to enhance the classification effect, there are still some samples that are wrongly classified into other classes. The specificity and precision of each ECG class also reveal great classification performance, especially the average specificity reaches 99.82%, and the average precision also achieves 99.3%.

Figure 4 depicts the validation accuracy curves of several models, which include CNN, 34-layer ResNet, DFCNN, and the proposed DS-ECGNet in this paper. It can be seen from the figure that the curves of these models fluctuate to varying degrees during the training process, while the curves of DS-ECGNet are more stable under the action of soft thresholding. The accuracies of CNN and ResNet are lower and eventually remain around

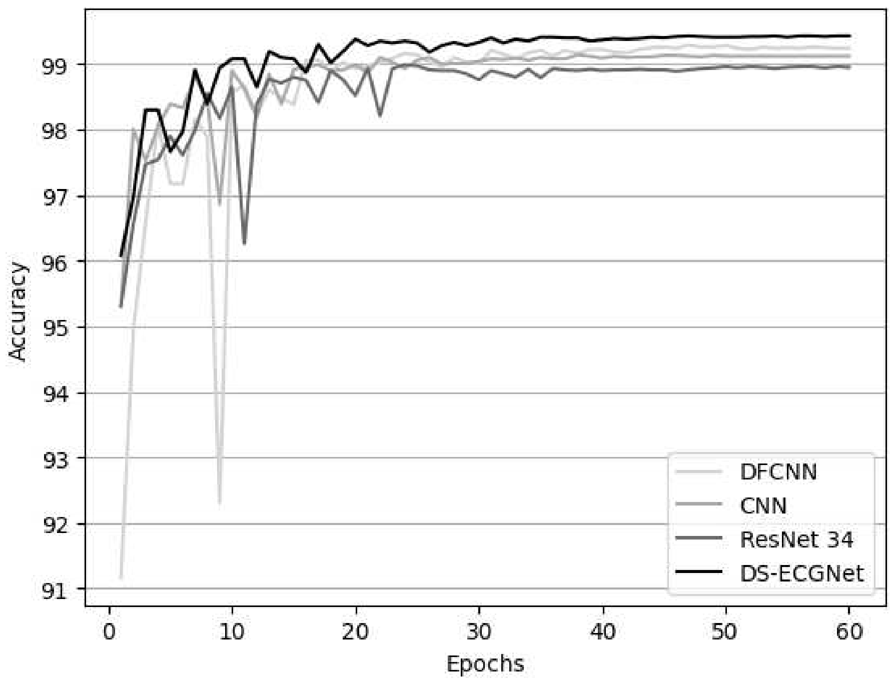

Figure 4. Training curve of several models

99%. Moreover, DS-ECGNet has higher accuracy and faster convergence in the validation set, keeping the accuracy around 99.4% after 35 epochs. Whereas DFCNN model curve tends to plateau after 40 epochs, and the accuracy is close to 99.2%, which proves the effectiveness of soft thresholding.

We summarize the classification methods for arrhythmia detection in other relevant literature and select typical classification methods based on 1-D signals and 2-D images, respectively. The results under the same dataset without additional noise are shown in Table 2. In the experiment of classifying 1-D signals, arrhythmia can be divided into 5 major classes according to the Association for the Advancement of Medical Instrumentation (AAMI), namely non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q). As can be seen from Table 2, the classification accuracy of 1-D ECG signal directly detected is lower, which is about 98%. Among them, the 1-D form of the proposed DS-ECGNet achieves the best performance, reaching 99.05%. Compared with several methods for arrhythmia detection using 2-D images, it can be seen that the accuracy of the proposed method has been significantly improved. The overall accuracy has reached 99.74% without manually added noise.

Table 2. Comparison of classification performance

Method	Dimension	Classes	Acc/%
CNN [13]	1D	5	97.99
CNN-LSTM [14]	1D	5	98.13
STFT + CNN [23]	2D	8	99.11
CNN-LSTM [19]	2D	8	99.01
ResNet	2D	8	99.45
Our method	1D	5	**99.05**
	2D	8	**99.74**

The detailed results of several 2-D classification methods with different SNRs are shown in Figure 5. As can be seen, the CNN-LSTM model performs poorly under noise conditions, and the test accuracy is about 10% lower than that of the proposed model when SNR $= -5$. The reason for the poor performance of LSTM is that it is more suitable for processing time series data and not robust to noise. The results of CNN and ResNet are relatively close, about 2.5% lower than DS-ECGNet. The difference in test accuracy between these models and DS-ECGNet gradually increases as the noise intensity enhances. This trend indicates that the greater the noise intensity is, the stronger impact it has on the feature extraction ability of the convolution kernel. At the same time, it is proved that the soft thresholding module can effectively eliminate the influence of strong noise. Outstanding performance advantages are exhibited in the DS-ECGNet, both with no additional noise or with noises of different intensities added.

5. **Conclusion.** In this paper, an arrhythmia detection algorithm based on DFCNN and soft thresholding is proposed, which is verified by using data from the MIT-BIH Arrhythmia Database and the MIT-BIH Noise Stress Test Database. Two-dimensional spectrograms are generated by STFT so that the convolutional layer can better extract the time and frequency domain features of the image. To solve the problem of imbalanced ECG data, the Focal Loss function is adopted. The experimental results show that the classification accuracy of DS-ECGNet on raw ECG signals reaches 99.74%. The embedded soft thresholding module can eliminate noise-related features well, and better classification

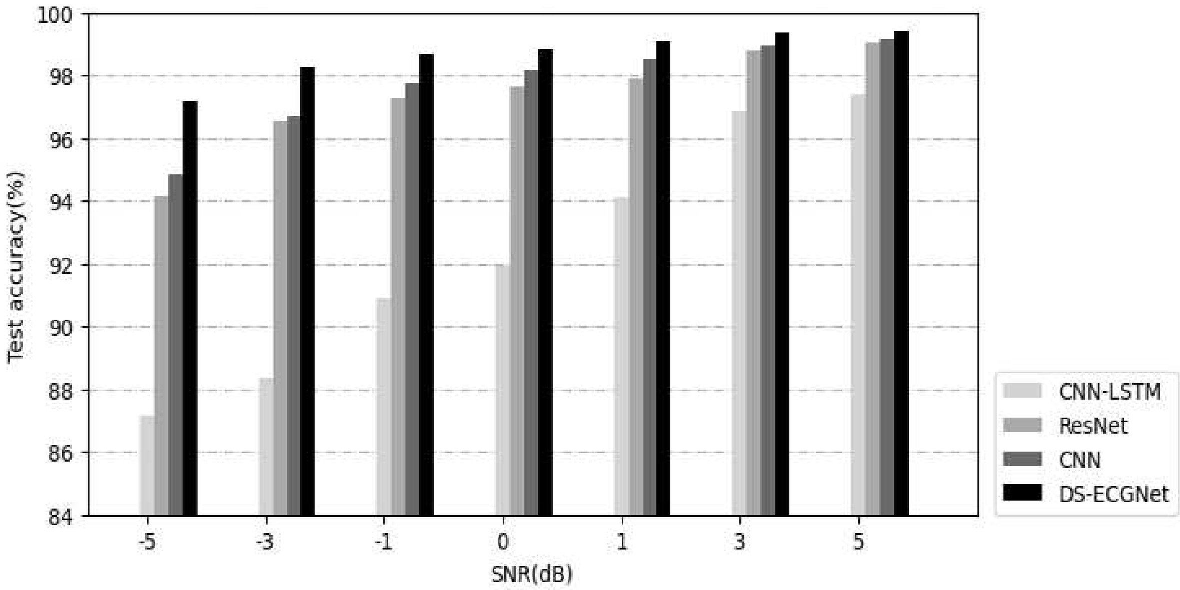

FIGURE 5. Test accuracies of several models with different SNRs

performance can also be achieved with manually added noise. Not only the classification accuracy is improved, but the detection efficiency is also guaranteed, which proves the feasibility of the proposed network in arrhythmia detection. As the goal of future work, we will make full use of 12-lead ECG recordings for classification optimization, providing efficient auxiliary means and approaches for clinical ECG diagnosis.

Acknowledgment. This work is partially supported by the National Natural Science Foundation of China (61772294, 61973179).

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