A New Intelligent ECG Recognition Approach based on CNN and Improved ALO-SVM

Dan Zhang (danzhang@zjut.edu.cn)
Zhejiang University of Technology
Zhitao He
Zhejiang University of Technology
Yongyi Chen
Zhejiang University of Technology
Wutao Yin
Zhejiang University of Technology
Hamid Reza Karimi
Politecnico di Milano

Research Article

Keywords: Electrocardiogram, Convolutional neural network, Lifting wavelet, Support vector machine, Antlion optimization algorithm

Posted Date: March 31st, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1499626/v1

A New Intelligent ECG Recognition Approach based on CNN and Improved ALO-SVM

Zhitao He[1], Yongyi Chen[1], Dan Zhang[1], Wutao Yin[1] and Hamid Reza Karimi[2]

[1]Department of Automation, Zhejiang University of Technology, Hangzhou, 310023, Zhejiang Province, China.
[2]Department of Mechanical Engineering, Politecnico di Milano, Milan, 20156, Italy.

Contributing authors: e-mail:danzhang@zjut.edu.cn;

Abstract

Cardiovascular disease is one of the most common diseases, which seriously threatens people's life and health. Therefore, the cardiovascular disease prevention becomes one of the most attractive research topics in health care system design. Intelligent recognition of electrocardiogram (ECG) signals represents an effective method for rapid diagnosis and the evaluation of cardiovascular diseases in medicine. Realization and efficiency of the classification of ECG signals in real time play major roles in detection of cardiovascular diseases. This paper is concerned with the proposition of an intelligent ECG signal recognition method on the basis of convolutional neural network (CNN) and support vector machines (SVM) with an improved antlion algorithm (ALO). First, the ECG signal is denoised and pre-processed by lifting wavelet. Subsequently, CNN is used to extract the signal characteristics of the denoising signal, and the extracted signal characteristics are used as the input characteristics of the SVM. Finally, an improved ALO algorithm is used to optimize the relevant input functions of the SVM to achieve a better signal classification. In our algorithm, the performance is enhanced by improving the threshold estimation method of the lifting wavelet, so as to improve the filtering effect. The proposed CNN architecture is tested with multi-lead ECG signals from the MIT-BIH ECG signal data set. The results display that the method has obtained an average accuracy, sensitivity and

specificity values of 99.97%, 99.97% and 99.99% respectively. Compared with those state-of-arts, our result has a better recognition performance.

Keywords: Electrocardiogram, Convolutional neural network, Lifting wavelet, Support vector machine, Antlion optimization algorithm

1 Introduction

The heart is the most important of the organs in body, it can maintain the human blood circulation. However, due to the lack of correct diet and exercise habits, the incidence rate of heart disease has been going rise in recent years, which seriously threatens people's life and health. Electrocardiogram (ECG) is a technique to record the changes of myocardial bioelectric current in the form of graph with ECG [1]. At present, ECG is still an important means of medical diagnosis and evaluation of cardiovascular diseases. The waveform of ECG signal is complex, and it contains a huge amount of information. Generally, doctors have to distinguish ECG signal by manual labeling, but it is easy to misjudgment, thus it greatly affects the identification and diagnosis to the patients suffering from cardiovascular diseases. Therefore, it is urgent to realize the automatic recognition and classification of ECG signals based on computer technology.

At present, there are many automatic ECG analysis methods proposed based on signal processing technology, such as wavelet transform (WT), support vector machine (SVM), decision tree, natural language processing (NLP) and so on [2]. For example, Li et al. firstly decomposed the ECG signal through wavelet packet decomposition (WPD), then used the decomposed coefficients as representative features to calculate the entropy, and finally used random forests (RF) to establish the ECG classification model [3]. Sangaiah et al. designed an enhanced filter to filter noise to improve ECG signal quality, then used WT and hidden markov mixture (HMM) to achieve signal classification [4]. Diker et al. used pan-tompkins algorithm and discrete wavelet transform (DWT) method to extract key points of ECG signals, then used an extreme learning machine based on an improved genetic algorithm to classify ECG signals [5]. Mousavi et al. proposed method based on NLP to classify ECG signals and achieved good performance [6]. Recently, Kumar proposed an automatic classification method that uses wavelet transform electrocardiogram to segment ECG signals, then used the least-squares support vector machine (LS-SVM) for signal classification [7].

In the era of big data, deep learning technology has extensively influenced many fields of scientific research [8–11]. In particular, convolutional neural networks (CNN) have broad application prospects in transforming biomedical big data into valuable knowledge, including the automatic classification of ECG signals [12]. Through the massive training data set, CNN can significantly

improve the classification accuracy [13]. In order to obtain better classification results, researchers have proposed many CNN-based methods to improve the recognition accuracy of the prediction model. For example, Salem et al. used spectrogram to convert one-dimensional ECG signal into two-dimensional image, then used a 2D-CNN to classify ECG signals [14]. Acharya et al. developed a 9-layer deep CNN, which can automatically identify five different types of heartbeats in ECG signals [15]. Rahhal et al. applied the continuous wavelet transform (CWT) to the analyzed ECG signals to generate a complete time-frequency representation, and the CNN preprocessed by imagenet was used to classify ECG signals [16].

In this paper, a new deep learning method is designed to effectively classify arrhythmias. Firstly, the improved threshold lifting wavelet is used to preprocess the raw ECG signal, and all kinds of noise interference in the original signal are filtered out as much as possible. Secondly, the CNN model with strong features and learning capabilities is selected to adapt and extract relevant features of the signal. Thirdly, the SVM classifier with the parameters that is optimized by the antlion algorithm (ALO) [17] is used to realize the specific classification of the ECG signal. Finally, the MIT-BIH ECG signal data set provided by the massachusetts institute of technology is combined to test the performance of the model, and comparison experiments are carried out through various practical indicators, including precision, sensitivity, and specificity. The results of comparison with existing methods show that our method further improves the accuracy of classification in the current results.

The rest of this paper is organized as follows. Section II presents the structure of the ECG recognition method developed in the article. The performance of the proposed algorithm and the comparison with classification results of existing methods are provided in Section III. Section IV concluded this paper.

2 ECG Recognition Method

2.1 System Overview

Fig. 1 shows the proposed ECG classification system architecture. First, the system receives the original ECG signal from the public data set and classifies the signals. Second, an improved lifting wavelet method is used to filter the noise. Then, the CNN is utilized to extract ECG signal features. In order to improve the system performance, an improved ALO algorithm is used to adjust the relevant parameters of SVM with the main goal to provide a more accurate classification performance.

2.2 Data preprocessing

The original ECG signal contains a lot of noise interference, which will seriously affect the accuracy of ECG data analysis. This is one of the difficulties in ECG classification. Therefore, it is necessary to denoise and preprocess the ECG data before model analysis to effectively filter out noise and improve the

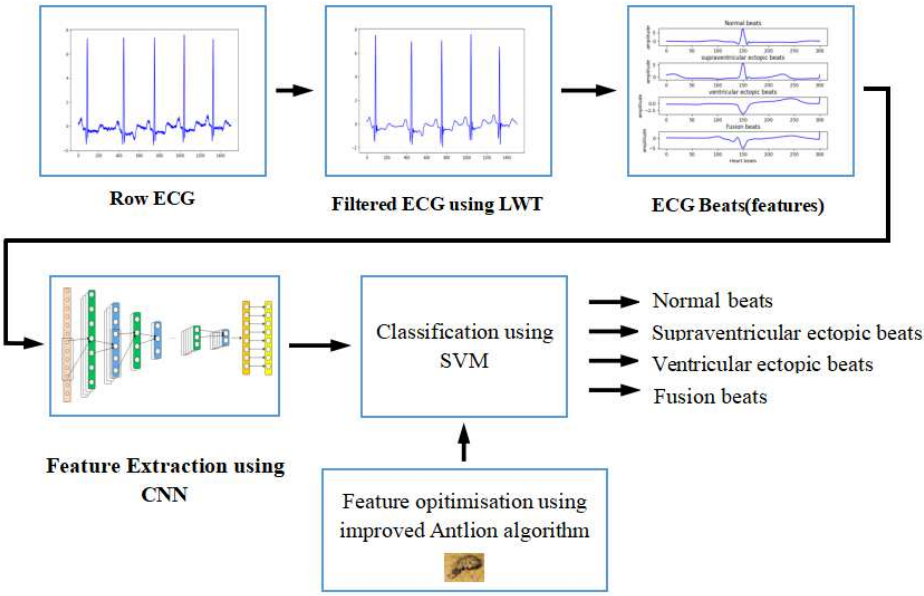

Fig. 1 ECG classification flow diagram.

accuracy of spectral analysis. Among them, the denoising method based on wavelet analysis is an effective preprocessing method, which has the characteristics of multiresolution, low entropy and decorrelation. However, due to the use of the Fourier transform, the denoising method based on wavelet analysis requires a large amount of calculation. On this basis, an improved threshold boosting wavelet will be used to improve computational efficiency.

Note that the lifting wavelet [18] refers to a second generation wavelet algorithm based on the time domain lifting method. Compared with the first-generation wavelet algorithm, the method adopted a simple multiplication operation to replace the original computationally complex fourier transform. Therefore, the calculation efficiency of the wavelet algorithm is highly improved compared with the first generation wavelet algorithm. There are three main steps for lifting wavelet decomposition:

2.2.1 Signal splitting

For the original signals to be processed, they are divided into two equally long and disjoint signal subsets manually. To facilitate processing, according to the parity of the sequence, the original signal is usually divided into odd sequence o_{j-1} and even sequence, which is defined in Eq. (1).

$$o_{j-1}(k) = s_j(2k-1), e_{j-1}(k) = s_j(2k) \tag{1}$$

2.2.2 Signal prediction

Since the original signal is correlated in time series, two sub-sequences can be conducted to achieve mutual prediction. The article selected the dual sequence e_{j-1} for prediction, and used the difference between the prediction result $P\left(e_{j-1}\right)$ and the actual value o_{j-1} as wavelet coefficient d_{j-1} (corresponding to the high frequency part of the original signal s), which is defined in Eq. (2).

$$d_{j-1} = o_{j-1} - P\left(e_{j-1}\right) \tag{2}$$

where P indicates the given prediction operator.

2.2.3 Signal update

In order to retain the overall characteristics (e.g., average) of the original signal change, we need to constantly update the signal. The original signal can be updated in real time using the wavelet coefficient d_{j-1} that is obtained by the prediction, which is defined in Eq. (3).

$$s_{j-1} = e_{j-1} + U\left(d_{j-1}\right) \tag{3}$$

where U represents the given update operator. When the lifting algorithm is actually used, different P and U can be selected to form different lifting algorithms according to the actual situation.

The reconstruction of lifting wavelet can be regarded as the inverse process of decomposition. The corresponding parity sequence is calculated based on the prediction operator P and the update operator U, after which the parity sequence is recombined to obtain the reconstructed signal s_j.

After decomposing the original signal by wavelet, the amplitude of the wavelet coefficient of the noise in the signal is smaller than the amplitude of the original signal. The threshold denoising method can be adopted to eliminate the signal noise. Among them, soft and hard threshold denoising are commonly applied in many practical applications. Despite the high popularity of the two methods, they both have some problems. The reconstructed signal obtained by the soft threshold method has good continuity, but it could cause the partial distortion of the original signal. The reconstructed signal obtained by the hard threshold method is closer to the original signal, but it could locally oscillate.

Aiming at the inherent defects of soft and hard thresholds, Zhou et al. proposed an improved threshold function [19], which is defined in Eq. (4).

$$W_{j,i} = \begin{cases} w_{j,k} - sign\left(w_{j,k}\right)\left(1-\alpha\right)\lambda, \mid w_{j,i} \mid \geq T \\ w_{j,k}\alpha\left(\frac{|w_{j,i}|}{\lambda}\right)^{\frac{1}{\alpha}}, \mid w_{j,k} \mid < T \end{cases} \tag{4}$$

where the parameter α tends for the adjustment factor of the threshold function, which can be flexibly selected within the range (0, 1]. When the value α is close to 0, the improved threshold function tends to be a soft threshold method. When the value α is close to 1, the improved threshold function tends to be a hard threshold method. On the basis of retaining the advantages of soft

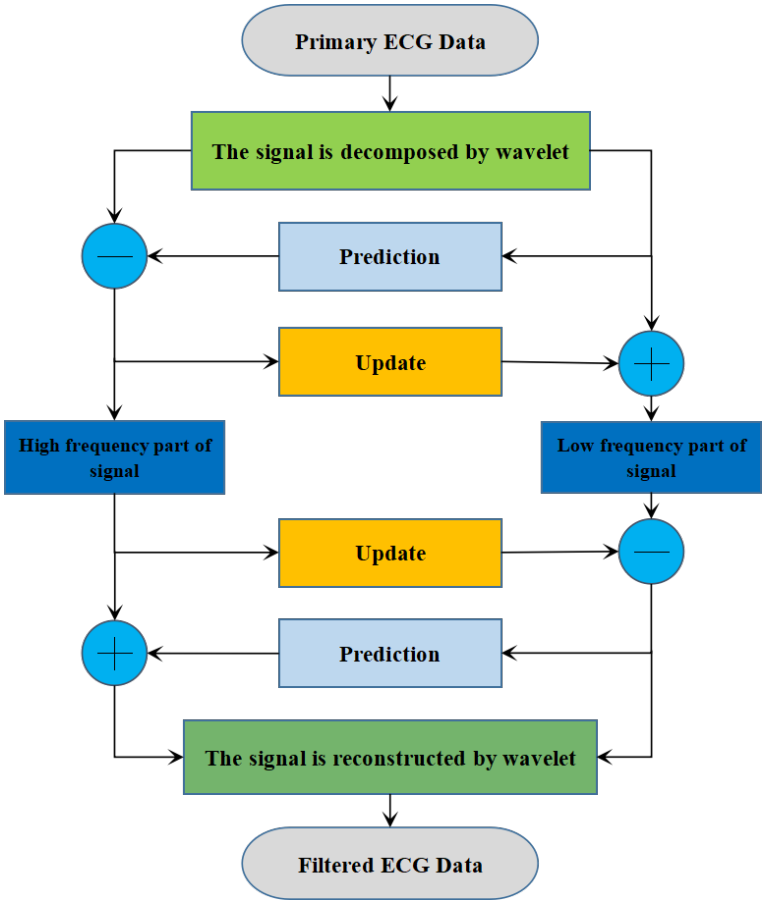

Fig. 2 Flow chart of lifting wavelet.

and hard thresholds, this adjustable threshold function overcomes its inherent shortcomings, so the obtained reconstruction function has good continuity while retaining a large amount of effective information.

At the same time, when the signal amplitude is close to or smaller than the noise, the traditional threshold estimation method will treat the signal as the noise, thus affecting the denoising performance. To avoid this problem, the traditional threshold estimation method needs to be adjusted. For the wavelet transform value at scale m, it is calculated with the adjacent dimension-related correlation $corr\ (m,\ n)$, and normalized to obtain the normalized result $k\ (m,\ n)$. At different scales of the wavelet transform, the trend of the noise wavelet signal and the wavelet coefficients of the original signal are opposite. Therefore, when $k\ (m,\ n) < 1$, the output result is a noise signal. In order to better filter out noise interference, the following adjustments are made to the traditional threshold.

$$\lambda_n = \frac{\lambda}{k\,(m,n)} \tag{5}$$

2.3 Signal detection system

Other scholars have analyzed all five types in the MIT-BIH database [20–22], which are normal (N), ventricular (V), supraventricular (S), fusion of normal and ventricular (F) and unknown beats (Q). Since the Q beat was very poor and it is usually meaningless. Therefore, only N, S, V and F were analyzed in detail. In this work, we use the CNN to extract the characteristics of the ECG data. CNN has a strong ability to characterize one-dimensional data and can adaptively extract relevant features, which significantly improves the accuracy of model classification. Then, SVM is used to classify the features extracted from the heartbeats. In addition, antlion algorithm will be to optimize the model parameters to further improve the classification accuracy.

CNN is one of the most widely used artificial neural networks [23]. Compared with other classification models, CNN's unique local perception and weight sharing operations greatly reduce model parameters and significantly improve model training efficiency, which makes CNN model easier to process high-dimensional data. The CNN model is mainly composed of convolutional layer, pooling layer and fully connected layer. In this study, we have proposed a CNN framework for extracting the characteristics of the signal, the CNN comprises of five convolution layers, three pooling layers, and a fully connected or dense layer, and its architechure in shown in Fig. 3.

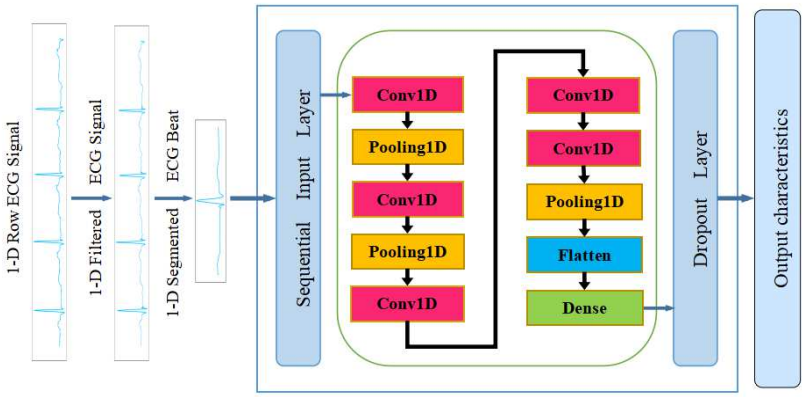

Fig. 3 CNN architecture for the detection of hypertension.

However, CNN has the problem of overfitting in the case of small samples. On this basis, various improved methods have been reported, and a common method is to combine CNN with other classification models. SVM [24] is a commonly used pattern recognition method, which solves problems encountered in

practical application by introducing various kernel functions. The core idea of this method is to find a suitable hyperplane that realizes the effective division of each category, and maximizes the distance between each sample data and the selected hyperplane, so as to realize the classification of the data [25]. This method is widely used in the area of small sample classification, and it can make up for the problem of insufficient generalization ability of CNN. When SVM is used to solve a specific classification problem, it is necessary to adjust the relevant parameters of the algorithm, including the relevant parameters *gamma* of the RBF kernel function and the penalty coefficient C. Traditional parameter adjustment is based on the manual adjustment of parameter characteristics. Although the manual adjustment parameters are guided by scientific theory, there still have great uncertainties, and it is easy to miss the optimal solution. In order to solve this problem, this paper adopts an improved ALO [26, 27] to intelligently adjust the C and *gamma* parameters, which avoids the inaccuracy of manual adjustment parameters and can find the optimal parameters more accurately. The improved ALO is easy to implement, and makes up for the deficiency that the traditional ALO [22, 28] is easy to fall into the local optimal solution. The specific improved ALO optimization process is as follows:

2.3.1 Real-time update of Antlion population

In the traditional ALO, the ants determine the position after the iteration through random walk, the procedure is as follows:

N ants in the search space is randomly placed, and each ant updates it's position through random walk, which is defined in Eq. (6).

$$P(X_{ant}) = [0, cumsum(2r(t_1) - 1), ..., cumsum(2r(t_{max}) - 1)] \tag{6}$$

where parameter *max* refers to the maximum number of iterations of the ant, *cumsum* is used to calculate the cumulative sum, and the random function $r(t)$ is defined as follows:

$$r\left(t\right) = \begin{pmatrix} 1, rand > 0.5 \\ 0, rand \leq 0.5 \end{pmatrix} \tag{7}$$

Due to the boundary of the search space, the random walk of ants is normalized, which is defined in Eq. (8).

$$X_i{}^t = \frac{(X_i{}^t - m_i) \times (H_i{}^t - L_i{}^t)}{M_i - m_i} \tag{8}$$

where the parameters M_i and m_i represent the maximum and minimum values of the ant's *i-th* dimension variable immediately, respectively, $H_i{}^t$ and $L_i{}^t$ represent the upper and lower bounds of the ant's *i-th* dimension variable after t iterations, respectively. When the ant location starts to update iteratively, it is necessary to normalize the entire iterative process to prevent the ant from exceeding the search space.

In the traditional ALO algorithm, the routes of each ant are not affected by each other, which leads to great differences in the fitness values of corresponding ant colonies. The fitness value of some antlions will always be higher than the average level of antlion, which weakens the optimization performance of the overall algorithm to a certain extent. In order to solve this problem, the idea of roulette selection is added in the optimization process to eliminate a certain proportion of individuals with poor fitness and realize real-time update of the ant colony, so as to ensure that there are more good individuals in the antlion population and reduce the possibility of the algorithm as a whole falling into the local optimum.

2.3.2 Antlion constructs trap

Each ant corresponds to an antlion hunting. The antlions hide in the retrieval space and construct sand traps around them. Ants' random walk could be affected by the traps made by the antlions, and they could slide towards the center of the trap, which is defined in Eq. (9).

$$\begin{cases} H_i^t = \frac{{H_i}^t}{I} \\ L_i^t = \frac{{L_i}^t}{I} \end{cases} \tag{9}$$

where the proportional coefficient I simulates the falling speed of the sand trap. When the ants are on the edge of the sand trap, the random walk could be less affected by the trap. At this time, I tends to 1. When the ants walk toward the center of the sandpit, the random walk could be greatly affected by the trap, thus making it difficult for the ants caught in the sandpit trap to get out of the trap range, and can only slide to the center of the trap. At the center of the trap, I tends to infinity. When actually simulating the influence of traps, the pit sinking proportional coefficient I increases in sections, which simplifies the algorithm and achieves rapid convergence of the algorithm. On the contrary, it may miss the global optimum solution, because the algorithm converges and shrinks and crosses part of the search space. To solve this problem, Meng et al. proposed a contraction model with smooth and convergent boundaries to simulate the process of bunker subsidence [26].

$$I = \psi x \frac{e^{wx} - e^{-wx}}{2} \tag{10}$$

$$x = \frac{t}{T} \tag{11}$$

In the formula, through two adjustment factors ψ and ω, the improved contraction model can ensure that the algorithm can search the search space more comprehensively while maintaining the rapid convergence of the algorithm, so as to avoid missing the optimal solution.

2.3.3 Capture prey and update the position of the antlion

There is a one-to-one correspondence between an ant lion and an ant. Each ant could only be captured by the corresponding antlion. The corresponding

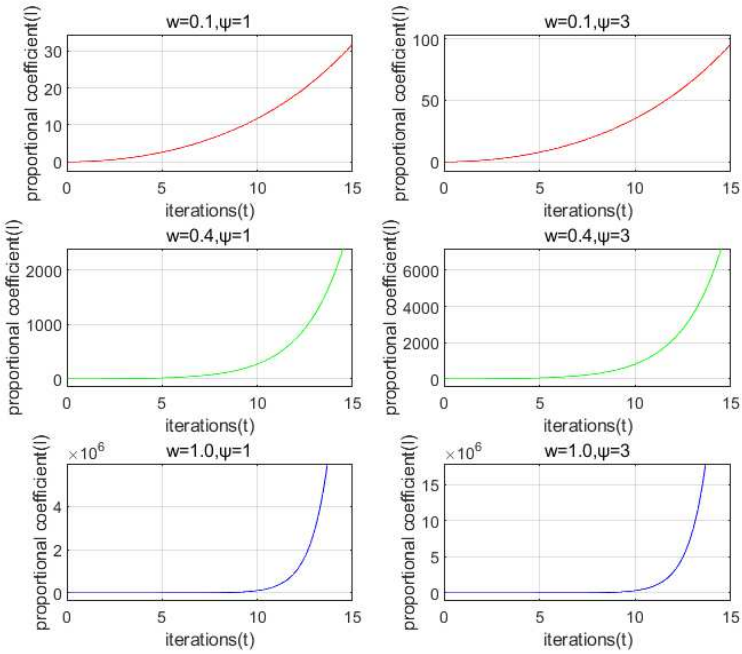

Fig. 4 Convergence of the model with different parameters.

relationship between the antlion and the ant is determined by the method of roulette. The fitness value is adopted to determine whether the antlion captures the corresponding ant. When the ant's fitness value is less than the antlion's fitness value, it is considered that the antlion successfully captures the ant. Meanwhile, the antlion updates its position based on the ant's position. The higher the antlion's fitness is, the greater the probability of successfully capturing the ant is. At the same time, the best antlion individual (the lowest fitness) in each iteration is regarded as the elite antlion. Each generation of elite antlions has the best fitness value. In order to better inherit the characteristics of elite antlions, it is believed that elite antlions can affect the random walk of all ants.

$$X_i^{t+1} = \frac{R_A^t(l) + R_E^t(l)}{2} \tag{12}$$

where R_A marks the value generated by the random walk of the ant at the *t-th* iteration under the influence of the corresponding antlion, and R_E represents the value generated by the ant's random walk at the *t-th* iteration of the *t-th* generation of elite antlions. The mean value is taken as the true random walk result of the ant's t iteration.

3 Simulation Results

3.1 Database

In this study, we utilize MIT-BIH arrhythmia database to evaluate the wave detection and arrhythmia classifification of our system. The MIT-BIH arrhythmia database includes records of 48 patients, these fragments were obtained from 47 subjects in the BIH arrhythmia laboratory between 1975 and 1979. Moreover, all heartbeat signals in the MIT-BIH arrhythmia database were labeled beatby-beat by more than one cardiologist. There are 15 major labels of arrhythmia in the MIT-BIH database. In order to compare the performance of classification algorithms with other scholars, the AAMI EC57 classification standards specified by the american association for the advancement of aedical devices are adopted to evaluate the performance of this classification algorithm. According to the standard, the ECG signals are classified into five categories, which are N, S, V, F and Q. In addition, data analysis of Q class is meaningless, therefore, it's perfectly normal to analyze ECG signals using only four classifications. Fig.5 illustrates the four categories of ECG signals, namely N, S, V, and F.

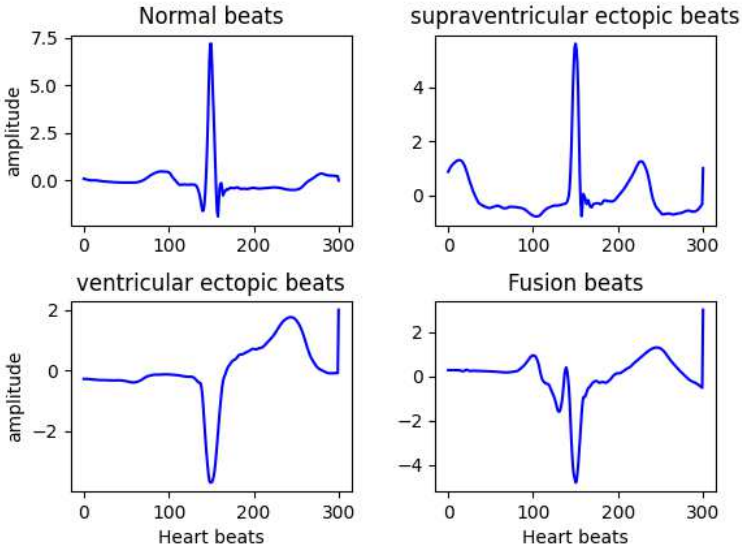

Fig. 5 N, S, V, and F ECG beats.

3.2 Performance evaluation

In order to further demonstrate the superiority of this method, the MIT-BIH arrhythmia database is also used to evaluate the wave detection and arrhythmia classification of our system, and confusion matrix is adopted to demonstrate the accuracy of four kinds of arrhythmia data respectively. Confusion matrix is a relatively common classification result display algorithm. By displaying the actual categories and predicted values after classification, it can visually display details such as the classification of samples, and often uses a series of classification indicators to evaluate model performance. Fig.6 illustrates the confusion matrix generated by the four categories of ECG signals, namely N, S, V, and F.

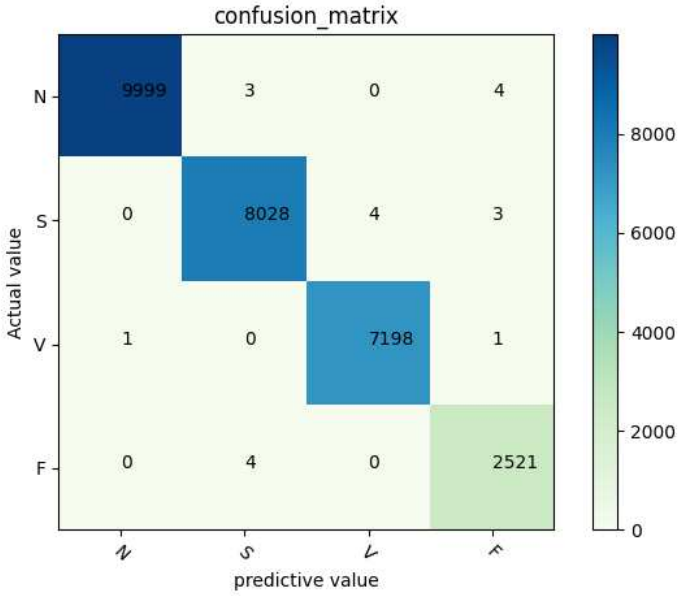

Fig. 6 Confusion matrix of the four-category validation set.

According to the confusion matrix, in order to better evaluate the effects of each classification method, three secondary indicators, including positive predictiveness, sensitivity and specificity are used as the classification results of the ECG signal classification indicator evaluation model. Positive predictivity (PPV) indicates the proportion of correct predictions for all positive samples (ie minority classes). The lower the accuracy is, the more negative samples (ie majority classes) are mistakenly injured. After the majority category is wrong, it is often applied to measure what is needed. The paid cost can help us judge whether every time the prediction of the minority category is accurate, and it is also often called the "precision rate", which is defined in Eq. (13).

$$PPV = \frac{TP}{FP + TP} \times 100 \tag{13}$$

Sensitivity (SEN) is called the recall rate, and represents the proportion of all positive samples that can be correctly predicted. It can be adopted to evaluate the model's ability, so as to capture minority samples. The higher the sensitivity is, the stronger the model's ability is to discriminate minority categories, which is defined in Eq. (14).

$$SEN = \frac{TP}{TP + FN} \times 100 \tag{14}$$

Specificity (SPE) is the proportion of negative samples that predict correctly in all negative samples. It is utilized to measure the ability of the model, so as to correctly distinguish the majority of classes. The higher the specificity is, the better the ability is to identify the majority of samples, which is defined in Eq. (15).

$$SPE = \frac{TN}{TN + FP} \times 100 \tag{15}$$

Table I is the PPV, SEN and SPE evaluation results of each category based on the confusion matrix.

Table 1 Performance evaluation of each type

Type	N	S	V	F
PPV	0.9993	0.9991	0.9997	0.9984
SEN	0.9999	0.9991	0.9994	0.9968
SPE	0.9996	0.9996	0.9999	0.9998

It can be seen from Fig.6 and table I that this model has excellent classification performance for ECG signals, and the PPV, SEN and SPE of each category can reach to 1. It reflects the excellent accuracy of the model and is very suitable for ECG signal classification. However, PPV and SEN were slightly lower in the model when dealing with F beats. After performing the experiment study, it is found that the reason for this phenomenon is possibly due to the imbalance of data.

In the MIT-BIH database, the data imbalances are significant, as the N, S and V heartbeats are about 90,000, 2,800 and 7,000, respectively. This severe imbalance can degrade the performance of the classifier, especially for the few sensitive and positive predictions. Therefore, it is necessary to expand the ECG data, especially the small sample of data. In this paper, the ECG data are extended based on Z-score normalization, and the formula is:

$$Z = \frac{X - \mu}{\sigma} \tag{16}$$

Then, new data samples are synthesized after preprocessing by changing the standard deviation and average value of the Z score calculated from the original ECG signal. Then, we take the segments of class N and keep them the same (because they are the most abundant), and increase the number of segments of the remaining types to match the number of segments of class N. After enhancement, the data volume of N, S, V and F classes is similar and the total number of segments is increased to 324000.

Table 2 Expanded sample size for each heart beat type

heart beat type	Sample size
N	90000
S	84000
V	70000
F	80000
total	324000

On this basis, we shall use the expanded data to conduct the experiment again, and the experimental data is recorded in table III.

Table 3 Performance evaluation of each type

Type	N	S	V	F
PPV	0.9999	0.9997	0.9998	0.9994
SEN	0.9998	0.9998	0.9995	0.9997
SPE	0.9999	0.9999	0.9999	0.9999

Comparing tables I and III, it is easy to see that the classification of *PPV* and *SEN* with small sample are also improved and thus the performance of the whole model is enhanced.

3.3 Comparison of results

In order to demonstrate the superiority of this method, comparison experiments with those of state-of-arts are performed. Table IV presents some classification results reported in recent literature. Sangaiah et al. used an enhanced filter to filter out noise, then used WT and HMM to achieve signal classification [4]. Mousavi et al. proposed an efficient DL model based on LSTM network for recognizing four ECG heartbeat classes, and the oversampling method called comprehensive minority oversampling technology (SMOTE)

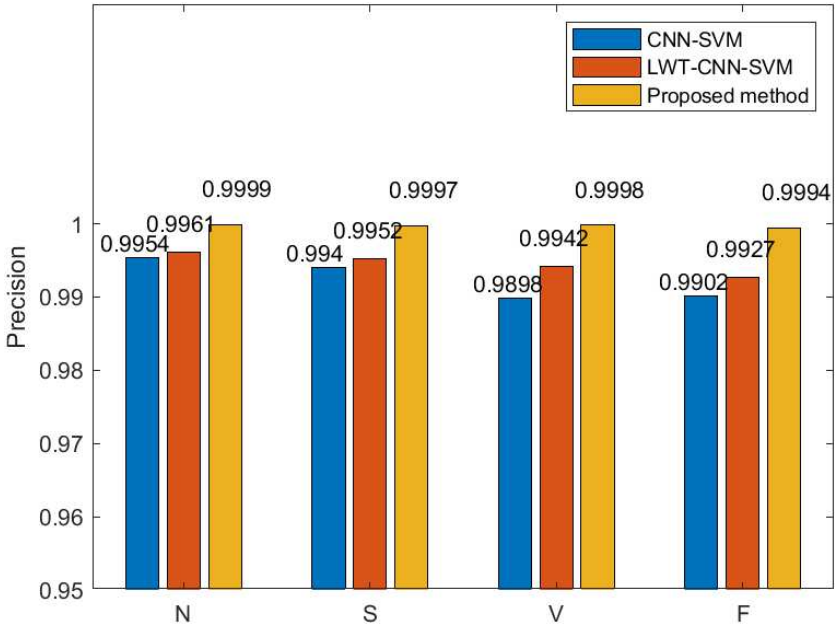

Fig. 7 Comparison of precision.

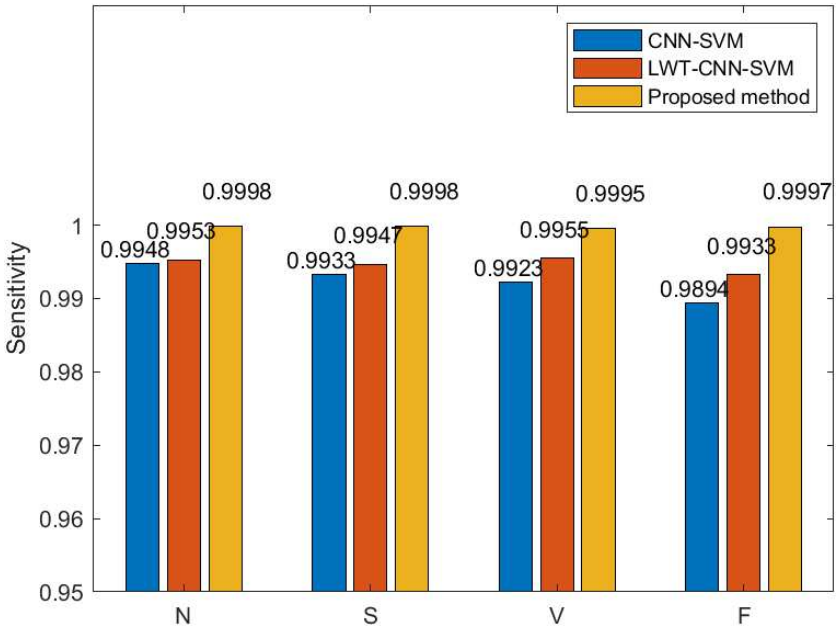

Fig. 8 Comparison of sensitivity.

was used to improve the accuracy of minority groups. In the intra-patient paradigm, excellent classification performance was achieved in [29]. Shaker et

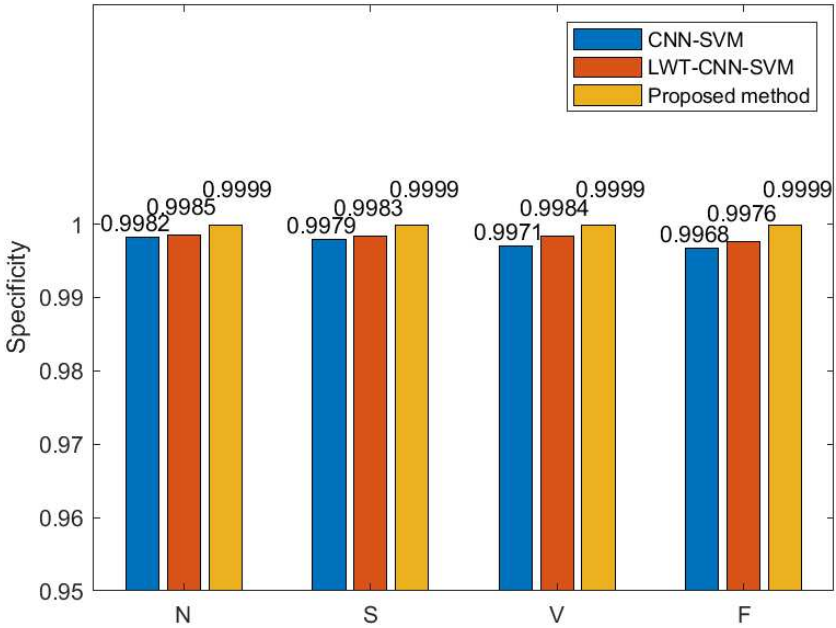

Fig. 9 Comparison of specificity.

al. utilized GNN to balance the data set and then used CNN for classification, which effectively improves the classification accuracy of minority groups [30]. Nurmaini et al. used stacked denoising autoencoder (DAE) and autoencoder (AE) for feature learning, then used DNN to achieve signal classification [31]. Oh et al. combined the CNN model with the LSTM architecture to identify five heart conditions. The system showed high classification performance in processing variable length data [32]. Kora et al. directly applied the hybrid firefly and particle swarm optimization algorithm (FFPSO) to optimize the original ECG signal, then used levenberg marquardt neural network (LMNN) to classify ECG signals [33]. It is shown from table IV, and Figs. 7-9 that the CNN and combined with improved ALO-SVM model proposed in this paper outperforms those models. Furthermore, a large number of data samples ensure that the model has high generalization ability and robustness.

3.4 Discussions on the advantage of our method

From Table IV, it can be seen that the proposed method can provide better performance. The reason for this result is that we made up for the shortcomings of the existing classification methods. More specifically, Shaker et al. [30] utilized CNN to classify signal directly, without considering the shortcomings of CNN's insufficient generalization performance in the small samples. Oh et al. [32] used raw data without denoising, which increases the possibility of prediction errors. The data set used in literature [31, 33] is too small for

Table 4 Comparison of results of each method

Author	Classifiifier	No.of beats	Accuracy
Sangaiah et al.[4]	WT+HMM	1000	99.7
Mousavi et al.[29]	LSTM+SMOTE	101290	99.92
Shaker et al.[30]	GNN+CNN	81021	98.3
Nurmaini et al.[31]	DAE+DNN	4274	99.34
Oh et al.[32]	CNN+LSTM	16499	98.10
Kora.[33]	FFPSO+LMNN	2806	99.3
Proposed study.	CNN+ALO-SVM	324000	99.97

signal classification, which seriously hinder the improvement of classification accuracy.

Compared with previous studies, the merits of proposed model are summarized as follows:

1) The improved ALO-SVM is used to process the signal features extracted by CNN, which improves the generalization ability of the model.

2) The lifting wavelet is used in the preprocessing stage, and the new threshold function and adjusted threshold estimation method are used to make up for the shortcomings of traditional threshold methods, which makes the proposed method more accurate and efficient.

3) The z-score method is used to expand the data, which greatly improves the accuracy of small sample data.

4 Conclusion

For the abnormal ECG signal detection problem, how to better extract the characteristics of the ECG signal and complete the classification task are important to improve the accuracy of the computer aided classification algorithms. In this paper, an ECG signal detection method based on CNN and improved ALO-SVM model has been propsed. We first adopted an improved threshold lifting wavelet to denoise the original ECG data, so as to avoid the interference of various noises on feature extraction and even specific classification. Then the convolutional neural network with powerful feature extraction function was used to effectively extract ECG features. Finally, the SVM model optimized by the ALO algorithm was used to classify the extracted ECG features, so that the specific ECG signal type can be accurately diagnosed. The

proposed new method was tested on the MIT-BIH data set, and the effectiveness of the method was verified in actual classification. It follows from the experiment study that, the newly proposed method can effectively distinguish different types of ECG signals, and the accuracy can reach a level close to 1. Finally, the advantage of our method was demonstrated via a comparison study, which showed that the method can identify and diagnose cardiovascular diseases more effectively.

References

[1] Ashkezari-Toussi, S., Sabzevari, V.R.: Early arrhythmia prediction based on hurst index and ecg prediction using robust lms adaptive filter. Signal, Image and Video Processing **15**(8), 1813–1820 (2021)

[2] Yan, K., Wang, X., Kim, J., Khadra, M., Fulham, M., Feng, D.: A propagation-dnn: Deep combination learning of multi-level features for mr prostate segmentation. Computer Methods and Programs in Biomedicine **170**, 11–21 (2019)

[3] Li, T., Zhou, M.: Ecg classification using wavelet packet entropy and random forests. Entropy **18**(8), 285 (2016)

[4] Sangaiah, A.K., Arumugam, M., Bian, G.-B.: An intelligent learning approach for improving ecg signal classification and arrhythmia analysis. Artificial Intelligence in Medicine **103**, 101788 (2020)

[5] Diker, A., Avci, D., Avci, E., Gedikpinar, M.: A new technique for ecg signal classification genetic algorithm wavelet kernel extreme learning machine. Optik **180**, 46–55 (2019)

[6] Mousavi, S., Afghah, F., Khadem, F., Acharya, U.R.: Ecg language processing (elp): A new technique to analyze ecg signals. Computer Methods and Programs in Biomedicine **202**, 105959 (2021)

[7] Kumar, M., Pachori, R.B., Acharya, U.R.: Automated diagnosis of myocardial infarction ecg signals using sample entropy in flexible analytic wavelet transform framework. Entropy **19**(9), 488 (2017)

[8] Murat, F., Yildirim, O., Talo, M., Baloglu, U.B., Demir, Y., Acharya, U.R.: Application of deep learning techniques for heartbeats detection using ecg signals-analysis and review. Computers in Biology and Medicine **120**, 103726 (2020)

[9] Yirtici, T., Yurtkan, K.: Regional-cnn-based enhanced turkish sign language recognition. Signal, Image and Video Processing, 1–7 (2022)

[10] Sun, L., Zhu, G., Li, P.: Joint constraint algorithm based on deep neural

network with dual outputs for single-channel speech separation. Signal, Image and Video Processing **14**(7), 1387–1395 (2020)

[11] Bodapati, J.D., Shaik, N.S., Naralasetti, V.: Deep convolution feature aggregation: an application to diabetic retinopathy severity level prediction. Signal, Image and Video Processing **15**(5), 923–930 (2021)

[12] Kumar, L., Sai, Y.P., et al.: A new transfer learning approach to detect cardiac arrhythmia from ecg signals. Signal, Image and Video Processing, 1–9 (2022)

[13] Soh, D.C.K., Ng, E.Y.K., Jahmunah, V., Oh, S.L., San, T.R., Acharya, U.R.: A computational intelligence tool for the detection of hypertension using empirical mode decomposition. Computers in Biology and Medicine **118**, 103630 (2020)

[14] Salem, M., Taheri, S., Yuan, J.-S.: Ecg arrhythmia classification using transfer learning from 2-dimensional deep cnn features. 2018 IEEE Biomedical Circuits and Systems Conference (BioCAS), 1–4 (2018). IEEE

[15] Acharya, U.R., Fujita, H., Oh, S.L., Hagiwara, Y., Tan, J.H., Adam, M.: Application of deep convolutional neural network for automated detection of myocardial infarction using ecg signals. Information Sciences **415-416**, 190–198 (2017)

[16] Al Rahhal, M.M., Bazi, Y., Al Zuair, M., Othman, E., BenJdira, B.: Convolutional neural networks for electrocardiogram classification. Journal of Medical and Biological Engineering **38**(6), 1014–1025 (2018)

[17] Mirjalili, Seyedali: The ant lion optimizer. Advances in Engineering Software **83**, 80–98 (2015)

[18] Li, Y., Via, B.K., Li, Y.: Lifting wavelet transform for vis-nir spectral data optimization to predict wood density. Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy **240**, 118566 (2020)

[19] Zhou, F., Li, C., Zhu, H.: Research on threshold improved denoising algorithm based on lifting wavelet transform in uv-vis spectrum. Spectroscopy and Spectral Analysis **38**(2), 506–510 (2018)

[20] Kiranyaz, S., Ince, T., Gabbouj, M.: Real-time patient-specific ecg classification by 1-d convolutional neural networks. IEEE Transactions on Biomedical Engineering **63**(3), 664–675 (2016)

[21] Ye, C., Kumar, B.V.K.V., Coimbra, M.T.: An automatic subject-adaptable heartbeat classifier based on multiview learning. IEEE Journal of Biomedical and Health Informatics **20**(6), 1485–1492 (2016)

[22] Dewangan, R.K., Shukla, A., Godfrey, W.W.: A solution for priority-based multi-robot path planning problem with obstacles using ant lion optimization. Modern Physics Letters B **34**(13), 2050137 (2020)

[23] Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., Liu, T., Wang, X., Wang, G., Cai, J., Chen, T.: Recent advances in convolutional neural networks. Pattern Recognition **77**, 354–377 (2018)

[24] Vapnik, V.N.: An overview of statistical learning theory. IEEE Transactions on Neural Networks **10**(5), 988–999 (1999)

[25] Zhang, Z., Xu, Z., Tan, J., Zou, H.: Multi-class support vector machine based on the minimization of class variance. Neural Processing Letters **53**(1), 517–533 (2021)

[26] Meng, D., Ge, B.: Antlion optimized adaptive routing algorithm based on cellular partition. Journal of Jinling University of Science and Technology **2**, 17–23 (2020)

[27] Singh, D., Singh, B.: Effective and efficient classification of gastrointestinal lesions: combining data preprocessing, feature weighting, and improved ant lion optimization. Journal of Ambient Intelligence and Humanized Computing, 1–16 (2020)

[28] Ali, E.S., Abd Elazim, S.M., Abdelaziz, A.Y.: Ant lion optimization algorithm for optimal location and sizing of renewable distributed generations. Renewable Energy **101**, 1311–1324 (2017)

[29] Mousavi, S., Afghah, F.: Inter- and intra- patient ecg heartbeat classification for arrhythmia detection: A sequence to sequence deep learning approach. In: ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1308–1312 (2019)

[30] Shaker, A.M., Tantawi, M., Shedeed, H.A., Tolba, M.F.: Generalization of convolutional neural networks for ecg classification using generative adversarial networks. IEEE Access **8**, 35592–35605 (2020)

[31] Nurmaini, S., Darmawahyuni, A., Noviar, A., Mukti, S., Tutuko, B.: Deep learning-based stacked denoising and autoencoder for ecg heartbeat classification. Electronics **9**(1), 135 (2020)

[32] Oh, S.L., Ng, E.Y.K., Tan, R.S., Acharya, U.R.: Automated diagnosis of arrhythmia using combination of cnn and lstm techniques with variable length heart beats. Computers in Biology and Medicine **102**, 278–287 (2018)

[33] Kora, P.: Ecg based myocardial infarction detection using hybrid firefly

algorithm. Computer Methods and Programs in Biomedicine **152**, 141–148 (2017)