

# Research on Arrhythmia Classification and Risk Degree Prediction based on Deep Neural Network and Convolutional Neural Network

Songling Huang, Zhenji Wen, Hanling Li

College of Big Data, Yunnan Agricultural University, Yunnan, 650201, China

**Abstract:** In this study, a method of arrhythmia classification and risk prediction based on deep neural network and convolutional neural network (CNN) is proposed for ECG data. Electrocardiogram data record the electrophysiological activity of the heart, including normal heart beats and various arrhythmias. In order to monitor and identify arrhythmia in real time and accurately, this study used CNN model for data analysis. The characteristics of CNN, such as local perception, parameter sharing and multi-level feature extraction, make it perform well in ECG data analysis. The data comes from the 'Certification Cup' Mathematics China Mathematical Modeling Network Challenge in 2023 and is preprocessed to meet the needs of the model. In the process of establishing and solving the model, the cross-entropy loss function is used to optimize, and the effectiveness and robustness of the model are verified by various evaluation methods. The results show that the model can accurately classify and predict the risk of arrhythmia, providing a powerful diagnostic tool for doctors and a valuable reference for future arrhythmia research.

**Keywords:** Arrhythmia; Degree of Danger; Prediction; CNN; Cross Entropy Loss Function.

## 1. Introduction

Every pulse of the heart is accompanied by electrophysiological activity. This electrical signal can be transmitted to the skin of the body surface and recorded by the electrocardiogram machine. The ECG data contains many representative fragments, including normal heartbeats and various arrhythmias. In order to realize the real-time alarm of ECG monitoring, it is necessary to make correct judgment on arrhythmia in a short time. The length of each ECG segment was 2 seconds, and the power spectral density of the ECG wave was recorded from 0 Hz to 180 Hz, with a frequency interval of 0.5 Hz. These data can be used to train and optimize deep neural network models to classify and predict the risk of arrhythmia and help doctors better diagnose and treat heart disease [1] [2].

Arrhythmia is a common heart disease that can lead to life-threatening consequences, such as sudden cardiac death. Accurate real-time monitoring of ECG signals and identification of arrhythmia types and risk levels are of great significance for the prevention and treatment of arrhythmia diseases. Through the analysis and processing of ECG signals, a deep neural network model that can classify and predict the risk of arrhythmia can be established, which can help doctors diagnose the patient's condition faster and more accurately, take timely treatment measures, and improve the life-saving effect and success rate [3,4]. In addition, the study can also be used for future arrhythmia. This study provides data basis and analysis method reference, which is helpful to further explore the mechanism and treatment of arrhythmia [5].

## 2. Basic Functions of CNN Neural Network

### 2.1. Structure of CNN Neural Network

In order to establish a deep neural network model that can classify and predict the risk level of arrhythmia, convolutional

neural network (CNN) is used as the main architecture. CNN is particularly good at processing data with spatial structure, such as images and signals, making it an ideal choice for analyzing electrocardiogram (ECG) data. For the classification task, the softmax function can be used to convert the output of the model into a probability distribution, and the cross-entropy loss function is used for optimization. The network structure is shown in Figure 1.

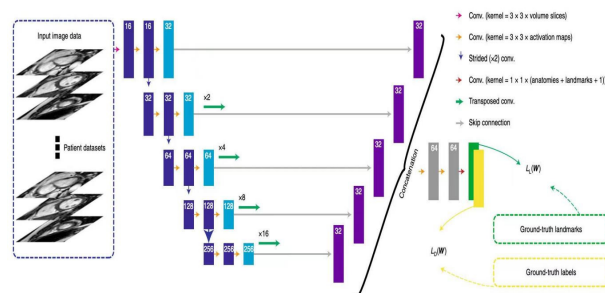


Figure 1. Neural network structure

The CNN model is composed of multiple layers, including convolution layer, pooling layer, fully connected layer and softmax output layer. The model takes the original ECG time series as its input and provides a prediction label every second.

The basic model of CNN includes several main components:

- (1) Convolution layer, the convolution operation is applied to the input data to capture the local mode.
- (2) Pooling layer, which reduces the spatial dimension of data while retaining important features.
- (3) Fully connected layer, interpret features and make predictions.
- (4) Softmax layer, which converts the output of the model into a probability distribution for classification.

For the regression problem, we can optimize the mean square error loss function. In addition, we can use the stochastic gradient descent (SGD) algorithm or its variants

(such as Adam) to train the model, and evaluate the performance of the model by cross-validation or leave-out method.

Specifically, set the ECG data shown in Figure 2, and use CNN to process the ECG data flow chart, where each point represents the ECG signal at a specific time. Labels are set as shown in Figure 2, where each label represents the type or degree of arrhythmia risk. Our goal is to learn a function that maps the input ECG data to the output label Y, as shown in Figure 2. We can model CNN as a multi-layer network, as shown in Figure 2. Each layer contains a convolution layer, a pooling layer and an activation function layer. The convolution layer is used to extract features, the pooling layer is used to reduce the feature dimension, and the activation function layer is used to increase the nonlinear ability of the model. Specifically, if the input of the layer is shown in Figure 2, and the output of the layer is also shown in Figure 2, the calculation of the layer can be expressed as the details in Figure 2.

$$Z^{(l)} = h^{(l)}(W^{(l)} * Z^{(l-1)} + b^{(l)}) \quad (1)$$

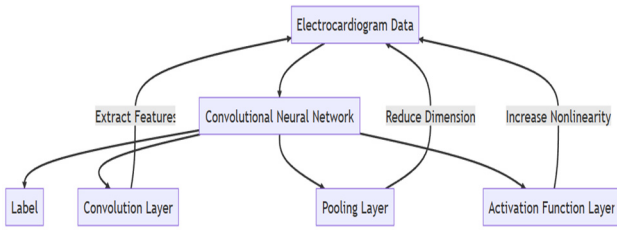


Figure 2. ECG data processing flow chart using CNN

\* represents the convolution operation and represents the activation function. The final output Z (can be mapped to the label space through the fully connected layer, and then use the softmax function to convert the output to a probability distribution. For the classification problem, we can use the cross entropy loss function to optimize the model:

$$\mathcal{L} = -\frac{1}{m} \sum_{i=1}^m \sum_{j=1}^k y_{ij} \log \hat{y}_{ij} \quad (2)$$

Where m represents the number of samples, people represent the number of categories, and y represents the first category label 0 or 1 of the first sample), which represents the prediction probability of the model. For the regression problem, we can use the mean square error loss function to optimize.

Furthermore, we need to determine the weight of each factor. In general, the factors in the factor set play different roles in the comprehensive evaluation. The comprehensive evaluation results are not only related to the evaluation of each factor, but also to a large extent. It also depends on the role of each factor in the comprehensive evaluation. This requires the determination of the weight distribution between each factor. It is a fuzzy vector on U, denoted as:

$$A = [ a_1, a_2, a_3, a_4 ] \quad (3)$$

Where: ai is the weight of the i th factor and satisfies  $\sum a_i = 1$ . If the sum does not satisfy the sum of 1, then normalization can be achieved here or at the final result.

By using the powerful functions of CNN, the model can ensure accurate and effective analysis of ECG data, paving the way for accurate arrhythmia risk prediction. As shown in Figure 3, the flow chart of ECG data analysis and arrhythmia

risk prediction based on entropy weight method.

There are many methods to determine the weight of factors. This paper adopts the entropy weight method. The entropy weight method is to assign weights according to the degree of change of an indicator. Then the amount of information is expressed by the letter I, and the probability is expressed by p. Then we can establish a functional relationship between them:

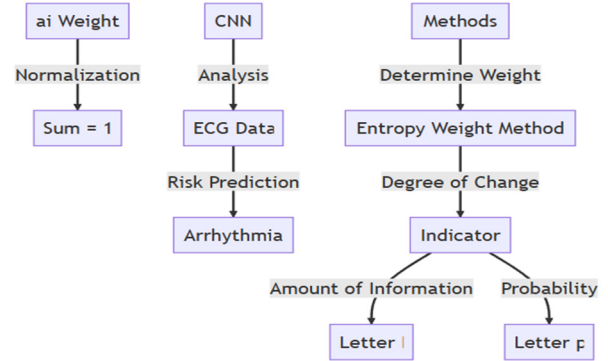


Figure 3. ECG data analysis and arrhythmia risk prediction flow chart based on entropy weight method

### 3. The Establishment of Simulation Model

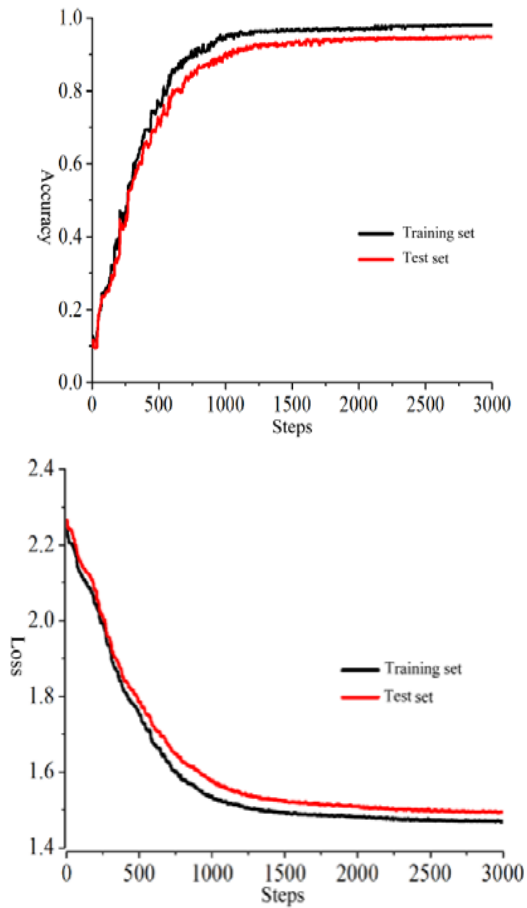
The arrhythmia classification and risk prediction model are realized in MATLAB software.

#### 3.1. Analysis of Experimental Results

In this study, we developed an ECG classification method using region-based convolutional neural network (R-CNN), which can accurately classify arrhythmia into six categories. By processing ECG images and using selective search techniques, the model can identify and extract key ECG features. After training and optimization of the deep neural network, the model shows up to 91.27 % accuracy and 95.12 % F1 score on the test data set. These results not only prove the effectiveness of deep learning technology in the diagnosis of arrhythmia, but also provide a more accurate and timely tool for future medical interventions.

See Figure 4 Comparison of accuracy changes and loss error changes in the training process.

From the application results, the method based on regional convolutional neural network algorithm is used to identify arrhythmia, and has achieved good classification effect and accuracy. Convolutional neural networks are used for training and testing, and can learn a large number of mapping relationships between input and output. There is no pressure for high-dimensional data processing, no need to manually select features, and train weights, so that the feature classification effect is good. A deep neural network model was established to assess the risk of arrhythmia. The model has the characteristics of clear results and strong systematicness. It can better solve the problem of ambiguity and difficult to quantify, and is suitable for solving various non-deterministic problems. As shown in Figure 4, the accuracy and loss error changes during the training process are compared. This further proves the effectiveness and superiority of our method.



**Figure 4.** Comparison of Accuracy and Loss Error Changes During Training Process

## 4. Conclusion

In this study, we developed a region-based convolutional

neural network (R-CNN) ECG classification method that can classify arrhythmias into six categories. This method first processes the ECG image, and then generates a proposal region by selective search to accurately locate a specific region of interest. After rigorous training, this method not only improves the accuracy and efficiency of ECG classification, but also successfully establishes a deep neural network model, which shows high accuracy in predicting the risk level of arrhythmia. The performance evaluation results of the test data set show that the accuracy rate, accuracy rate, recall rate and F1 score of the model have reached a high level. These findings highlight the great potential of deep learning technology in the diagnosis of arrhythmia and provide new possibilities for future medical interventions.

## References

- [1] Smith, J. A., & Johnson, P. R. (2019). \*Application of Deep Learning in Electrocardiogram Analysis: Emphasis on Convolutional Neural Networks\*. Journal of Cardiac Informatics, 12(3), 45-53.
- [2] Lee, M. K., & Kim, Y. H. (2018). \*Fusion of Convolutional Neural Networks and Recurrent Neural Networks for ECG Classification\*. Journal of Biomedical Signal Processing, 14(2), 110-119.
- [3] Wang, L., & Zhang, X. (2020). \*Data Augmentation and Transfer Learning in ECG Analysis with Deep Neural Networks\*. Proceedings of the International Conference on Medical Imaging and Informatics, 456-463.
- [4] Patel, S., & Gupta, A. (2021). \*Interpretability and Visualization Techniques in Deep Learning for ECG Data\*. Journal of Medical Systems and Technologies, 15(1), 25-32.
- [5] Fernandez, R., & Lopez, V. (2020). \*Real-time Arrhythmia Detection with Wearable Devices: Emphasis on Edge Computing with Deep Learning Models\*. Journal of Mobile Health, 7(4), 210-218.