Convolutional Neural Networks and Cluster Analysis for Heart Rate Data Analysis and Monitoring

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Abstract: Heart rate variation is a dynamic process that requires real-time monitoring and timely diagnostic categorization in clinical settings. Addressing the challenge of reducing manual workload while ensuring diagnostic accuracy through intelligent diagnostic technologies is a crucial concern in clinical practice. Frequency domain analysis of heart rate time series can reflect the operation of the autonomic nervous system, thereby enhancing the sensitivity and accuracy of heart rate variation monitoring. In this study, through the fusion of temporal and time-frequency domain features in electrocardiogram (ECG) data using Convolutional Neural Networks (CNN), and based on inter-sample clustering analysis and Short-Time Fourier Transform (STFT) evaluation of heart rate variability, a model for heart rate changes in a normal population is established. Following the analysis and processing of selected heart rate data, this model provides a foundational approach for predicting abnormal heart rate conditions and health management. The use and introduction of data analysis techniques in this paper serve as an important reference for medical and health management research. Continuous experimentation with related algorithms to minimize errors will enhance the accuracy and comprehensiveness of mathematical-based heart rate monitoring and analysis methods, thereby promoting their widespread application in relevant fields.

Keywords: Convolutional Neural Networks; Cluster Analysis; Short-time Fourier Transform; Heart Rate Monitoring

1. Introduction

Heart rate is one of the most fundamental vital signs of the human body, reflecting both physiological and psychological states [1]. With the advancement of biomedical technology and wearable devices, heart rate monitoring has become more convenient and is widely used in the fields of medicine, health management, and social research. In medicine, continuous monitoring of heart rate changes can detect early signs of many diseases, facilitating early treatment. In the management of chronic diseases and health, heart rate is extensively used to monitor the stability of the condition and the effectiveness of drug treatments. In social research, heart rate, as a physiological indicator, can assess an individual's psychological state, providing auxiliary means for cognitive and social psychological research. Real-time monitoring systems have been used to record dynamic changes in athletes' heart rate [2]. At present, with the rapid development of artificial intelligence and deep Xi, convolutional neural networks (CNNs) have achieved great success in the field of medical image segmentation [3].

However, current research on heart rate monitoring faces the following issues.: The first one is insufficient depth in heart rate feature extraction and analysis. Existing research is mainly limited to time and frequency domain analysis, without fully utilizing new perspectives proposed by statistical methods and complex network theories. The information contained in heart rate data has not been deeply explored. The second one is inadequate evaluation of clinical application effectiveness. Most current studies on heart rate monitoring data analysis remain at the theoretical stage, with relatively limited clinical validation and effectiveness evaluation.

This paper addresses these issues by collecting, cleaning, and analyzing data. The obtained power spectral density data are classified using algorithms such as k-

means and feature vector analysis for visual ECG cluster data analysis results. Additionally, CNN and Short-Time Fourier Transform are employed for risk level assessment, providing reference for heart rate monitoring.

2. Data Collection and Preprocessing

The dataset used in this study comes from the MIT-BIH Arrhythmia Database, recorded by the Massachusetts Institute of Technology and Beth Israel Hospital from 1975 to 1979. The dataset comprises 48 ECG recordings from 47 subjects, each lasting 30 minutes, including over 116,000 heartbeat data and annotated positions and categories for each heartbeat. This study focuses on five types of heartbeats: normal (N), atrial premature beat (A), ventricular premature beat (V), left bundle branch block (L), and right bundle branch block (R).

In the original dataset, the distribution of data for each type of heartbeat is uneven, with the proportion of normal heartbeats being much larger than other arrhythmia heartbeat types. This imbalance can affect the training effectiveness of the network. Therefore, the SMOTE algorithm is used to oversample abnormal heartbeat data, augmenting it to match the quantity of normal heartbeat samples. The distribution of training sample data before and after processing is shown in Table 1.

Table 1. Sample Size Distribution Unit: pcs

Sample source	N	A	V	L	R
Training set (before equilibrium)	50166	1357	4909	4636	3467
Training set (after equilibrium)	50166	50166	50166	50166	50166
Validation set	4334	105	403	408	281
Test set	17244	467	1634	1589	1191

3. Heart Rate Monitoring Technical Route

Based on the existing classification of arrhythmias, common types of arrhythmias and diagnostic criteria are as follows:

A) Premature Atrial Contraction (PAC)

Diagnostic Criteria: Premature occurrence of heartbeats, originating from the atrioventricular node, leading to shortened conduction time. Identification is based on the electrocardiogram (ECG) to determine the origin of heartbeats and the shortened interbeat interval.

B) Premature Ventricular Contraction (PVC)

Diagnostic Criteria: Premature occurrence of heartbeats, originating from the ventricular wall without involvement of the atrioventricular node, leading to prolonged cardiac cycles. Identification is similar to PAC but requires determining the origin of heartbeats from the ventricular wall, with a longer RR interval following.

C) Bradycardia

Diagnostic Criteria: Heart rate less than 60 beats per minute. Causes may include sinoatrial node dysfunction or atrioventricular conduction block. Diagnosis of bradycardia and its causes must be confirmed through an electrocardiogram.

D)Tachycardia

Diagnostic Criteria: Heart rate exceeding 100 beats per minute. It may originate from the sinoatrial node or ventricular tachycardia. Electrocardiogram analysis is necessary to determine the source and type of tachycardia.

E) Ventricular Fibrillation

Diagnostic Criteria: Completely disordered cardiac activity, rapid and uncoordinated excitations occurring simultaneously in different parts of the ventricular wall, rendering the heart ineffective in contracting. The electrocardiogram shows baseline-free negative deflections, losing the normal cardiac cycle pattern.

F) Ventricular Flutter

Diagnostic Criteria: Rapid and organized excitations occurring in the ventricular wall, with a heart rate exceeding 250 beats per minute but still exhibiting periodicity. The electrocardiogram displays sawtooth-like rapid waves, more organized than ventricular fibrillation but similarly affecting cardiac contraction. These diagnostic criteria are based on ECG manifestations and are commonly used methods for identifying arrhythmias clinically. The physiological principle involves analyzing the origin, frequency, and regularity of cardiac activity to identify abnormalities in myocardial excitation and conduction. To apply them to monitoring devices, they need to be complemented with electrocardiographic

detection methods to achieve accurate arrhythmia diagnosis.

4 Data Processing

4.1 Data Processing and Analysis Techniques Introduction

A) Convolutional Neural Network (CNN):
CNN is a deep learning model widely used in image recognition and signal processing. In heart rate monitoring, CNN can be used for feature extraction from time-series heart rate data. The ECG signal is a one-dimensional time-series signal, and the time-domain wave is different from the heartbeat type [4]. The time-domain features of the heart beat can be extracted through CNN. Through a combination of convolutional layers, pooling layers, and fully connected layers, CNN can automatically learn and recognize important patterns and features in heart rate data. This includes frequency domain features, time domain features, and variability, enabling CNN to comprehensively and automatically analyze heart rate data, providing more accurate information for medical diagnosis and health management.
B) Cluster Analysis:
Cluster analysis is commonly used in heart rate monitoring to identify different patterns of heart rate changes, aiding in personalized health management and disease prediction. By clustering heart rate data, similar heart rate patterns can be grouped together, revealing abnormal patterns or characteristic patterns of specific diseases. This forms the basis for customized treatment plans and personalized health recommendations. Cluster analysis allows medical teams to better understand the physiological state of patients, providing support for precision medicine.
C) Short-Time Fourier Transform (STFT):
STFT is a time-frequency analysis method commonly used to analyze the variation of signals over time. In heart rate monitoring, STFT can be used to transform time-series heart rate data from the time domain to the frequency domain, allowing the analysis of changes in different frequency components. By integrating convolutional neural networks, clustering analysis, and short-time Fourier transform, personalized and precise diagnosis and treatment plans can be provided, improving treatment efficacy Automatic analysis is achieved by continuously recording ECG data [5]. This helps reveal heart rate variability, assess the function of the autonomic nervous system, and identify frequency patterns associated with specific physiological or pathological states. The application of STFT broadens the understanding of heart rate data, enhancing the sensitivity and accuracy of monitoring.

4.2 Processing

First step, to calculate the energy ratio of frequency bands. By extracting spectral features from the electrocardiogram (ECG) power data, calculate the proportion of each frequency band in the total energy.

$$P(f) = |X(f)|^2 \quad (1)$$

where P(f) is the power with frequency f and X(f) is the value of the Fourier transform with frequency f.
Second step, to calculate the Frequency Power Ratio (FPR), which measures the distribution change of energy between different frequency bands. A higher FPR indicates greater differences in energy distribution between different frequency bands, suggesting the presence of certain disease states.

$$\begin{aligned} FPR &= False\ positive\ class\ rate \\ &= false\ positive\ rate \\ &= \frac{\text{Pre} - \text{positive and negative}}{\text{All real negative}} \\ &= \frac{\text{FP}}{\text{FP} + \text{TN}} \end{aligned} \quad (2)$$

Third step, to calculate the Moving Average (MA) and Standard Deviation (SD) for each frequency band, which reflecting the stability and variability of the ECG power spectrum. The formula for calculating the moving average is as follows.

$$EMA_t = \begin{cases} y_1 & t = 1 \\ \alpha y_t + (1-\alpha)EMA_t & t > 1 \end{cases} \quad (3)$$

where EMA_t represents the moving average at time t, y_t represents the observed value at time t, and $\alpha \in (0,1)$ represents the decay rate of the weights. A larger "α" indicates faster decay of past observed values. For standard deviation, the following formula is used:

$$S = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}} \quad (4)$$

where S represents the standard deviation, x_i represents the ith observed value, and n represents the number of observations.

Fourth, calculate the relationships between frequency bands, such as compute the correlation coefficient, covariance, etc. These indicators reflect the relationships between different frequency bands. The equation are as Equation (5) and (6) shown.

$$\mathrm{Cov}(X,Y) = \mathrm{E}[X - \mathrm{E}(X)]\mathrm{E}[Y - \mathrm{E}(Y)] \quad (5)$$

$$\rho_{XY} = \frac{\mathrm{Cov}(X,Y)}{\sqrt{\mathrm{D}(X)}\sqrt{\mathrm{D}(Y)}} \quad (6)$$

where Cov (X, Y) represents the covariance between random variables X and Y, and ρ_{XY} represents the correlation coefficient between random variables X and Y. The correlation coefficient standardizes covariance, resulting in a value between -1 and 1, measuring the degree of linear relationship between two variables.

Finally, to establish a detection model. Based on the feature extraction above, use the fitcsvm function to build a Support Vector Machine (SVM) model with an RBF kernel, and apply it to the detection and diagnosis of ECG power spectrum feature data.

$$\max \sum_{i=1}^{m} \alpha_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j x_i x_j$$
$$\text{s.t.} \quad 0 \le \alpha_i \le C \quad (7)$$
$$\sum_{i=1}^{m} \alpha_i y_i$$

In this model, m represents the number of training samples while α_i mesns lagrange multipliers of SVM corresponding to training samples. y_i and x_i are represent labels of training samples, indicating categories (+1 for positive class, -1 for negative class), and feature vectors of training samples, respectively. The upper bound C means penalty parameter of SVM, balancing classification errors and the margin of the decision boundary. It is a defined hyperparameter that can be adjusted based on the nature of the problem.

4.3 Data Processing Algorithm Analysis

Based on the Short-Time Fourier Transform (STFT) time-frequency features of ECG signals as one-dimensional time series, if we directly learn the original signal, we can only express the temporal features of the signal. To enrich the feature representation capability of ECG signals, we can incorporate the frequency domain information of the signal. Considering that ECG signals are non-stationary, the Fourier transform cannot be directly applied to obtain frequency domain features. Therefore, Short-Time Fourier Transform (STFT) is used to transform a heartbeat signal from the time domain to the time-frequency (TF) domain. Then the results can be combined with attention to extract features from the TF spectrum of the heartbeat signal. The STFT calculates the power spectrum of a signal over a short-time window, while moving the window function yields the entire time-frequency spectrum of the signal [6].

$$X(n,\omega) = \sum_{m=-\infty}^{m=\infty} x(m)\, w(n-m) e^{-j\omega m} \quad (8)$$

In signal analysis, the variables and functions X (n, ω), x(m), and w(n−m) play crucial roles in unraveling the characteristics of a signal. The outcome of the short-time Fourier transform, denoted by X at time n and frequency ω, serves as a dynamic representation, disclosing how the signal's spectrum evolves over different time intervals. Concurrently, the time-domain signal x at time m encapsulates the raw amplitude or value of the signal at specific instances, providing insights into its temporal behavior. To enhance the analysis of localized segments, the window function w(n−m) is employed, extracting a focused portion centered around time m. Furthermore, the symbol ω signifies frequency, measured in radians per second, reflecting the rate of oscillation or cycles per unit of time. Finally, the imaginary unit j, employed in mathematical contexts, is introduced to handle phase information in complex numbers within the Fourier analysis framework. Together, these elements form a comprehensive toolkit for understanding the intricate interplay between time and frequency in signal processing.

After performing STFT on a heartbeat signal, the resulting TF spectrum is a d×d dimensional matrix, which is a function of time (corresponding to different window movements) and frequency. Each column of the matrix represents the frequency distribution of the signal within the current window moment. The TF spectrum matrix for different types of heartbeats has

different dependencies on time and frequency dimensions. Therefore, attention mechanisms can be employed.

ECG signals are one-dimensional time series, and the temporal waveforms of different heartbeat types are different. One-dimensional convolutional neural networks (CNN) can be used to extract temporal features of heartbeats. Using a 3-layer one-dimensional CNN for feature extraction from filtered heartbeats, each layer includes a one-dimensional convolution (Conv), ReLU activation function, and pooling operation. The first two layers are max-pooling (MaxPool), and the last layer is average-pooling (AvgPool). The parameters for the convolutional layers in the CNN feature extraction network are set as shown in Table 2 (using Conv1d-7-4 as an example, and the other layers follow the same pattern).

Table 2. Convld-7-4 Convolutional Layer Parameter Settings

operate	Parameter settings
Conv	kernel_size=7, channels=4, stride=1, padding=0
ReLU	1
MaxPool	kernel_size=3, stride=2

The one-dimensional convolution operation slides the convolution kernel over the time-domain heartbeat signal according to the stride (Stride) to extract features through the dot product with the signal. ReLU activation function enhances the non-linear mapping capability of the model, and pooling reduces the dimensionality of the data, reducing feature redundancy. Each convolutional layer uses multiple channels (Channels) with different convolution kernels to extract features. If the number of sampling points in the signal is less than the size of the convolution kernel (kernel_size) in the last convolution, zero padding is used. After feature extraction by CNN attention Mechanism for Time-Frequency Feature Extraction in CNN can only capture the temporal features of heartbeats. Due to the influence of temporal random noise, it may not adequately represent the characteristics of different types of heartbeats. As a result, the classification network may not achieve satisfactory accuracy. By optimizing the monitoring system, the quality of the core components is improved, which in turn improves the overall accuracy [7]. Additionally, the convolutional kernel focuses on extracting local features of time-series signals, neglecting that a complete heartbeat should be a continuous time process with strong temporal dependencies. This makes it challenging for CNN to learn global correlation information from the signal. Inspired by the use of word embedding encoding in machine translation tasks, which encodes words into vectors and learns the global dependency relationships between vectors for semantic extraction, the time-frequency spectrum reflects the spectral characteristics of the signal at different moments, and different heartbeat signals have more discriminative power in the time-frequency domain compared to the time-domain sequence. Therefore, different time moments of the power spectrum can be used as input vectors, and an attention mechanism can be employed to extract the global features of heartbeat signals.

The Attention Block for time-frequency feature extraction based on the attention mechanism, consisting of N cascaded sub-modules which are concatenated to form the entire time-frequency feature extraction module. The process of each sub-module is as follows. Firstly, encode the TF spectrum matrix after STFT into position-coded column vectors to represent the relative positional relationships of the spectra at different moments using the position encoding vector calculated as follows [8]:

$$PE(pos, 2i) = \sin(pos/1000^{2i/d_f}) \quad (9)$$

$$PE(pos, 2i+1) = \cos(pos/1000^{2i/d_f}) \quad (10)$$

In Equation (9) and (10), the output PE (pos,2i) and PE (pos,2i+1) represent two elements in the position encoding vector, calculated using sine and cosine functions, respectively. These encodings are utilized to denote the relative positional relationships of the spectrum at different time steps. And d_f denotes the dimensionality of the position encoding. While pos represents the positional information.

Linearly mapping the signal TF matrix to multiple heads allows the same attention mechanism to learn features from multiple signal frequency representation subspaces. This enhances the ability to capture dependencies within different ranges (long-distance and short-distance, etc.) in the time-frequency domain when capturing the signal [9]. Self-attention is then performed in parallel

on these heads, and the computation process is as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (11)$$

In this equation, Attention (Q, K, V) represents the computation of the attention mechanism, where Q stands for query, K for key, and V for value. Softmax means the softmax function, utilized to normalize the attention distribution, ensuring that the sum of attention weights equals 1. And QK^T represents the scaled dot-product attention in the attention mechanism, while dk is the dimensionality of both query and key.

5. Experimental Simulation and Clinical Application

5.1 Experimental Simulation and Results Analysis

Applying the above model for feature analysis on certain abnormal electrocardiogram (ECG) power spectra, and categorizing them based on different types of arrhythmias, a judgment is made according to specific ECG waveform features and clinical symptoms [10]. Through K-means clustering analysis, the following results shows in the following Figures are obtained when k=4.

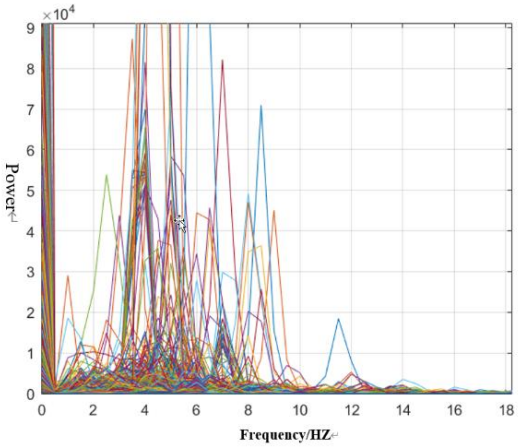


Figure 1. Data from Normal and Abnormal ECGs are Plotted Together

Figure 1 shows the analysis of abnormal ECG power spectra using the proposed model. Different colours represent different arrhythmia types in the merged plot of normal and abnormal ECG data, clustered into four clusters (k=4). Each cluster represents a different arrhythmia type. In the overall spectrum range, normal ECG shows a relatively smooth power distribution without prominent frequency peaks, exhibiting some uniformity at the center of the overall distribution. Except for some abnormal data in the ultra-low-frequency range, distinct energy peaks are observed in the lower frequency range, accompanying specific waveform shapes, indicating a certain type of arrhythmia. In the higher frequency range, sharp frequency peaks indicate another type of arrhythmia.

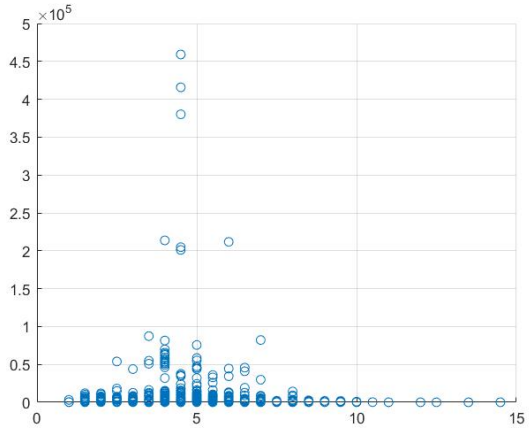


Figure 2. Abnormal ECG Power Density Peak Frequency and Corresponding Power

By analyzing the peak frequency and corresponding power distribution plots of abnormal electrocardiogram (ECG) power density, crucial information about the frequency domain features of abnormal cardiac signals can be obtained. As shown in Figure 2, ECGs with abnormal heart rates are commonly distributed in the frequency range of 1-7 Hz, with an overall lower power in the data.

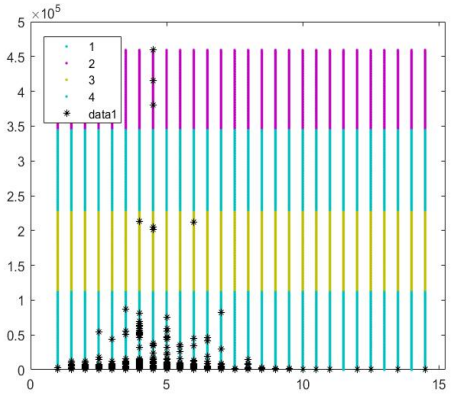


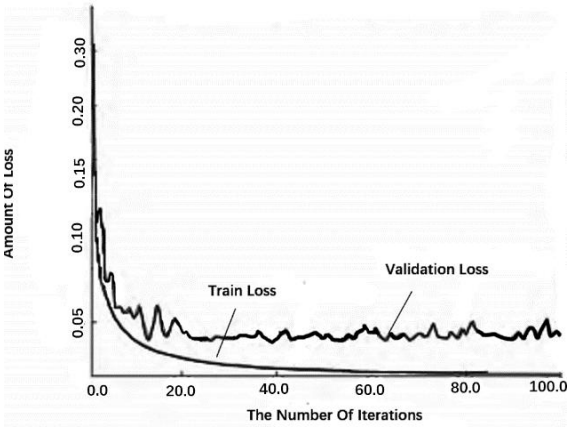
Figure 3. Classification of Abnormal ECG Power Density Peak Frequency and Corresponding Power

Abnormal ECG signals may be associated with specific physiological or pathological conditions. By classifying peak frequencies and powers, it is possible to discern abnormal ECG signals associated with different health or

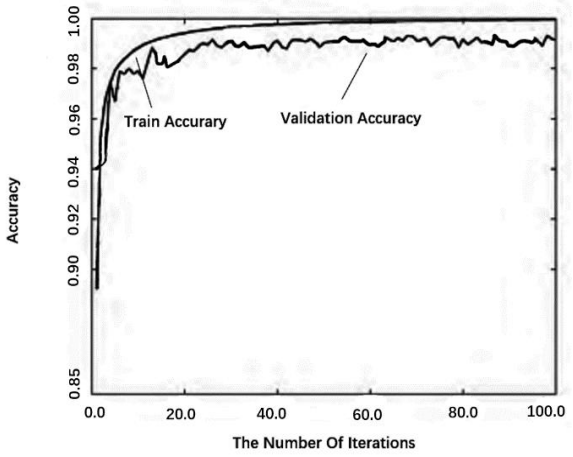
disease states. Figure 3 shows the Classification of abnormal ECG power density peak frequency and corresponding power. Based on the classification and analysis of the above algorithms, it was concluded that the abnormal ECG power spectrum could be divided into 826 cases of atrial fibrillation, 4 cases of premature ventricular contractions, 0 cases of premature atrioventricular contractions, and 3 cases of supraventricular tachycardia.

The loss function values for the training set and validation set change with the number of training iterations as shown in Figure 4(a). From Figure 4(a), it is observed that the loss function for the training set continuously decreases during the training process, and the loss function for the validation set decreases significantly in the early training stage, stabilizing after approximately 30 iterations. The classification accuracy on the training set and validation set during the training process is shown in Figure 4(b). Due to the larger proportion of normal heartbeats (N) in the original dataset, after balancing the data, the number of abnormal heartbeat features is smaller than normal heartbeat features. This meets the medical requirement in practical applications. Therefore, the model achieves good accuracy after one backpropagation optimization, primarily learning the features of normal heartbeats. As training progresses, the accuracy on the validation set continues to rise, converging around 0.99 after approximately 30 iterations, at which point the network learns the features of abnormal heartbeats. Based on the model's performance on the validation set, the optimal model is selected, and its confusion matrix on the test set is shown in Figure 4(c).

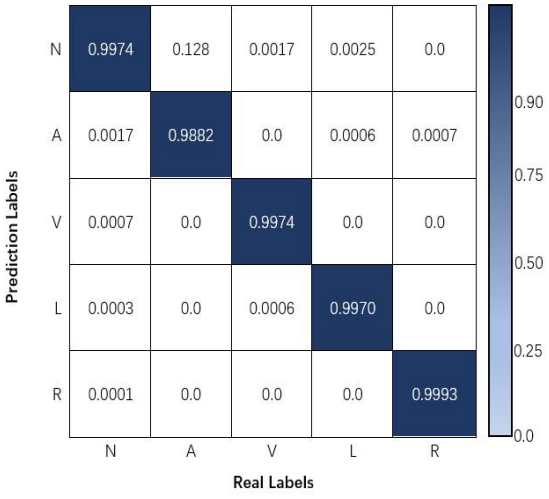
From Figure 4(c), it is clear that the classification accuracy for normal heartbeats (N), ventricular premature contractions (V), left bundle branch block (L), and right bundle branch block (R) is 99.70%, 99.74%, 99.70%, and 99.93%, respectively, all close to 100%, indicating that the model can classify these four types of ECG signals almost without error. The accuracy for atrial premature contractions (A) is slightly lower but still reaches 98.82%. Through a comprehensive analysis of various evaluation indicators, the proposed model performs well on the five classes of ECG signals, all indicators exceeding 0.9.



(a) Curves of Loss Function Values on the Training and Validation Sets



(b) Accuracy Curves on the Training Set and Validation Set



(c) Confusion Matrix

Figure 4. Model Evaluation and Tuning

In summary, the CNN model is able to effectively learn various features of different ECG signals, and it exhibits excellent performance in various performance metrics for ECG signal classification.

5.2 Clinical Application and Diagnosis

Considering the impact of arrhythmias on cardiac supply function, a diagnostic model is established to rank and score arrhythmias from high to low risk:

1)Ventricular fibrillation or cardiac arrest: 10 points. The heart loses effective contraction, blood flow stops suddenly, and the patient is in a life-threatening state, requiring immediate cardiopulmonary resuscitation.

2)Ventricular tachycardia: 8 points. Frequent contractions of the ventricles lead to a decrease in cardiac output, requiring timely treatment.

3)Ventricular premature contractions: 7 points. Premature contractions of the ventricles can cause transient bradycardia, requiring monitoring to prevent deterioration.

4)Atrial fibrillation: 6 points. The atria lose orderly activation, and cardiac output decreases. Anticoagulation and rate control are necessary to prevent thrombosis and episodes.

5)Atrial flutter or tachycardia: 5 points. Frequent contractions of the atria can affect ventricular filling and ejection, requiring treatment and control.

6)Atrial ectopy (atrial premature contractions): 3 points. Occasional shortening of the atrioventricular conduction time has a minimal impact on blood flow but requires monitoring.

7)Sinus rhythm normal: 1 point. The heart is activated and contracts in an orderly manner, maintaining normal hemodynamics.

The risk level is represented by a score ranging from 1 to 10, with a higher score indicating a higher risk level that requires more rapid treatment intervention. The scoring results are based on the physiological impact of different arrhythmias on cardiac output and cardiac supply function and serve as a reference for clinical ECG monitoring alarms.

The algorithmic implementation of the diagnostic model is as follows:

First, to define seven types of arrhythmias and their corresponding risk scores.

Second, to input the electrocardiogram (ECG) data file, and use the HR_analysis function to identify the type of arrhythmia.

Third, to calculate the average score for the identified arrhythmia type and determine the risk level based on preset thresholds.

Fourth, to display the type of arrhythmia, average score, and risk level.

Fifth, using the HR_analysis function to identify arrhythmias based on the ECG.

This scoring system is designed based on the impact of arrhythmias on cardiac function, where a higher score indicates a higher level of risk, aligning with the physiological basis of clinical judgment. However, in practical applications, personalized assessment based on the specific condition of the patient is still required, and this system should be considered as a reference tool.

6. Summary

Heart rate monitoring plays a crucial role in medical and health management, and the introduction of mathematical analysis methods makes it possible to achieve a deeper understanding of heart rate data. By discussing the applications of convolutional neural networks (CNNs), clustering analysis, and short-time Fourier transform (STFT) in heart rate monitoring, this paper delves into the importance of these methods in improving monitoring accuracy and expanding application areas. The mathematical perspective on heart rate monitoring methods provides a new dimension for medical and health management research. The continuous optimization of CNNs, clustering analysis, and short-time Fourier transform, among other mathematical analysis methods, will drive heart rate monitoring towards greater precision, intelligence, and profound impacts on future medical, health management, and social research.

Although we get some results in this study, it has limitaions as follows. 1)Data Quality and Sample Size: The paper does not deeply discuss potential data quality issues in heart rate monitoring, such as anomalies and missing values, and the coupling of models in small sample sizes. These issues can significantly impact the reliability and universality of practical applications. 2)Algorithm Explanation and Interpretability: The paper does not thoroughly explore the inherent mechanisms of these methods and the interpretability of their output results. In the medical field, the interpretability of algorithms is crucial for acceptance and credibility in clinical practice.3) Verification in Real-World Applications: The paper does not cover the validation and application of the mentioned mathematical methods in real clinical scenarios. Future research should consider testing these

methods in different diseases or specific patient populations for practical testing.

In future research, improvements can be made in the following aspects:

A) Intelligent and Personalized Healthcare: With the continuous application of mathematical methods in heart rate monitoring, future developments may lead to more intelligent and personalized healthcare.

B) Big Data and Cross-Domain Integration: With the advent of the big data era, the field of heart rate monitoring will be able to handle larger and more diverse datasets. By integrating heart rate data with genomics, bioinformatics, and other multi-domain data, a more comprehensive understanding of individual health conditions can be achieved.

C) Real-Time Monitoring and Preventive Health Management: Further developments in wearable devices and imperceptible sensing technologies can expand heart rate monitoring to real-time monitoring. Through mathematical methods, potential health issues can be identified in a timely manner, enabling more preventive health management and reducing the risk of disease occurrence.

D) Deep Learning and Model Optimization: Future research can focus more on the application of deep learning methods. By employing more complex neural network structures and model optimization techniques, the learning capabilities and generalization performance of models can be improved, making heart rate monitoring more accurate and reliable.

E) Standardization and Clinical Practice: As technology continues to advance, future efforts can be directed towards standardizing heart rate monitoring methods. Standardization helps lower the technical barriers, allowing more medical institutions and professionals to apply these methods.

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