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Research Progress of Intelligent Auscultation Technology Based on Deep Learning in Congenital Heart Disease

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Abstract: Congenital heart disease (CHD) is one of the most common congenital birth defects. With the deepening of people's understanding of CHD disease and the continuous improvement of screening methods, children with CHD have been able to receive diagnosis and treatment at an early stage, thus improving the survival rate and quality of life. The main means of early screening of CHD are heart sound auscultation and percutaneous oxygen saturation detection. At present, there are relatively mature commercial equipment for transcutaneous oximetry, but the heart sound assessment is greatly affected by personal experience and external factors, which is prone to misdiagnosis and missed diagnosis. In recent years, the continuous development of artificial intelligence (AI) makes the digital collection, storage, and analysis of heart sound signals, and then makes the intelligent auscultation-assisted diagnosis technology of cardiovascular diseases possible. At present, it is based on deep learning. DL's AI algorithm has been extensively studied in CHD cardiac sound auscultation assisted diagnosis, but most of them are still in the algorithm research stage and are implemented based on specific data sets, and have not been verified in clinical Settings. In this paper, the development and research status of AI auscultation technology at the current stage are reviewed, the development of DL based intelligent auscultation technology in the field of CHD in recent years is summarized and the problems to be solved in the clinical application of heart sound auscultation are proposed.

Keywords: Congenital heart disease; Artificial intelligence; Deep learning; Auscultation of heart sounds

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1. Introduction

Congenital heart disease (CHD) is one of the most common congenital birth defects, accounting for about 1%–1.2% of live births and occupying the first place in the case fatality rate of neonatal non-infectious diseases [1]. At present, with the deepening of people's understanding of CHD disease, CHD screening methods are constantly improved and children with CHD can be diagnosed and treated at an early stage, to improve the survival rate and improve the quality of life. With the inclusion of CHD screening in China's neonatal disease screening spectrum and the promotion of the "dual index" program, the diagnosis and treatment of CHD screening has been carried out in an all-round way [2]. At present, there are mature commercial equipment for pulse oxygen determination in the "double index" scheme, while cardiac auscultation requires the examiner to make subjective experience judgment through the stethoscope, which is greatly affected by personal experience and external factors, and is prone to misdiagnosis and missed diagnosis. Currently, fundamental decision-making methods, such as heart sound auscultation, used to identify cardiac abnormalities and assess cardiac function classification based on indicators like heart sound intensity and murmurs, still encounter significant challenges and limitations [3].

In recent years, with the development of modern information technology and the wide application of non-invasive detection such as cardiac Doppler color ultrasound and electrocardiogram, machine learning (ML) and artificial neural network (artificial neural network) have been combined. Artificial intelligence (AI) technologies, such as ANN and deep learning (DL), enable the digital collection, storage and analysis of heart sound signals, and then make the intelligent auscultation technology of CHD heart sound possible [4, 5]. AI technology, which simulates the brain's thinking operation mode through intelligent systems to obtain memory and decision-making ability, has become a hot spot in modern science and technology in the medical field [4]. AI auscultation technology mainly involves the denoising, segmentation, feature extraction, classification, and recognition of heart sound signals [6, 7]. This paper reviews the relevant literature on the combination of heart sound signal and AI technology, summarizes the development and application of DL based intelligent auscultation technology in CHD in recent years, and puts forward the problems to be solved in clinical application.

2. Heart sounds and heart murmurs

Heart sound is a complex sound produced by the opening and closing of heart valves, the diastolic contraction of heart tendons and muscles, the impact of blood flow, and the vibration of the cardiac wall, which can be recorded as a heart sound signal which is also known as phonocardiography (PCG) [6]. PCG is quasi-periodic and the cycle of each heart sound signal is called the cardiac cycle. According to the order in which they occur during the heartbeat cycle, heart sounds are divided into four segments: first (S1), second (S2), third (S3), and fourth (S4). S1 occurs at the beginning of the systolic period of the heart, with a low pitch and a long duration (frequency :50–100Hz, duration: 50–100ms), which is caused by the contraction of the ventricular muscle, the sudden closure of the atV valve and the subsequent ejection of the main artery. S2 occurs at the beginning of the diastolic period of the heart, with a high frequency and a short duration (frequency :50–200Hz, duration: 25–50ms), which is caused by the closure of the semilunar valve, the impact of the valves on each other, and the vibration caused by the deceleration of blood in the great artery and the rapid drop in indoor pressure [8]. S1 and S2 (S3 appears only in the heartbeat cycle of some healthy young people, S4 does not appear in the normal heartbeat cycle) are easier to hear and often serve as the basis for the localization of heart sound segments [9]. The period between S1 and S2 of the same PCG is called systolic and the period between S2 and S1 of the next cycle is called diastolic. A complete cardiac cycle is 0.8 seconds, normal systole is about 0.35 seconds, and diastole is about 0.45 seconds. These values are closely related to cardiovascular diseases [10].

Cardiac murmur refers to the abnormal sound of ventricular wall, valve or blood vessel vibration caused by turbulent blood flow in the heart or blood vessels during cardiac contraction or diastole in addition to heart sounds and additional heart sounds (heart sounds other than S1 and S2). It is a group of non-heart sound vibration with a long duration, different frequency, and different amplitude [4]. The intensity, frequency and quality characteristics of heart sounds reflect the condition of heart valves, myocardial function, and intracardial blood flow. The generation of heart murmurs has a crucial relationship with cardiovascular diseases, especially in the early screening of CHD [10]. However, artificial auscultation of heart sounds is a method based entirely on subjective experience. AI auscultation technology helps to discover the relationship between heart sounds and related diseases by analyzing heart sounds to obtain quantitative characteristic parameters [6, 8, 10].

3. Artificial intelligence heart sound auscultation technology

AI-assisted detection technology is a fast, efficient and economical tool that can be applied to the quantitative analysis of heart sound signals to obtain more intuitive diagnostic results and further infer potential cardiovascular diseases by extracting key parameters in PCG [10]. Artificial intelligence auscultation technology mainly involves PCG signal denoising, segmentation, feature extraction, and classification recognition [6, 7].

3.1. Denoising of heart sound

Due to the influence of external environment, heart sound signals are inevitably coupled with electromagnetic interference, random noise, respiratory sound, lung sound, etc. [11]. The diagnostic accuracy of heart sound diagnosis is directly affected by signal quality and subsequently extracted features. Therefore, before analyzing the heart sound signal, it is necessary to carry out noise reduction processing. At present, the widely studied and applied methods of heart sound noise reduction include discrete wavelet transform (DWT), empirical mode decomposition (EMD), singular value decomposition (SVD) and other methods [11–15].

In addition, the combined method can obtain better results in the noise reduction of heart sound signal, which is helpful to improve signal quality and detection accuracy. Mondal *et al.* proposed a method for heart sound noise reduction based on the combination of DWT and SVD, while Zheng *et al.* proposed an innovative denoising framework based on the combination of improved SVD and compressed sensing (CS) [11, 15]. The framework has a larger signal-to-noise ratio, while retaining the high correlation between the de-noised heart sound signal and the original heart sound signal.

Some interference signals (lung sound, environmental sound, etc.) may have obvious frequency aliasing phenomenon with heart sound signals, which makes the noise reduction method based on signal frequency decomposition difficult to apply and greatly affects the extraction of heart sound features in congenital heart disease. To solve this problem, Shah *et al.* performed nonnegative matrix factorization (NMF) on the time spectrum of single-channel mixed heart sound signals according to the correlation of the signal components of heart and lung sound and combined with the clustering method to distinguish the basis matrix and coefficient matrix of NMF [16]. The parts belonging to heart sound or lung sound are obtained, and the source signal is obtained by signal reconstruction, to realize the noise reduction extraction of heart sound.

3.2. Heart sound segmentation

The segmentation of heart sound is the premise of classifying the characteristics of heart sound to determine the position interval of S1, systolic, S2, and diastolic states in heart sound signal. Segmentation of heart sounds is beneficial to extract the characteristics of heart murmurs from each state of heart sounds, to analyze and diagnose congenital heart disease with the help of the rich pathological information in the murmurs. In this regard, domestic and foreign scholars have proposed a large number of segmentation methods of heart sound. **Table 1** summarizes some literature on segmentation of heart sound in recent years [17–22].

3.3 Extraction and classification of heart sound features

Before classifying heart sounds, it is necessary to extract a small number of representative categorical features of heart sounds from segmented heart sounds to replace high-dimensional original signals [7]. In general, classification models based on feature training are more efficient and accurate than those based on raw signal training. Common methods for extracting heart sound features include: DWT, continuous wavelet transformation (CWT), short-time fourier transform, STFT), mel-frequency cepstral coefficient (MFCC), and variational mode decomposition (VMD)[23–25].

After extracting heart sound features, the heart sound classification algorithm classifies the extracted heart sound features, to realize the screening and auxiliary diagnosis of CHD. Classification problems usually adopt methods such as binary classification, multiple classification and regression, and the selection of classification tasks will also affect the classification results to some extent [26]. According to the principle of machine learning (ML) algorithm, heart sound classification algorithms can be divided into two categories: classification algorithms based on traditional machine learning and classification algorithms based on deep learning [27, 28].

Classification algorithms based on traditional machine learning allow computer systems to efficiently access and analyze data by manually designing effective features of heart sounds, adjusting and improving functions based on patterns and experience, without the need for explicit programming. Currently, the commonly used classification algorithms include: support vector machine (SVM), random forest (RF), decision tree, MFCC and other algorithm models [27]. Deng *et al.* used DWT to calculate the envelope from the subband coefficient of heart sound signal, and extracted the autocorrelation features from the envelope [29]. Then, the autocorrelation features are fused to obtain a unified feature representation with diffusion mapping. Finally, the unified features are input into the SVM classifier to complete the heart sound classification task. Yaseen *et al.* proposed to combine MFCC features with DWT features to achieve heart sound classification and compared SVM, K-proximity algorithm based on centroid displacement, and deep neutral networks (DNN) algorithm [30]. The results showed that SVM classifier achieved optimal classification performance. The average accuracy rate is 97.9%.

In terms of intelligent auscultation-assisted diagnosis of CHD, Aziz *et al.* proposed to extract MFCC features from heart sound signals and combine them with One-Dimensional Local Ternary Patterns to realize the tripartite classification of atrial septal defect, ventricular septal defect and normal heart sound [27]. One-dimensional local ternary pattern(1D-LTP) features were used to classify congenital heart disease. SVM classifier was used in the training stage, and the final average accuracy was as high as 95.24%. Zhu *et al.* used the backpropagation neural network as a classifier to analyze and extract the features of heart sounds by using two methods: MFCC features and linear predictive cepstral coefficients (LPCC) [31]. The results showed that MFCC feature (specificity: 93.02%, sensitivity: 88.89%) was superior to LPCC feature (specificity: 86.96%, sensitivity: 86.96%).

Algorithms based on traditional machine learning rely on artificially designed effective features of heart sounds and once the feature selection is not ideal, the algorithm performance will be poor, so the feature selection is crucial. However, for heart sounds with different pathologies in various environments, it is extremely difficult to manually design and screen effective heart sound features, which makes it difficult for classification algorithms based on traditional machine learning to further optimize [27]. With the increasing incidence of cardiovascular diseases, the amount of heart sound data that needs to be processed is also increasing. To ensure the accuracy of classification while processing a large amount of data, deep learning algorithms have emerged.

4. Development and application of deep learning in the classification of heart sounds

Deep learning (DL) is the general term of machine learning technology that applies neural networks [32]. Through deeper learning than traditional machine learning, neural networks are built layer by layer to form a multi-level deep neural learning network. The machine can autonomously identify, extract, and express the more essential data features hidden in the data from the database or data set, thereby improving the accuracy and efficiency of classification [3]. In 2006, Hinton *et al.* proposed the concept of deep learning for the first time, which combines low-level models to form more complex high-level models by using the relative relationship of space, thus greatly improving the training performance of the system [33]. In recent years, DL algorithm has shown good practicability and reliability in image recognition, biomedical data analysis, signal processing and other fields [34–37]. DL model has been applied to the classification of heart sound signals, mainly including DNN, convolutional neural network (CNN), recurrent neural network (NN), etc. RNN, long short term memory (LSTM), etc. [27, 32, 38].

The classification algorithm based on DL is the pointer to the waveform diagram of the heart sound signal or the extracted time-frequency domain features, the artificial design features and the combination of deep neural network to automatically extract more advanced abstract features, and finally realize the classification of heart sounds. Compared with traditional heart sound classification algorithms, deep learning technology avoids the problems of manual intervention, complex process and poor generalization ability [26]. Potes *et al.* extracted 124 time-frequency domain features of heart sound signals and used AdaBoost classifier to classify these features [28]. In addition, signals of 4 frequency bands were extracted and input to 1D-CNN for classification. Won first place in the 2016 PhysioNet Heart Sound Classification Challenge. Oh *et al.* used a new deep wave network model to perform the quintuple classification task (normal, aortic stenosis, mitral valve prolapse, mitral stenosis and mitral regurgitation) on the heart sound data set, with an accuracy of 97% and a classification accuracy of 98.20% for normal heart sounds [39].

Among many artificial neural network models, CNN model is superior to traditional artificial neural network in extracting image feature values by converting original data into two-dimensional matrix format [26]. Thanks to its convolution, pooling, and other operations, the CNN model can build a deep CNN model by stacking multiple convolutional layers and pooling layers, which can achieve excellent performance in computer vision tasks (images, video data, etc.) [40-42]. Kui *et al.* combined log mel-frequency spectral coefficients (L-MFSC) and CNN to classify heart sounds, and the binary classification accuracy of this method was 93.89% and the multi-classification accuracy was 86.25% [41].

Krishnan *et al.* used one-dimensional CNN and feedforward neural network to classify unsegmented heart sounds, with an average accuracy of 85.7% [42]. Li *et al*. extracted the deep features of heart sounds by noise reduction autoencoder, and used one-dimensional CNN as a classifier, so that the classification accuracy was 99% [43]. However, the study extended the original data set to allow fragments of the same record to appear in the training set and the test set, so the classification accuracy is higher than the actual, which is not in line with the clinical application environment. In the study on the influence of different DL models on heart sound classification, Deng *et al.* used MFCC features combined with first-order and second-order differential features as network input to achieve heart sound classification and compared different network models, the results showed that CNN had the optimal classification accuracy (98.34%) [40].

5. Application status of intelligent auscultation technology in CHD

Intelligent heart sound auscultation technology uses deep learning to efficiently identify cardiac audio signal abnormalities, such as heart murmurs and arrhythmias, to provide doctors with auxiliary diagnostic information. Xiao *et al.* constructed a pediatric heart sound dataset containing 528 high-quality heart sound recordings from 137 subjects and developed a DL-based computer-aided diagnosis system for CHD in children using two lightweight CNN models [44]. Xu *et al.* established a children's CHD heart sound database containing 941 heart sound signals and on this basis adopted random forest-based classifier and Adboost classifier to achieve accurate classification of CHD [45]. The results showed that the sensitivity, specificity and F1 scores of this method for CHD classification were 0.946, 0.961, and 0.953, respectively.

The intelligent heart sound auscultation device combined with Internet technology realizes the remote transmission and monitoring of heart audio signals, which is of great significance for long-term monitoring of heart health patients. The intelligent digital stethoscope system proposed by Chowdhury realizes wireless communication through Bluetooth low-power technology and can monitor patients' heart sounds in real time and carry out abnormal diagnosis [46]. The test results show that the system can classify abnormal and normal heart sounds with 97% and 88% accuracy, respectively.

Heart sound intelligent auscultation technology can be used in medical education and training to help medical students and physicians learn and familiarize themselves with the characteristics and diagnostic methods of cardiac audio signals. Auscultation relies on the subjective experience of doctors, and there are great differences in auscultation diagnosis among different doctors. The lack of senior cardiologists in primary medical units and the lack of auscultation ability of young interns limit the promotion and application of auscultation screening in CHD [47]. Through intelligent auscultation equipment and teaching software, medical students and doctors can perform virtual auscultation and simulated diagnosis, as well as improve their auscultation skills and diagnostic ability. Therefore, the development of computer-aided auscultation algorithm and system is not only an effective way to realize CHD screening and diagnosis, but also can be used in retrospective teaching and clinical teaching.

6. Problems and challenges faced by intelligent auscultation of congenital heart disease

Although the intelligent auscultation of heart sound has a broad application prospect in the medical field, there are still some challenges and limitations. With the continuous development and maturity of AI technology, intelligent auscultation of heart sound is expected to provide a more accurate and convenient method for the early screening, diagnosis, and monitoring of heart diseases.

In terms of heart sound preprocessing and data set problems, the acquisition of heart sound signals is subject to a variety of interferences, including environmental noise, acquisition equipment noise, and interference from other organs. Commonly used noise reduction techniques, such as DWT and EMD, struggle to accurately differentiate between heart sound signals and noise [11–14]. As a result, obtaining a precise adaptive threshold function is challenging. Moreover, spatial transformation and linear filtering methods often fail to fully separate heart sounds from noise, which can easily lead to distortion of the heart sound signal. In addition, the segmentation of heart sounds is the basis of feature extraction and classification. However, because abnormal heart sounds are seriously disturbed by pathological murmurs and noises, it is difficult to divide the cardiac cycle accurately. Some researchers use intercepted heart sounds of fixed duration as research objects, while others use original heart sound sequences of irregular duration [28, 29, 48]. The lack of temporal structure information leads to inconsistent starting time of different segments or sequences, which affects the matching between feature extraction and cardiac cycle structure, and affects the recognition performance.

DL model training requires a large number of feature parameters and label sample data, but insufficient data or inconsistent distribution will lead to performance degradation. For this reason, domestic and foreign teams have also created multiple data sets and used them to develop and verify AI algorithms, most of which have an accuracy rate of more than 90% [20, 45, 49]. However, the existing data sets generally have problems such as small amount of data, less noise, incomplete labels, and lack of standardized recognition, which makes the robustness and universality of the algorithm in practical application need to be improved. Especially in China, the lack of high-quality, standardized, well-labeled, and open heart sound database has become the biggest obstacle restricting the improvement and testing of intelligent auscultation algorithm of heart sound. Therefore, the establishment of a standardized heart sound database is a top priority and it is necessary to further organize experts to reach a consensus to standardize the heart sound signal acquisition process, unify the acquisition equipment, clarify the database architecture and signal characteristic parameters, to improve the level of heart disease screening, diagnosis and monitoring, and promote the establishment and improvement of artificial intelligence assisted auscultation system.

In terms of heart sound algorithm and model construction, the existing algorithms and models are mainly aimed at adult heart valve and large blood vessel diseases, while the differences in disease types, heart rate, and heart sound characteristics in children need to be targeted. In addition, the construction of DL model requires a large amount of computing resources, especially powerful central processing unit (CPU) and graphics processing unit (GPU) to perform calculations [10]. Future research should focus on optimizing the structure of DL model, reducing the number of feature parameters, and improving the generalization performance of the model. Develop more effective training methods and utilize techniques such as transfer learning.

DL models optimize parameters through error backpropagation, making it difficult to explain the correlation or causality between input data and output diagnostic results in clinical applications. As a result, these models cannot provide a clear diagnostic rationale or insights into etiology and pathology. The lack of interpretability in the classification results of heart sounds makes them difficult for clinicians to trust and adopt in practice. Therefore, to realize the clinical application of the model, seeking the explainability of the model is also the challenge facing DL technology at this stage. The development of heart sound decision system needs interdisciplinary cooperation, involving medicine, engineering, computer science and other fields, and the solution of these problems also needs close cooperation between researchers, clinicians and engineers to promote interdisciplinary collaborative work, to promote the heart sound auscultation assisted diagnosis system to serve more widely in the medical field.

7. Conclusion

With the continuous development of artificial intelligence technology, intelligent auscultation-assisted diagnosis technology of cardiovascular diseases has become possible. In recent years, DL based AI auscultation technology has been widely studied and applied in the field of CHD, but these technologies still face many challenges and uncertainties in clinical practice. Although AI auscultation technology shows considerable potential in theory, its effectiveness and reliability in clinical Settings have not been fully validated. There are still deficiencies in the practicability, consistency and interpretability of this AI auscultation technology in clinical applications, which also leads to the lack of mature commercial products to be widely used in clinical CHD screening. To solve this problem, relevant medical institutions should organize experts to jointly develop a common and standardized procedure for the screening of heart sounds for congenital heart disease, and on this basis, a complete database of CHD heart sounds in children should be established to support follow-up research and development.

At the same time, to further improve the performance and reliability of intelligent auscultation technology, relevant research institutions need to further improve and optimize the heart sound classification algorithm and improve the interpretability between the input and output results of the heart sound classification model so that medical personnel can make correct clinical judgments. Through these efforts, we aim to achieve intelligent auscultation-based screening, diagnosis, and monitoring of congenital heart disease (CHD). AI-driven auscultation technology will offer CHD patients more timely, comprehensive, and accurate medical services, enabling full life-cycle management for children with CHD. Furthermore, it will accelerate the development of a nationwide CHD screening and diagnostic network, making significant contributions to safeguarding children's health.

Disclosure statement

The authors declare no conflict of interest.

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