

Retraction

Retracted: Intelligent System of Somatosensory Music Therapy Information Feedback in Deep Learning Environment

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] N. Zhao, "Intelligent System of Somatosensory Music Therapy Information Feedback in Deep Learning Environment," *Complexity*, vol. 2021, Article ID 9935504, 11 pages, 2021.

Research Article

Intelligent System of Somatosensory Music Therapy Information Feedback in Deep Learning Environment

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In the treatment of children with autistic spectrum disorder (ASD) through music perception, the perception effect and the development of the disease are mainly reflected in the fluctuations of the electroencephalogram (EEG), which is clinically effective on the brain. There is an inaccuracy problem in electrogram judgment, and deep learning has great advantages in signal feature extraction and classification. Based on the theoretical basis of Deep Belief Network (DBN) in deep learning, this paper proposes a method that combines the optimized Restricted Boltzmann machine (RBM) feature extraction model with the softmax classification algorithm. Brain wave tracking analysis is performed on children with autism who have received different music perception treatments to improve classification accuracy and achieve the purpose of accurately judging the condition. Through continuous adjustment and optimization of the weight matrix in the model, a stable recognition model is obtained. The simulation results show that this optimization algorithm can effectively improve the recognition performance of DBN, with an accuracy of 94% in a certain environment, and has a better classification effect than other traditional classification methods.

1. Introduction

With the rapid development of music perception diagnosis and treatment, clinical music perception diagnosis and treatment of children with autism are also gradually expanding. Studies have shown that, in order to improve the ability of attention and concentration and the ability to communicate with others and enhance the coordination of the limbs of autistic patients, the treatment of music perception is the best choice [1]. A large number of studies have shown that the excitement of the brain when listening to music is mainly manifested in the right brain, which can also control many emotions and behaviors of people [2]. Listening to music can promote the communication between people and the outside world and express their inner emotions, thereby regulating people's emotions and behaviors. This is the main principle of music perception therapy [3]. Music can improve the functions of different areas of the brain, can promote the coordination of the left and right hemispheres of the brain, thereby promoting the development of infants and young children's intelligence,

and can also improve the behavior of children with intellectual disabilities. It is a mainstream trend to apply it to special education and education for children with autism [4]. EEG signal is the best indicator to reflect the working state of the human brain, because EEG collects electrical signals from brain neurons [5]. EEG is closely related to mental disorders. A large number of studies have shown that brain waves have different amplitude, power, and left-right asymmetry for autistic patients than healthy people [6]. With the continuous development of EEG signals and the achievements of mental disorders through EEG analysis, researchers have become more convinced that EEG contains useful information for diagnosis and treatment. This will be of great significance for the prevention of mental disorders and its diagnosis and treatment [7].

In the clinical analysis and diagnosis of the EEG signals of patients with autism, doctors' diagnostic skills are limited. Manual diagnosis is usually slow and subjective. Therefore, more and more researchers are beginning to pay attention to deep learning algorithms and use them. It is applied to the automatic recognition and classification of EEG signals [8].

Deep learning has a major breakthrough in the field of machine learning, especially in the application of speech signal recognition and image recognition, which makes it of great practical significance in the EEG classification problem [9]. But not all problems can be achieved with deep learning. For example, in natural language processing and logical inference, deep learning is not good [10]. Whether music perception therapy has a positive effect on children with autism and how to effectively apply deep learning to the classification of the EEG of children with autism, improve the accuracy of EEG classification, and achieve the purpose of accurately judging the condition are yet to be investigated.

One of the reasons for the inaccurate artificial judgment of EEG is that the collected EEG data is doped with a series of noises such as power frequency interference and ocular artifacts. Before collecting data, it is necessary to screen experimental subjects, select suitable music works, and set up an experimental environment. Next, the specific operations of these contents will be described. In order to provide relatively pure data support for the subsequent EEG classification, this paper uses the convolution neural network (CNN) method to detect the ocular artifacts of the original signal and uses the Hilbert-Huang transform (HHT) combined with FastICA method to remove noise. Compared with traditional denoising methods, CNN's predetection method greatly saves the workload of subsequent noise removal. HHT has shown great advantages in the process of processing nonstationary signals. FastICA is faster than traditional ICA methods. With convergence speed and less CPU usage, through the evaluation of the denoising effect, it is found that the signal-to-noise ratio (SNR) after denoising has been improved, and the root mean square error (RMSE) is reasonable. Aiming at the shortcomings of traditional DBN recognition performance that is not very high, this paper proposes an improved algorithm for DBN EEG recognition based on the dual features of frequency band energy ratio (FBER) and moving average sample entropy (MVSE). This method first extracts the characteristics of both from the sample EEG data according to the extraction process of FBER and MVSE and then inputs the matrix of these characteristics as the characterization information of the original waveform into the DBN network.

2. Related Work

Since the 1950s, machine learning, as a subfield of artificial intelligence, has provided advanced ideas and technologies that keep pace with the times in many industries. As one of the latest development directions of machine learning, deep learning has achieved the greatest creative breakthrough in almost every application field and has made remarkable achievements. Related terms in machine learning have long been published by the Google Engineering Education team. It is expressed in multiple languages. In recent years, deep learning has made great progress in target recognition, especially language recognition, license plate recognition, and clothing images recognition, etc., which makes deep learning more and more recognized by the academic and commercial circles. Whether in the clinical analysis of bioelectricity, or

the processing of signals and information in the field of science and technology, in-depth learning has brought great convenience and far-reaching influence to researchers. In recent years, Brotons and Koger [11] analyzed 34 epileptic seizures of 9 patients at the Research Center of the Freiburg Medical School in Germany, which verified the high standard of the accuracy of the Conviction Network in classifying EEG abnormalities in patients with epilepsy. In 2017, Thaut et al. [12] used the classification method of support vector machine (SVM) to classify emotions stimulated by music by using EEG signals as a medium and achieved a good classification effect. In 2020, Hatwar and Gawande [13] used the KNN (nearest neighbor) classifier to analyze EEG signals to recognize human emotions, and the effect was significant. From this point of view, as one of the most popular concepts in the field of artificial intelligence, deep learning, coupled with its technology that keeps pace with the times, is having a significant impact on human life in the past, present, and future.

The brain's cognition of music is a complex process. The cognitive effect is mainly manifested by changes in the EEG waveform. The shallow EEG characteristics can no longer interpret music emotions well. Therefore, more and more scholars are gradually exploring the deep features of EEG. The development of brain science and cognitive science has greatly promoted researchers from all over the world to explore the relationship between music and brain function [14]. According to information from academia, in 2020, Jackson and Gardstrom [15] combined the advantages of multiple machine learning algorithms in response to key issues in the "multimodal interactive perception of music" and made detailed verification and reports on the classification of music emotion regression. Then they put forward the design plan of "music visualization," which provided new ideas for the majority of researchers. Music perception ability is also related to many other cognitive abilities, such as language talent, attention, memory, visual stimulation cognition, and auditory cognition. Murphy [16] and others once compared deaf children with cochlear implants and normal hearing children in terms of their perception of music. In order to assess the ability of listening to music, the music perception test was used. The researchers found that there were no significant differences in the scores in the perception of pitch and discordant tones between the two groups of subjects, except the auditory performance and melody. There is a positive correlation with the discernment. Experimental results show that deaf children with cochlear implants have significant characteristics that are different from ordinary people's perception of music melody, but not all music melody tests have such findings. Researchers from Spain used 116 sixth-grade primary school students in four schools in the Basque Country as experimental subjects in 2014 to analyze the correlation between music perception and auditory motivation. The research showed that the difficulty of music perception is related to the students' motivation [17]. In addition, the most motivated students prefer activities related to instrument performance and music audition. In 2018, researchers from East China Normal University in China combined the principles of

electronic information technology and music therapy, respectively selected hypersensitivity music therapy and brain wave induced music therapy to conduct research, developed a kind of listening suitable for children in special education and method music therapy aids, and made a hardware system [18]. The research results and status quo in recent years have shown that domestic and foreign scientific researchers, medical workers, etc. have devoted great enthusiasm and research efforts to the application of music perception. The treatment of music perception is for people with physical disabilities or for people with physical disabilities. Patients who are healthy but have mental illnesses all have an active therapeutic effect.

In the 1980s, some researchers studied the relationship between the high and low frequency bands of the beta rhythm in brain waves and emotional processing, and the results showed that the difference in brain activity is caused by the different high and low frequency bands of positive and negative emotions in each rhythm, especially the activity and instability in the temporal and right temporal lobes of the brain [19]. Studies have confirmed that, in the process of exploring the mechanism of brain action, music can be used as a source of emotional cognition. This view can be reasonably explained in biomedicine. In order to collect the ERP produced by the human brain, some staff used brief sounds as the stimulus source and studied the brain's role in processing music by analyzing the changes in the characteristics of the brain electrical signal during the experiment and found the role of the right half of the temporal lobe. Some scholars have introduced the research method of music characteristics into the related research of music therapy, proposed a SVM-based music emotion recognition model, and analyzed the heart rate, electrical skin conduction rate, respiratory frequency, blood pressure from the perspective of the physiological impact of music, body temperature, and other perception effects on music. Some researchers have published academic papers on the study of emotional models based on brain wave music. The research interprets the emotional information contained in brain wave signals in the form of music. The feature vectors can represent emotional information. The author uses machine learning algorithms. First, we established a machine learning sample library through manual annotation and built an artificial neural network to classify the emotions represented by EEG music [20].

At present, researchers at home and abroad are increasing their efforts to analyze the condition of autism from the perspective of EEG, and many topics are also devoted to interventions from the external environment (such as music stimulation, visual stimulation, and behavior intervention) [21–25]. In the direction, let patients receive treatment through noninvasive sensory treatment. In 2019, some researchers confirmed that music activities are particularly effective in improving the language communication skills of cases. Studies have shown that the characteristics of special biomarkers in the brains of children with autism, through the interventional treatment of the marked brain regions, and the analysis of changes in EEG signals, the low-frequency oscillations of children with autism have increased

compared with normal children [26–27]. The significance of band oscillations is lower than that of healthy people. Therefore, from the perspective of EEG signal analysis, to study the therapeutic effect of music perception on children with autism can not only analyze the scientific nature of certain phenomena in psychology but also show the accuracy of deep learning optimization algorithms.

3. Intelligent Model of Somatosensory Music Therapy Information Feedback in Deep Learning Environment

3.1. Basic Theory of Deep Learning. Deep learning was first proposed by Hinton in 2006. It is a branch of machine learning and is also called deep structure learning or hierarchical learning. It is a method based on the representation learning of a large amount of seemingly irregular data. The representation of the data can be low-level features such as slope, linear regression, spatial curve, or it can be high-level abstraction. To put it simply, deep learning can automatically dig out the hidden information with special relationships from a large amount of data. When the number of network layers of the deep model reaches enough, some complex functions that the simple model cannot simulate can be modeled and learned. The superiority of deep learning compared with the usual shallow classification model is that it does not need to manually extract signal features but uses unsupervised or semisupervised stepwise and layered extraction. Therefore, in the modeling of deep neural network models, at this time, a large amount of prior knowledge is not needed, and the samples can be automatically classified without marking the category information in advance. For time-based ordered sequences such as EEG signals, deep networks can also give full play to its advantages.

Autoencoder (AE) neural network is a kind of unsupervised learning algorithm. In addition to autonomously learning the characteristics of the input data set, it can also use the greedy layer-by-layer training algorithm to initially assign the weight of the network. The network parameters are fine-tuned to the propagation algorithm to optimize the performance of the entire model, so as to reproduce the original data information as comprehensively as possible. The specific algorithm is shown in Figure 1. The most basic autoencoder is composed of an input layer, a hidden layer, and an output layer. The hidden layer represents the new information automatically extracted after encoding and represents the main components of the original signal. For an original data, suppose it contains M unlabeled samples, expressed as $\{a_1, a_2, \dots, a-i, \dots, a-M\}$; the autoencoder network model needs to learn a mapping $f-w$; make the output b as close to a as possible; at this time, the mathematical expression of the cost function of the autoencoder is

$$v(i) = \frac{w(i, j) \cdot f(i) + w(i-1, j-1) \cdot f(i-1)}{w(i, j) \cdot f(i) - w(i-1, j-1) \cdot f(i-1)} \quad (1)$$

For a fixed input sequence $T-x$, x (located in mR), the output $h-h$ $h-T$ (also located in mR) and the output layer

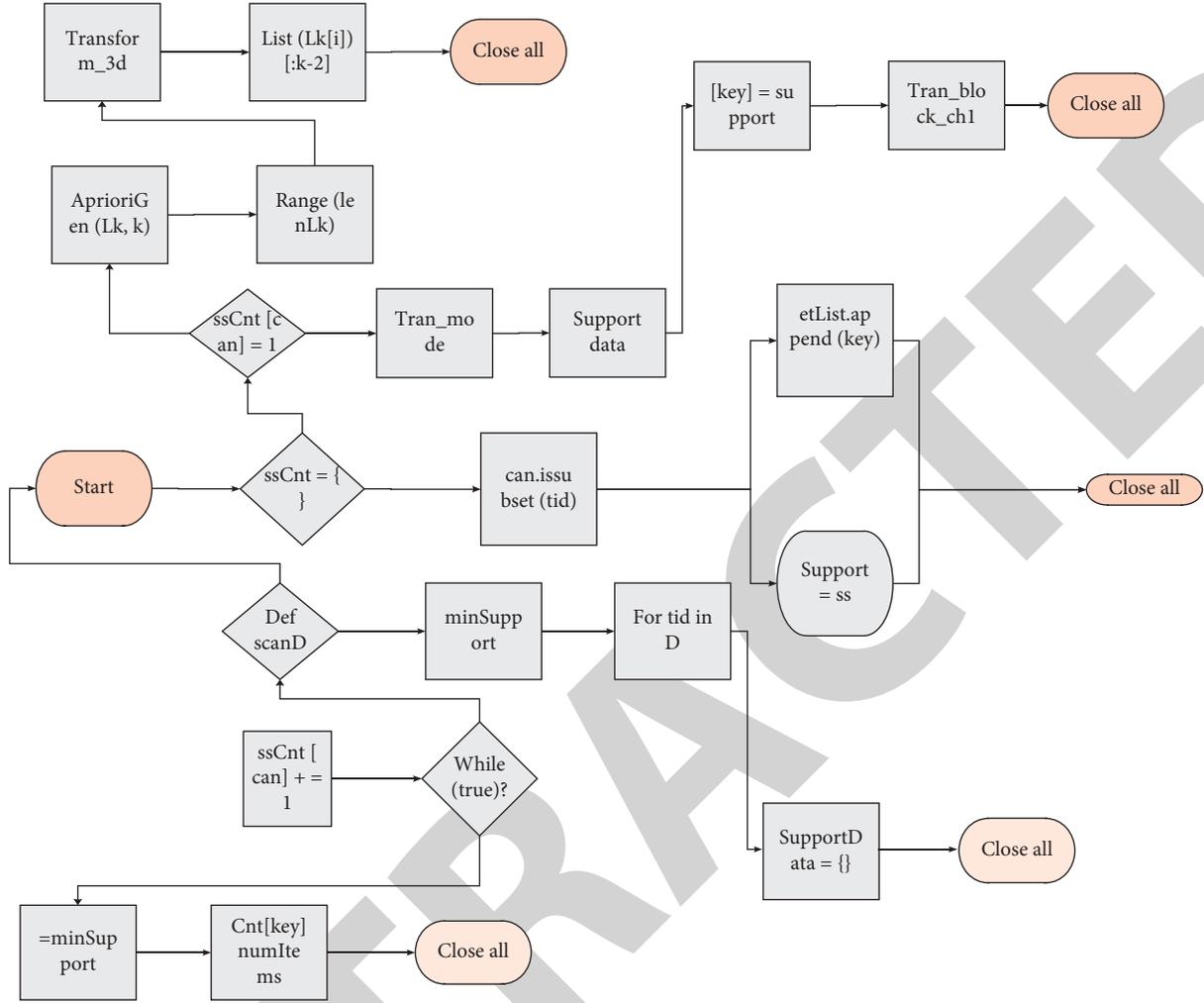


FIGURE 1: Flowchart of deep learning algorithm.

Forecast $T-y$, \hat{y} (also in mR), the expression m , the fixed input sequence $T-x$ in mR represents the weight matrix, and the output layer $T-y$ represents the bias term. T and s represent the input of the hidden layer and the input unit, respectively, e and g are nonlinear functions set in advance. Deep belief network (DBN) is a probabilistic generative model that combines supervised learning and unsupervised learning. It can realize the advantages of automatic feature learning, extraction of more essential features of data, and unsupervised pretraining. It has been widely used in natural speech processing, speech recognition, image recognition, target prediction, and other fields. For the classification of EEG data based on moving image tasks, deep learning algorithms are applied. For the classification of left- and right-hand moving images, firstly, based on a certain single channel, Deep Belief Network (DBN) is used to train the weak classifier. At the end of the branch, the two information sources are combined through a feature fusion structure. The fusion method can choose to manually adjust the weight or the

attention mechanism. For the fusion feature, a feature extraction module is subsequently connected in series, which also has a full convolutional network. The features are further merged, and the tumor mask is output at the end of the final model to achieve pixel-level segmentation. The mathematical model of the proposed multimode cosegmentation framework can be expressed by the following formula:

$$\begin{cases} u_1 = f_1(x(1), y(1)), \\ u_2 = f_2(x(2), y(2)). \end{cases} \quad (2)$$

In the formula, x_1 and x_2 are the inputs of the two branches, respectively, x_1 and x_2 represent the parameters of the two branches, respectively, and $1-h$ and $2-h$ represent the PET and the features of CT image extracted by two branches. Suppose $X-N$ represent the input image (PET or CT), $Y-N$ is the label, and $P-N$ represent the probability map that each pixel of the image is divided into foreground labels; then the probability map that each pixel of the image is

divided into background is $1-P$, and N represents the batch size. Therefore, the total loss of the model proposed in this paper can be expressed by the following formula:

$$y(s, t) = \sum_{i=1}^n \frac{w(k) \cdot (f(s, t), g(s, t)) + (1 + f(s, t)) \cdot g(s-1, t-1)}{w(k) \cdot (f(s, t), g(s, t)) + (1 - f(s, t)) \cdot g(s-1, t-1)} \quad (3)$$

Then borrow the idea of the AdaBoost algorithm to combine the trained weak classifiers into a more powerful classifier. This method performs well in 8 hidden layers. Comparing the recognition accuracy results with the support vector machine (SVM), the DBN classifier showed better performance in all test cases, with an improvement of 4% to 6% in some cases. The other two comparison methods based on the variational model are the extension of the classic fuzzy set algorithm [28] on the multimodal variational model, which is specially used for the cosegmentation task of PET/CT images. Experiments have proved that fuzzy set theory can effectively deal with the feature segmentation problem with low spatial resolution similar to PET images. Among them, the first variational model based on fuzzy set theory (FVM_CO_1) regards the PET image and the CT image as two channels of a hypergraph (assuming that the images of the two modalities share the same label), and its mathematical model is as follows:

$$U(x, y, s, t) = \int \frac{I(x, y) - c(1) + (s-1) \cdot I(x, y, s, t)}{I(x, y) + c(1) - (s-1) \cdot I(x, y, s, t)} dA. \quad (4)$$

Among them, DSC 0, 1 indicates the similarity between the segmentation result and the label. The larger the value, the higher the accuracy of the segmentation. When the DSC value is 0, it means that there is no spatial overlap between the segmentation result and the label. On the contrary, when the DSC value is 1, it means that the segmentation result is exactly the same as the label. The CE indicator is used to measure the spatial position deviation between the segmentation result and the label, and the calculation formula is as follows:

$$CE(x(a), x(b)) = \frac{f(s) + f(t)}{f(a, b)(f(s) - f(t))}. \quad (5)$$

In the formula, VFP means the part that is mistakenly divided into the target area is actually the part of the background, VFN means the part that is mistakenly divided into the background is actually the part of the target area, CE 0, 1, where the larger the value of CE, the lower the accuracy of the segmentation. The VE index is used to measure the volume difference between the segmentation result and the label, and the calculation formula is as follows:

$$VE(y(a), y(b)) = \frac{\text{abs}(f(x) + f(y))}{f(a, b)(f(x) - f(y))}. \quad (6)$$

For a fixed input sequence, the output h -T (also located in mR) and output layer predicting (also located in mR) can be obtained by using the following mathematical formula and iterative method:

$$y(i, j) = \sum g(s, t) \cdot f(i). \quad (7)$$

In the semisupervised paradigm, DBN is used to model the EEG waveforms for classification and anomaly detection. The performance of DBN is comparable to the standard classifier on the EEG data set, and the classification time is found to be 1.7–103.7 times faster than other high-performance classifiers. The article demonstrates the unsupervised steps of DBN learning and how to generate a natural encoder, which can be naturally used for anomaly measurement.

$$\begin{cases} g(a, b) = \frac{w(a, b) \cdot x + w(s, t) \cdot x(i-1)}{w(a, b) \cdot x - w(s, t) \cdot x(i-1)}, \\ w(s, t) = f(i, x). \end{cases} \quad (8)$$

By comparing the use of raw unprocessed data (rare data in automatic physiological waveform analysis) with manually selected features, it is found that raw data can produce comparable classifications and better abnormal measurement performance. These results indicate that DBN and raw data input may be more effective than other commonly used techniques for online automated EEG waveform recognition.

3.2. Music Perception Signal Collection. In order to improve the accuracy of the DBN classification effect and prevent environmental interference during the collection process and the influence of the subject's eye movements and muscles on the collected data, this chapter will also propose EEG signal denoising from the process of EEG signal preprocessing. The improved algorithm first uses Convolutional Neural Network (CNN) to detect the noise of the EEG signal and then combines the Hilbert-Huang transform (HHT) and FastICA to remove the noise. EEG signal acquisition is an essential part of analyzing EEG signal characteristics and subsequent processing and application. EEG data acquisition methods are mainly divided into implanted and non-implanted methods. Since the nonimplantable EEG acquisition method has the advantages of simple operation, noninvasiveness, little harm to the human body, low risk, etc., this experiment uses a nonimplantable method to collect EEG data. In the process of EEG signal preprocessing, after the CNN model is used to detect the electrooculogram artifacts, the target signal that needs to be denoised is then subjected to empirical mode decomposition. The remaining information components are reconstructed to obtain the desintered signal. This experiment will use a supervisor's research laboratory, obtained with an EEG cap with electrodes. Before collecting data, it is necessary to select experimental subjects, select suitable music works, and set up

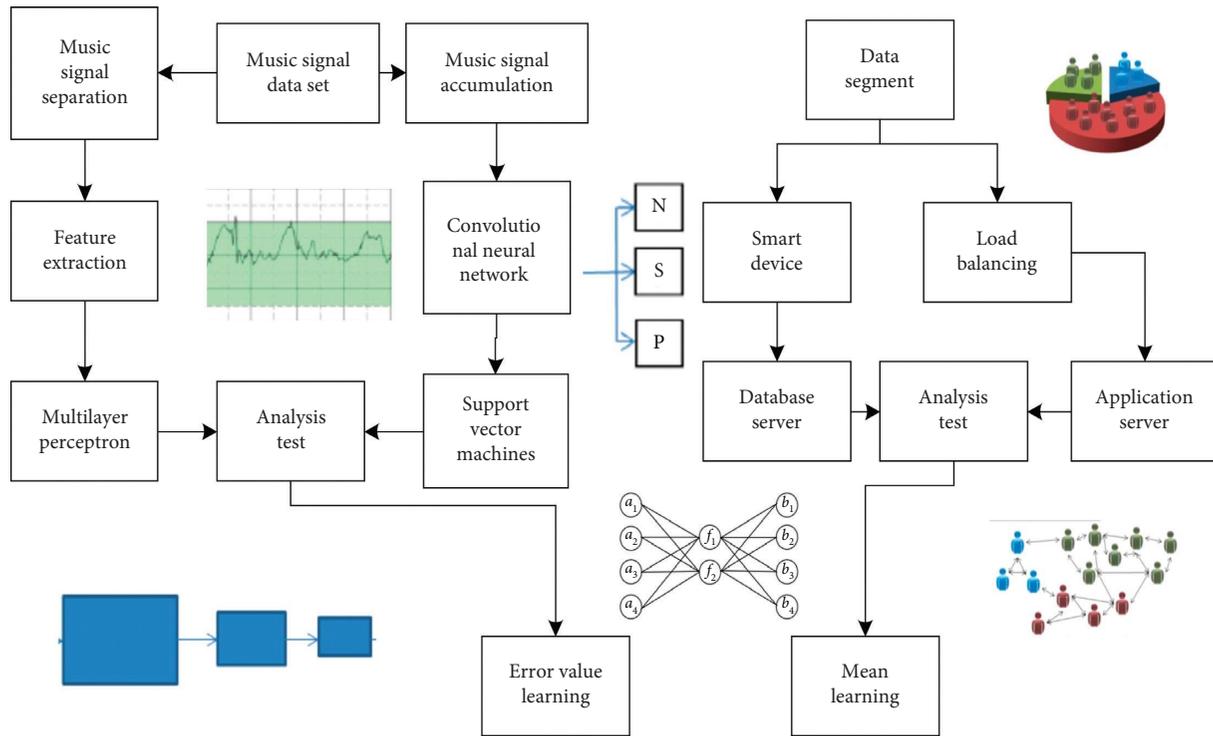


FIGURE 2: Intelligent model of somatosensory music therapy information feedback in deep learning environment.

an experimental environment. The specific information feedback intelligent model of music therapy is shown in Figure 2.

When children are under 12 years old, it is a critical period for physical, mental, cognitive, and other aspects of development. During this period, education and treatment of music perception for children with autism can also occupy the physical advantage of the best mental energy and physical recovery ability. After communicating and cooperating with children hospital, we screened 28 autistic children who were recently inquired in the psychology department. Among them, considering the possible IQ limitations or aggressive behaviors of the autistic children, it may be possible during the experiment. We have stipulated the conditions for selecting experimental subjects: (1) age 3–12 years; (2) no serious excessive behavior (such as hurting and self-harm); (3) not accompanied by other serious illnesses (such as Pa Jinsen, epilepsy); (4) no strenuous exercise before the experiment; (5) no symptoms such as cold or fever. After the initial screening, several children who meet the requirements are given an intelligence test, mainly by means of a warm dialogue with a psychologist, an intelligence question and answer for the corresponding age group, and the parents providing the patient's behavioral performance. After screening by various standards, the experiment finally selected 15 children with autism as key experimental subjects, and other participants as preliminary experimental subjects. Among them, the students who participated in the volunteer activities were required to be healthy, have no colds or fevers during the period of receiving music perception and collecting EEG data, and not be able to exercise

vigorously before the experiment. Among the students from the first to third grades, 37 actively participated in the registration. First, the observation signal is deaveraged, and then the deaveraged observation signal is whitened to remove the correlation between the data, and finally the independent components are extracted to achieve separation and denoising. After screening by various standards, the experiment finally selected 25 healthy children as key experimental subjects, and other participants as preliminary experimental subjects. After that, we conducted surveys and statistics on each subject's music experience and music needs, mainly using questionnaire survey method, interview method, and literature data analysis method and statistics and records of each subject's favorite songs, most frequently heard songs, unfavorable songs, unfamiliar song styles, etc. With reference to these records, coupled with the method of selecting music works in the music therapy of children with autism in medicine, 4 types of music were finally determined, namely, (1) sad music, (2) strange symphony, (3) cheerful music, and (4) unfamiliar plain music. In addition to the comparison of the nonmusic experimental environment, (5) experimental environments are set up. The current study of EEG signals under music perception mainly analyzes whether the signals in the right hemisphere of the brain are diseased, because the human body's response to music is mainly controlled by the right hemisphere of the brain. In terms of EEG acquisition, there are many theories about the placement of electrodes on the scalp in the practice of clinical and scientific research. This experiment selects the most recognized international 10–20 standard distribution in clinical medicine and scientific research to place the

electrodes. This standard makes it easier for scholars from all walks of life to analyze and discuss the characteristics of EEG information under the same acquisition conditions.

3.3. Model Feature Optimization Classification. Because the DBN training process itself requires a large number of training samples, there are also shortcomings such as slow convergence and easy to fall into local minimums, which requires a lot of energy and time, and the learning efficiency is relatively low. Prior to this, this chapter will first collect and preprocess brain electrical signals for music-perceived children with autism and healthy children in order to provide data support for subsequent experiments. Therefore, this chapter proposes the DBN optimization algorithm. Firstly, it proposes the optimal selection of features based on the frequency band energy ratio and the moving average sample entropy, and then through training the DBN model, constantly adjusting the parameters, combined with the softmax classifier, and the EEG of children with autism and healthy children under different music perceptions classification. DBN's EEG signal recognition method can make the computer automatically extract the low-level and high-level features that characterize these sample signals from the input data in an unsupervised way, so that the classification and recognition performance is better.

Since the EEG of patients with autism who have been clinically diagnosed and the distribution of each rhythm will be very abnormal, in order to intuitively analyze the EEG data collected in scientific, clinical research, etc., we choose the frequency band energy ratio of each rhythm (FBER). As one of the features, first select a segment of brain wave data sample that has been intercepted and determine its value range to match the frequency band of each rhythm of the brain wave. The change of the energy of any rhythm with time can be calculated from the wavelet coefficients, so the harmonic wavelet packet transform must be performed first. FastICA has faster calculation speed and less CPU usage than traditional ICA methods. Comparing the denoised waveform with the original noise signal, it can be clearly seen that the FastICA method successfully removed the interference of electrooculogram artifacts. Use the transformed wavelet coefficient $s-i-k$ to calculate the frequency band energy of each rhythm. To illustrate the role of this feature in the process of distinguishing between autistic and healthy children, take an EEG sample of a child with autism in a nonmusic environment and an EEG sample of a healthy child in the same environment. Select the F3 channel data (the F3 channel acquisition point is located in the temporal area of the human brain), obtain the power spectrum of the original signal and the power spectrum of each rhythm after decomposing into four typical rhythms. The specific distribution is shown in Figure 3.

From the decomposed rhythm waveforms and FBER trends of the EEG of children with autism and healthy children in Figure 3, the analysis and comparison show that doctors can clearly see the changes in the FBER of each basic rhythm through these curves. In order to improve the accuracy of the DBN classification effect and prevent

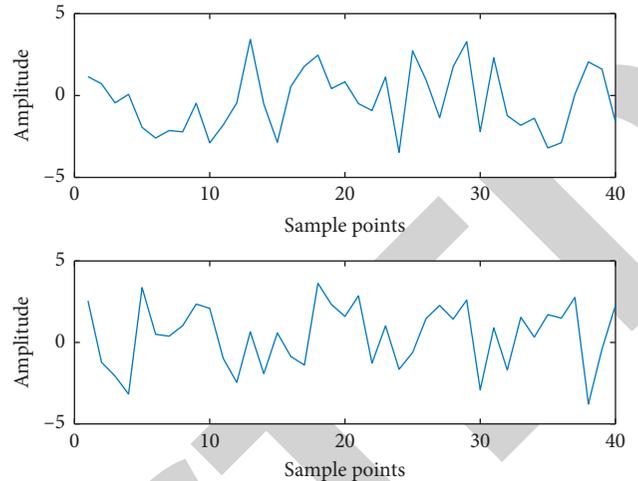


FIGURE 3: Music signal power spectrum under deep learning.

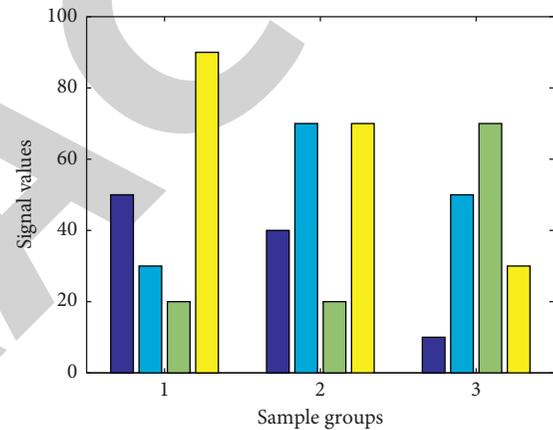


FIGURE 4: Histogram of the proportion of patients' brain wave signals in music therapy.

environmental interference during the collection process and the influence of the subject's eye movements and muscles on the collected data, this chapter will also propose EEG signal denoising from the process of EEG signal preprocessing and judge whether it is normal. In Figure 4, in the EEG waveforms of children with autism, we can also see that in the frequency band energy ratio of autistic patients, the energy occupied by alpha rhythm is significantly lower than that of healthy children in this brain area, and the energy of the delta rhythm of autistic patients is significantly higher than that of children in the healthy group, and the energy of the frequency band of the beta rhythm is also improved. These characteristics are clearly distinguished and the positioning is accurate.

Entropy is a parameter that can quantitatively describe an unstable physical system or signal. Sample entropy has good consistency and antinoise performance and is suitable for the analysis of shorter data. Therefore, it is often used in the analysis of clinical EEG signals. For example, in the current multiscale entropy analysis process of EEG data of children with autism, the sample entropy algorithm is applied to the entropy calculation, but it is limited to the

comprehensive analysis of EEG information with shorter data length. At the principle level, sample entropy represents the entropy estimation of stationary time series data. Therefore, this article proposes a sliding analysis of long time-domain EEG data. In each analysis window, it can be assumed that the processed data is relatively stable, in order to study the moving average sample entropy (MVSE) of EEG. It used to reflect the overall situation of brain activity in continuous complex background conditions. Through the RBM network, the unsupervised greedy layer-by-layer training method is used to pretrain each layer to obtain the weight of the generative model. The reconstruction error is used as the objective function, and then the contrast divergence (CD) algorithm is used to perform the RBM layer by layer. Unlabeled training continues until the function converges, which realizes the hierarchical feature extraction of the EEG signal and ensures that the optimal feature vector is obtained. Then a layer of supervised softmax algorithm is used to fine-tune the entire network. It is mainly for the treatment of music perception for patients with autism, and healthy children immediately make comparisons. During this period, we collected the brain waves of each experimental subject at one week, two weeks, and one month and kept the statistics. The parameter values obtained in the previous step are used as the initial value of the fine-tuning, and cross entropy is used as the objective function. The labeled training samples are used to output the RBM through the softmax network. The feature vector is classified to realize the recognition of EEG signals.

4. Application and Analysis of the Intelligent Model of Somatosensory Music Therapy Information Feedback in Deep Learning Environment

4.1. Feedback Model Application Simulation. The system modules used in this article to collect cerebral cortical EEG data mainly include 3IT_EHV1 EEG cap, 8-channel OpenBCI_V3 EEG board, and supporting data analysis software OpenBCI_GUI. (1) EEG caps: 3IT_EHV1 EHV1 EEG caps are brand new EEG caps, all dry electrodes, no conductive paste, compatible with OpenBCI Ultracortex_Mark3/4 series EEG caps. (2) 8-channel EEG board: OpenBCI_V3 is an open source human brain or bioelectric-computer conversion interface. The detection and measurement of brain waves (EEG) are completed through the built-in high-precision dedicated chip, with 8 independent signal acquisition channels, the main control is Arduino UNO, and the brain power chip is provided by the world-renowned semiconductor company TI (Texas Instruments). (3) Data analysis software: the data analysis software OpenBCI_GUI is the supporting software of the equipment, which can set the acquisition parameters and analyze the data and can observe the changes of brain waves in real time. In order to facilitate the observation of the waveform in the experiment, the sampling frequency of each electrode is set to 250 Hz, accuracy is 8 bits, and bandpass filter is set to 0.5 Hz~100 Hz and 50 Hz notch filter, but the setting of observation parameters does not affect

the size of EEG data stored in the background. Since the nonimplantable EEG acquisition method has the advantages of simple operation, noninvasiveness, little harm to the human body, and low risk, this experiment uses a non-implantable method to collect EEG data. This experiment will use a supervisor's research laboratory obtained with an EEG cap with electrodes. The specific signal simulation is shown in Figure 5.

During the experiment of collecting EEG data, the subjects were placed in a comfortable and warm environment without excessive noise interference. Place experimental tables, chairs, and utensils in the collection room to exclude irrelevant electrical equipment. Data collection was performed on 15 ASD children and 25 healthy child volunteers selected in the early stage. Similarly, the sample entropy features are extracted and classified. When the number of network layers is 4, the classification accuracy is greatly improved by one less layer, and the running time is reasonable, and an appropriate amount of calculation is maintained. For details, see Figure 6. As the number of network layers increases, not only does it not improve the accuracy, but it also increases the computer overhead and consumes more time.

4.2. Example Results and Analysis. The equipment conditions of the laboratory determine that we select the eight data channels that best reflect the condition to obtain the brain signal, which are the F3, F4, C3, C4, T5, T6, O1, and O2 channels. The EEG signal is a typical nonstationary and nonlinear signal, and the Convolutional Neural Network (CNN) can train the detection model based on the extracted EEG features. Its convolution operation can enhance the original signal features and reduce interference. In the acquisition of EEG signals, two electrode positions are usually used to determine a segment of EEG signals. One of the electrodes is used as the zero potential electrode, which is the reference electrode. The potential difference between the collector electrode and the reference electrode in other parts is the potential change value of the former, which is the specific value of the brain electrical signal we collected. (3) Data analysis software: the data analysis software OpenBCI_GUI is the supporting software of the equipment, which can set the acquisition parameters and analyze the data and can observe the changes of brain waves in real time. In order to facilitate the observation of the waveform in the experiment, the sampling frequency of each electrode is set to 250 Hz, accuracy is 8 bits, and bandpass filter is set to 0.5 Hz~100 Hz and 50 Hz notch filter, but the setting of observation parameters does not affect the size of EEG data stored in the background. The time domain data is shown in Figure 7. First ask the participant to be quiet for 2 to 3 minutes in order to enter a relaxed state. Then, according to the experimental conditions preassigned by each experimenter, the corresponding music was played. First, the Convolutional Neural Network (CNN) is used to detect the noise of the EEG signal, and then the Hilbert-Huang transform (HHT) and FastICA are combined to remove the noise. During the process of listening to the music, the brain

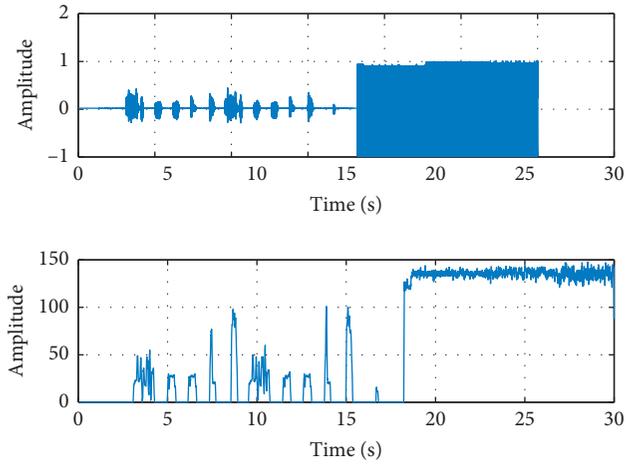


FIGURE 5: Time domain simulation of music signal feedback model.

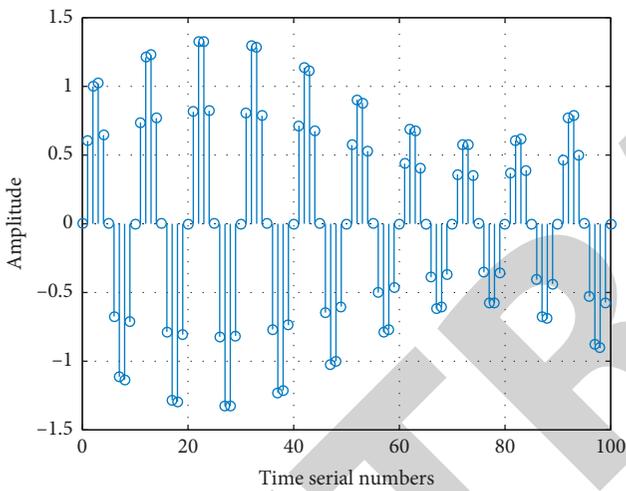


FIGURE 6: Timing dependence of music signal after deep learning.

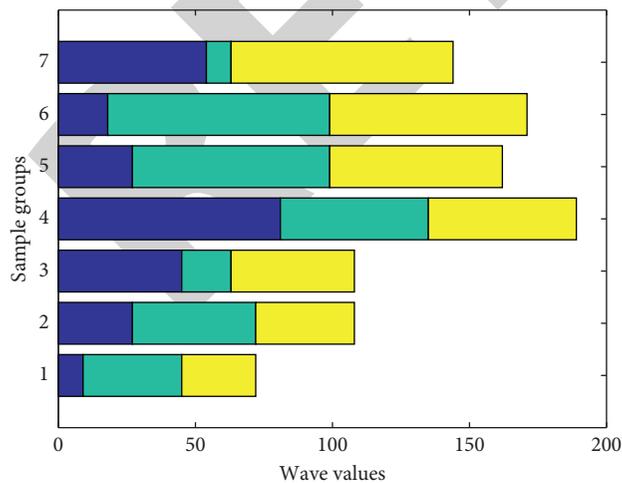


FIGURE 7: Brain wave data distribution of different music signal sample groups.

wave data of 60 s was collected and saved and stored for subsequent analysis and processing. If the location of the reference electrode is not properly selected, the zero potential will be mixed with many other physiological electrical signals, which will make it impossible to play the role of the reference electrode zero potential. Therefore, it is necessary to select a suitable reference electrode before collecting EEG signals. The earlobe is not far from the scalp, and its position is independent, and it is not easily disturbed by physiological reactions such as eye movement and muscle contraction.

Among them, it is found that when the number of network layers is 3, the classification accuracy of FBER has reached 93.27%, which is already a relatively high level. With the increase of the number of layers, the accuracy is slightly improved, but the more the layers, the greater the number of model iterations, the amount of calculation, and the CPU overhead, which consumes more time and trade-offs. Pros and cons: finally choose 3 hidden layers. When extracting frequency band energy features, because the abnormal EEG of children with autism is mainly reflected in α rhythm, the input data of the first visual layer is the frequency band energy feature of α rhythm. In each acquisition process, each experimental object stores a 60 s brain wave signal, 3 s of which is selected as a sample, the overlap rate is 25%, then the data saved in each lead includes 26 samples, the sampling rate is 128 Hz, and then each sample contains 3×128 , a total of 384 data points. Regardless of the intensity of the added noise, the signal after HHT denoising of the noise ratio SNR is higher than the signal-to-noise ratio before denoising, and the root mean square error RMSE is lower than the data before denoising. This proves the effectiveness of HHT for ordinary noise removal. Therefore, the initial input data of the RBM training model is the value of the 384 alpha rhythm band energy characteristic ratios. The distribution of data points and the fitting curve are shown in Figure 8.

It can be seen from Figure 9 that whether it is the EEG classification of children with autism or the EEG classification of healthy children, the classification accuracy of the optimized DBN model is always higher than that of other methods. This shows that, under the experimental conditions of this article, the DBN classification method achieves a good classification effect, which is more conducive to the analysis of autism. In each group, 5 people are assigned to 5 kinds of music conditions. After that, each person will listen to the music once every morning and evening according to the assigned music conditions for one month. The results of classification statistics for 15 children with ASD, the histogram shows that there are still differences in the classification accuracy between different children with autism, which shows the differences in the sensitivity of different people to music. The classification accuracy of EEG of most subjects is between 75% and 94%, the highest is 94.07%, the lowest is 76.24%, and the average accuracy is 84.78%, which also shows the stability of the DBN classification model. Similarly, the classification results of 25 healthy children were counted separately, and the accuracy of EEG

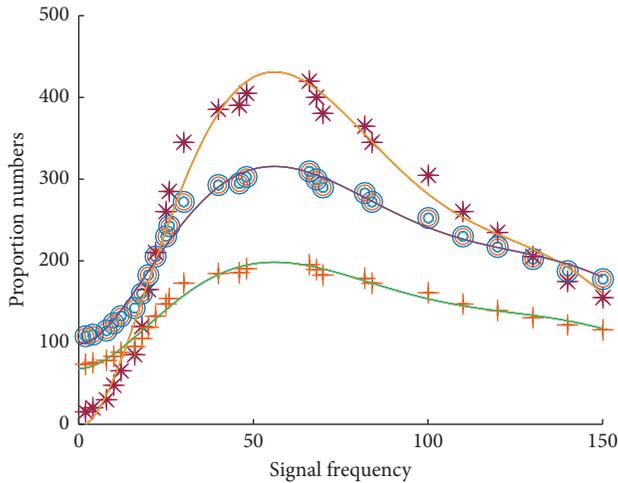


FIGURE 8: Fitting curve of each rhythm of the patient's EEG decomposition after music therapy.

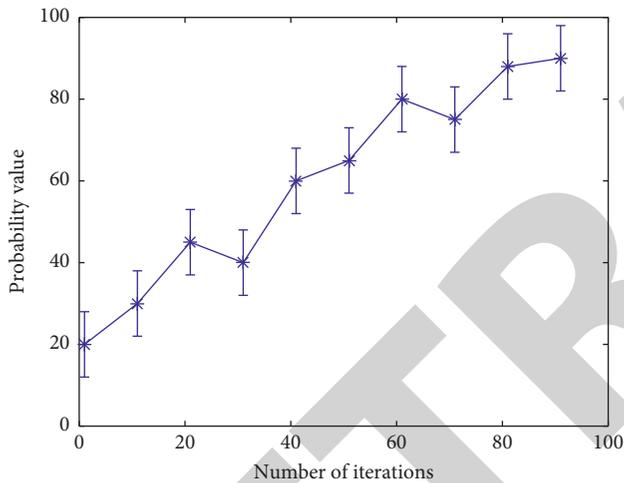


FIGURE 9: Classification accuracy error distribution of the deep learning feedback model.

classification of different healthy children was also different. In this experiment, the highest accuracy rate was 92.37%, the lowest was 76.24%, and the average accuracy rate was 85.77%. This also proves the stability and practicality of DBN classification accuracy.

Comparing the EEG signal amplitude characteristics of children with autism in the music 1 and music 3 environments with the EEG characteristics of healthy children in the corresponding environment, there is no regular finding, indicating that this comparison is meaningless. Compare the EEG signal amplitude characteristics of autistic patients in music 1 and music 3 with the EEG characteristics of healthy children in a music-free environment. In this EEG analysis experiment, it is found that different people (whether children with autism or healthy children) have differences in their perception of music, but this difference fluctuates within a certain range, and the classification accuracy is low. Probably the range is 75%~94%, and the average classification accuracy fluctuates around 85%. We found that the

EEG amplitude under the music 1 environment is far lower than the normal EEG characteristics of healthy children not listening to music. The EEG amplitude under the music 3 environment is similar to the normal brain electrodes of healthy children not listening to music. Explain that music 1 has a counterproductive effect on the condition of autistic patients. After listening to music 3, children with autism have very similar EEG amplitudes to those of healthy children; that is, their emotional excitement is very similar, which is closer to the health standard. It shows that music 3 (i. e., cheerful music) has a significant effect on alleviating the patient's autistic mood.

5. Conclusion

The music perception method under deep learning has achieved good results in the adjuvant treatment of many diseases. The brain waves have great sensitivity and relevance in reflecting the brain's mechanism of action. Therefore, the analysis of the music perception treatment was from the perspective of brain electrical signals. As a new field in machine learning, deep learning has achieved remarkable results in computer vision, image processing, and speech recognition. In this paper, the optimized Deep Belief Network (DBN) model is applied to the feature extraction and classification of brain waves, focusing on the development of children with autism under different music perception treatments, and studying the brain waves of children with autism classification and comparison with the EEG characteristics of healthy children in the same environment, and it is concluded that music perception has an auxiliary therapeutic effect, and the model successfully realized the preprocessing, feature extraction, and classification of EEG signals in different environments research and discussion and achieved certain results, providing new ideas for follow-up research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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