

Psychological Evaluation of Nervousness in Symphony Performance Based on Artificial Intelligence Technology

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ABSTRACT For symphony orchestra players, controlling stage-performance nervousness is essential for maintaining technical stability and performance quality. Traditional psychological assessment methods are limited by subjective judgment, static questionnaires, and the inability to capture real-time physiological changes. To improve the timeliness and objectivity of psychological assessment, this study develops an artificial-intelligence-based evaluation method for nervousness in symphony performance. Physiological signals and behavioral data are collected through wearable and wireless sensing devices, and a convolutional neural network combined with recurrent neural network modeling is used to analyze multi-source signals such as EEG, ECG, pulse, facial expression, voice, and gesture. Fourier and wavelet-based signal processing are introduced to extract frequency-domain features related to involuntary tremor and autonomic response. Experimental results show that the proposed model improves assessment accuracy by 7.3% compared with traditional methods. The study provides a practical intelligent assessment framework for performance anxiety and demonstrates the value of electromagnetic-compatible wearable signal acquisition in real-time psychological monitoring.

INDEX TERMS artificial intelligence, psychological tension, wearable sensing, electromagnetic signal acquisition, symphony performance

I. INTRODUCTION

Symphony performance is a kind of performance activity involving various human perceptions, and it is closely related to human psychological activities. For performers, mastering advanced technical skills and maintaining sound psychological well-being are the two most critical prerequisites. Symphony performances are large-scale and public activities, which often cause a nervous psychological burden to the performers. And this will affect the performance of the player's skills and hinder the smooth progress of the performance. Artificial intelligence technology has been widely used in mental health in recent years. For symphony performers, stress assessment is an essential task before the official performance. Traditional stress assessment relying solely on self-report questionnaires suffers from subjective bias, lacks temporal resolution, and cannot detect subconscious physiological responses that precede conscious awareness of nervousness. An effective psychological evaluation model is constructed through artificial intelligence technology to provide players with an intelligent psychological evaluation method, which plays an important role in whether they can perform normally.

Artificial intelligence technology has promoted the vigor-

ous development of traditional industries such as education, medical care, and transportation, that the market prospect is very broad. At present, the research work of artificial intelligence is also in full swing. Li Y proposed a forecasting method that combined data preprocessing algorithms and artificial intelligence optimization, and then analyzed warehouse management. The results showed that this method can solve problems existing in the company's warehouse management from the aspects of warehouse design and planning, warehouse design, and warehouse comprehensive management [1]. Ding Y built a performance analysis model of public management teaching and training based on artificial intelligence technology. System performance was investigated through actual scoring and training with large amounts of data. The research results showed that the model proposed in this paper had certain effects [2]. Liu L constructed an e-commerce management performance model based on artificial intelligence technology. Finally, it was shown that the model could improve the performance of e-commerce enterprises [3]. Jianjun W established an image processing system based on artificial intelligence technology. The system had been verified, and the feasibility and advanced nature of the system had been demonstrated

with specific data [4]. Based on artificial neural network, Wu W and Huang H proposed an optimized radial basis function (RBF) model based on genetic algorithm (GA). Finally, the goal of intelligent building was achieved by using neural network system and intelligent decision-making system [5]. Huang W, Ren J team researched the application of artificial intelligence system in all aspects of intelligent construction based on artificial intelligence technology. The connotation of urban texture was re-excavated with the methods of quantification and data analysis. Taking the texture data of multiple cities as an example, urban images were constructed by methods such as convolutional neural network classification and machine learning [6]. Meshram S G used artificial intelligence technology to predict the flow of water into the Indian watershed. The results showed that AI models with recurrent terms had better performance [7]. These artificial intelligence research efforts are very detailed and specific, but there is no mention of its application in psychological assessment.

With the enhancement of social competition and efficient operation, many people are facing increasing pressure. With the enhancement of social competition and efficient operation, many people face increasing pressure, and an increasing number of incidents resulting from psychological problems have been reported. Therefore, many experts and scholars have conducted research and analysis on psychological assessment. Editor explored models of mental assessment in elders and introduced context for understanding the cognitive impacts that occur during aging. Finally, the model tested the overall clinical presentation of the elderly was the most consistent with “pseudo-dementia” [8]. Am A tested the vulnerability of forensic doctors responsible for the mental health of criminal suspects to contextual effects in psychological assessments. It was concluded that training programs for forensic psychological assessment should focus on bias [9]. Ylmaz T used biofeedback to perform a psychological assessment of an inpatient with adjustment disorder who displayed less verbal and nonverbal expression and had difficulty getting a good outcome from treatment. The assessment revealed the underlying problem behind the symptoms, and no clinical intervention, including medication, was required after discharge [10]. Everhart J S researched traffic psychological assessment system. The drivers were assessed by observers who measured the participants’ cognitive and psychomotor abilities using a psychometric assessment system. Finally, it is proposed to increase the weight of these predictive tests when deciding on safe driving for each system [11]. Fox B, Verona E utilized a range of assessment methods to illuminate complex problem-solving abilities, making psychologists unique among other mental health professionals. Detrimental trends in psychological assessment were discussed, and psychological assessment was redefined [12]. Byrd D A constructed a psychological evaluation model based on the emotional characteristics of texts. Finally, the text vector was used as the input of the Bayesian regularized neural network to

predict the mental state of the students. The experimental results showed that the model effect was ideal [13]. The above analysis of psychological assessment is relatively rich. But basically it is still a traditional psychological assessment method without using artificial intelligence technology.

Based on artificial intelligence technology, this paper studied and analyzed the psychological evaluation of nervousness in symphony performance. A psychological evaluation model was built by using artificial intelligence technology and combining with convolutional neural network, which provided an intelligent, accurate and efficient stress psychological evaluation method for symphony players. When using the psychological assessment model for assessment, the player’s psychological data information and behavioral data information were collected. Through the convolutional neural network algorithm, the Fourier transform algorithm, etc., the data information was processed and analyzed intelligently. Finally, the entire psychological assessment model was simulated and tested to improve the accuracy of the assessment results.

II. ARTIFICIAL INTELLIGENCE TECHNOLOGY

When automation and mechanization develop to a certain extent, the next development trend is bound to be intelligence. The exploration of artificial intelligence technology promotes human exploration of self-wisdom. Innovation and development of “intelligent” machines can enable human beings to enhance their self-strength, free their hands, and promote human beings to pour more energy into the field of science and technology, thereby promoting economic and social development [14]. In addition, the further development of modern information technologies such as big data analysis and the Internet of Things also requires the support of smart technology. Therefore, the development of modern artificial intelligence is of vital significance to today’s society. Artificial intelligence is an emerging science and technology, which is based on intelligence and forms a new system with its own characteristics. Its related research and applications cover a wide range of fields, such as knowledge representation, search technology, machine learning, etc. The research and application areas involved are shown in Figure 1.

III. CONSTRUCTION OF AN ASSESSMENT METHOD FOR NERVOUSNESS IN SYMPHONY PERFORMANCE BASED ON ARTIFICIAL INTELLIGENCE TECHNOLOGY

A. NERVOUS MENTAL PERFORMANCE IN SYMPHONY PERFORMANCE

The nervousness produced by symphony performance is defined as stress response [15]. Stressful events are generally thought to stimulate the nervous system, causing the adrenal glands of the endocrine system to release adrenaline, which stimulates the body and responds to stressors, such as increased heart rate, increased breathing rhythm, and tremors in skeletal muscles.

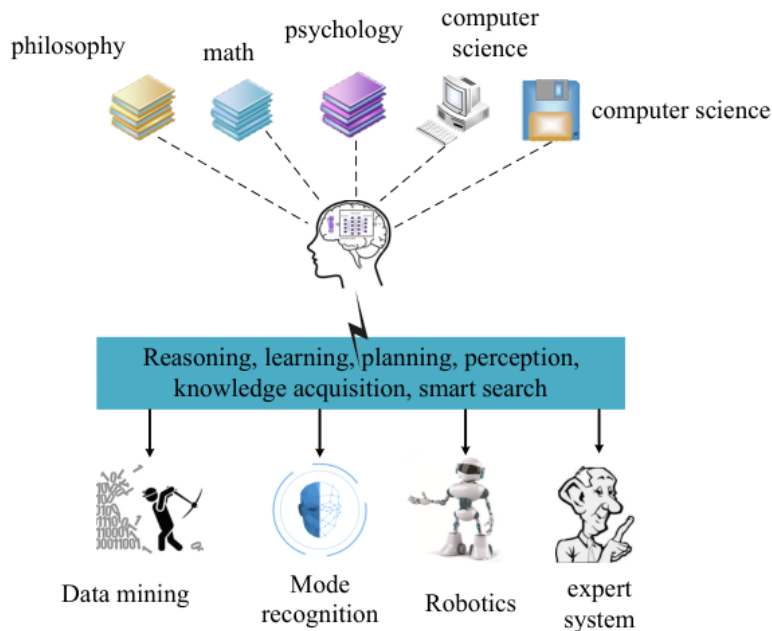


FIGURE 1. Research and application of artificial intelligence

Psychological stress conditions often depend on an assessment of the surrounding environment. Fear and anxiety are experienced if the assessment results in a threat. Excitement is experienced if the assessment result is considered a challenge. Therefore, emotion also directly reflects the evaluation of psychological stress on the environment, and the two are interrelated and affect each other [16]. Everyone has different degrees of stress when they step on the stage and play in front of everyone. Players with rich stage experience and stronger self-regulatory capacity are more likely to feel excited. Ordinary symphony players are more likely to feel intimidated. This shows that the experience of psychological stress is related to the ability to counteract stressors. Confident people believe they are capable of meeting the demands of stressful situations. This self-conviction generates a sense of internal empowerment. People who lack confidence or abilities feel restless and passive. However, different body types behave differently when confronted with stress. Some people show stiffness, unable to move their fingers normally, whereas others exhibit flaccid muscle tone to the extent that they cannot maintain stable finger posture or hand control.

B. CONSTRUCTION OF PSYCHOLOGICAL ASSESSMENT METHODS

This paper proposed a psychological assessment method based on artificial intelligence technology to intelligentize the psychological assessment process. The study recruited 120 symphony players from three professional orchestras, all of whom provided informed consent, and each participant completed a standardized performance scenario consisting of a solo passage from Tchaikovsky's Symphony No. 5 in

front of a panel of five judges, with nervousness ground truth established by averaging three independent clinical psychologist ratings on the State-Trait Anxiety Inventory for performance anxiety and the Performance Anxiety Rating Scale. Using artificial intelligence technology to transform psychological assessment questions into scenarios that were easy for players to understand, as shown in Figure 2. At the same time, the player's physiological data, behavioral data and question and answer data were collected, and the three kinds of data were analyzed and evaluated through intelligent information processing technology. EEG signals were recorded from the frontal and parietal lobes using a 32-channel dry electrode system with a sampling rate of 500 Hz, while ECG was measured via a two-lead chest strap and pulse oximetry was obtained from a finger clip sensor, and all physiological recordings were synchronized with behavioral video capture in a quiet room maintained at 22°C and 40% humidity, with each participant seated three meters from a simulated stage setup. The variety and authenticity of the assessment method make assessment easier, avoiding inaccurate assessment results due to external interventions, and players refusing to answer questions due to psychological stress. Before the performer performs on stage, a brief psychological question and answer session will be conducted to grasp the basic psychological condition of the performer. Then, real-time behavioral data and real-time physiological data were collected respectively. Behavioral data includes voice, facial expressions and gestures, and physiological data includes real-time EEG, cerebral blood flow, pulse, and ECG. The gesture and movement data were time-locked to the musical score, and the system subtracted the expected purposeful movements derived from a refer-

ence motion template of each musical passage performed under non-stressful rehearsal conditions, leaving residual motion components that were analyzed for frequency content between 4 and 12 Hz to isolate involuntary tremors from intentional playing actions, with movements exceeding the 95th percentile of the reference amplitude distribution being classified as nervousness-related rather than performance-required. The analysis results of all these data can be used as an input in the mental state assessment model, and can also be used as a judgment condition in information processing and logical analysis. The intelligent processing of mental health problems is determined by setting various relevant conditions and selecting evaluation strategies according to the actual situation, including but not limited to the processing of related problems in clinical practice. Finally, the system analyzes the mental health status of the symphony players in real time and gives a psychological assessment report.

Psychological assessment model is an important part of psychological assessment method. This paper used convolutional neural network and recurrent neural network to build the model architecture. As shown in Figure 3, the player's behavioral information, psychological question-and-answer data, and physiological information will be sent to the convolutional neural network and the recurrent neural network, and then sent to the psychological evaluation model through feature fusion. The convolutional neural network contained three convolutional layers with 32, 64, and 128 filters respectively, each with a kernel size of 3×3 and ReLU activation, followed by two fully connected layers of 256 and 128 units, while the recurrent neural network employed two stacked long short-term memory layers each with 128 hidden units, and the model was trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32 for 200 epochs, with early stopping based on validation loss. The clinical evaluation labels are first injected into the entire softmax layer, and then also into the psychological evaluation model.

IV. PSYCHOLOGICAL ASSESSMENT DATA PROCESSING ALGORITHM

A. FOURIER TRANSFORM ALGORITHM

Fourier transform is the most common analysis method used in signal processing. In fact, it is a simple frequency domain analysis. Although the frequency domain resolution is very high, it cannot analyze the time domain mapping resolution [17]. Wavelet analysis is a further development of the traditional Fourier analysis method, and its basic idea mainly comes from scaling and translation.

Figure 4 is a wavelet time domain waveform diagram. For a function $\varphi(t)$, if it is square integrable, that is $\varphi(t) \in L^2(R)$, if the Fourier transform $\varphi(w)$ satisfies the condition:

$$\int_R \frac{|\varphi(w)|^2}{w} dw < \infty \quad (1)$$

Then $\varphi(t)$ is called the wavelet function, and Equation (1) is called the acceptance condition of the wavelet function.

Based on the definition of the wavelet function, the wavelet transform function refers to selecting a function family that conforms to the allowable transformation conditions of the base wavelet function as a base wavelet. Another basis function family is generated by using it to continuously stretch and translate the basis wavelet function [18]. The function family constructs a frame of function space, and then all the signals to be analyzed are projected onto this frame.

Continuous wavelet transform is defined as making the wavelet function $\varphi(t) \in L^2(R)$. According to the properties of the wavelet function, it satisfies the conditions:

$$\int_R \varphi(t) dt = 0 \quad (2)$$

The wavelet mother function $\varphi(t)$ is used for scaling and translation, so that a set of function sequences generated by it is $\varphi_{a,\tau}(t)$, and the expression is as follows:

$$\varphi_{a,\tau}(t) = \frac{1}{\sqrt{a}} \varphi\left(\frac{t-\tau}{a}\right) \quad (3)$$

Among them, $a, \tau \in R$, $a \neq 0$, a is the scale factor, which is a coefficient about scale; τ is a translation factor, which is a coefficient about time. $\varphi_{a,\tau}(t)$ is the wavelet basis function that depends on parameter a, τ . From this, it can be concluded that the continuous wavelet transform equation of signal $f(t)$ is:

$$Wf(a, \tau) < f, \varphi_{a,\tau} > = \int_{-\infty}^{+\infty} \varphi_{a,\tau}(t) f(t) dt \quad (4)$$

Among them, $< f, \varphi_{a,\tau} >$ is the inner product of the signal and the wavelet basis, which can be regarded as the projection of the function $f(t)$ on the translation signal of various scales. When implementing the wavelet transform, usually only binary discretization is performed on the scale [19]. If the scale factor a is taken as 2^k , and the displacement is still continuously changed, that is, $\Delta\tau = 0$. This type of wavelet is called a binary wavelet, and the expression is:

$$\varphi_{2^k,\tau}(t) = \frac{1}{2^k} \varphi\left(\frac{t-\tau}{2^k}\right) \quad (5)$$

The binary wavelet transform of function $f(t) \in L^2(R)$ is defined as:

$$WT_{2^k}(\tau) = f(t) * \varphi_{2^k,\tau}(t) = \frac{1}{2^k} \int f(t) \varphi\left(\frac{\tau-t}{2^k}\right) dt \quad (6)$$

When k is small, the corresponding scale is small, the time field window is reduced, and the time resolution is high, which is suitable for analyzing high-frequency signals, especially for observing signal details; when k is large, the corresponding scale is large, the time field window is increased, and high-frequency resolution is high, which is suitable for analyzing low-frequency signal, mainly focusing on observing the entire signal image.

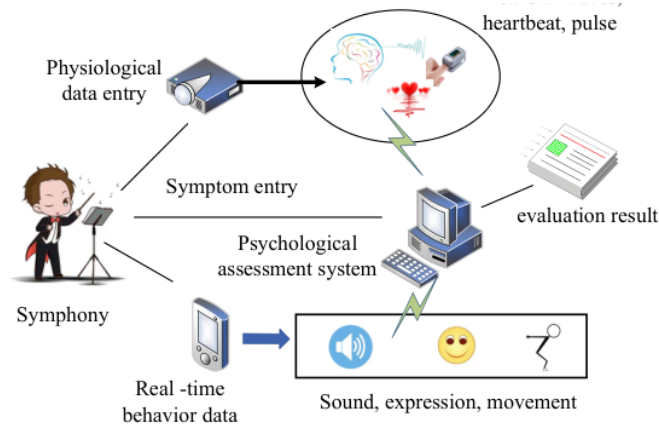


FIGURE 2. Artificial Intelligence Psychological Assessment System

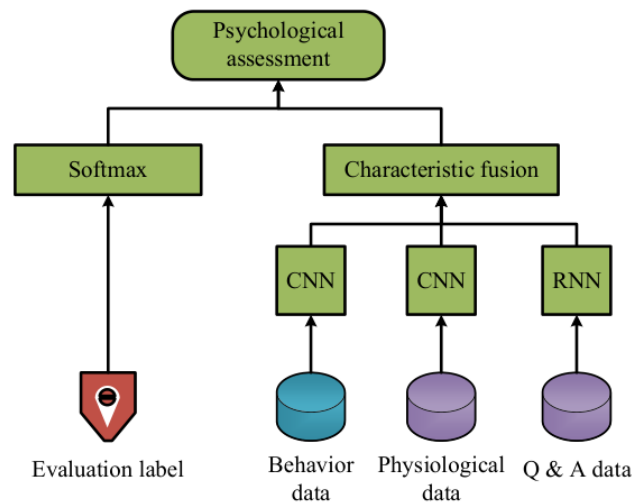


FIGURE 3. Psychological Assessment Model Framework

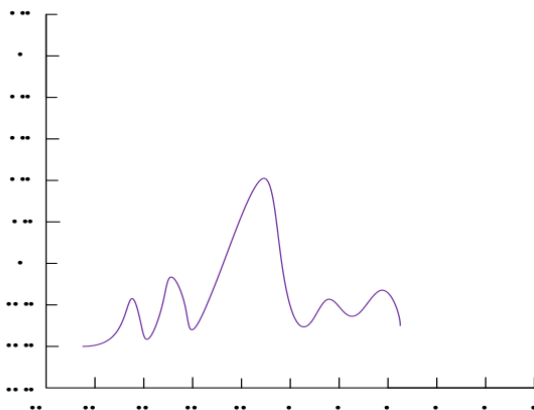


FIGURE 4. Wavelet in time domain

The reconstruction equation of binary wavelet transform

is:

$$f(t) = \sum_{k \in \mathbb{Z}} \int_{\mathbb{R}} [WT_{2^k}(\tau)] \tilde{\varphi}_{2^k}(t) d\tau \quad (7)$$

where $\tilde{\varphi}_{2^k, \tau}(t)$ is a dual frame of $\varphi_{2^k, \tau}(t)$.

B. MALLAT'S ALGORITHM

Multiresolution analysis is a theory based on the concept of functional space. Mallat specifies a fast binary particle transformation algorithm called Mallat's algorithm [20].

Analyzed and defined by multiresolution:

$$V_{j-1} = \text{span} \left\{ 2^{(-j+1)/2} \phi(2^{-j+1}t - k) \right\}_k \quad (8)$$

Then the expansion of any $f(t) \in V_{j-1}$ in V_{j-1} space is:

$$f(t) = \sum_k c_{j-1, k} 2^{(-j+1)/2} \phi(2^{-j+1}t - k) \quad (9)$$

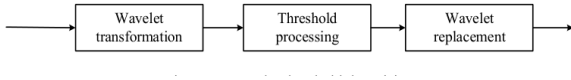


FIGURE 5. Wavelet threshold de-noising

Projecting $f(t)$ to V_j, W_j space respectively, there are:

$$f(t) = \sum_k c_{j,k} 2^{-j/2} \phi(2^{-j}t - k) + \sum_k d_{j,k} 2^{-j/2} \varphi(2^{-j}t - k) \quad (10)$$

$c_{j,k}$ and $d_{j,k}$ are the expansion coefficients on the j scale. $c_{j,k}$ is the scale factor and is gradually discretely approximated at resolution 2^{-j} . $d_{j,k}$ is the wavelet coefficient, also the discrete detail at resolution 2^{-j} . $\phi(t)$ and $\varphi(t)$ are the corresponding scale function and wavelet function, respectively. The Mallat tower decomposition algorithm can be expressed as:

$$c_{j,k} = \sum_m h_0(m - 2k) c_{j-1,m} \quad (11)$$

$$d_{j,k} = \sum_m h_1(m - 2k) c_{j-1,m} \quad (12)$$

Where h is the fast response of the mirror band. It can be obtained from the above equation that in the scale space j , both the scale coefficient $c_{j,k}$ and the wavelet coefficient $d_{j,k}$ can be obtained by the weighted summation of the band coefficient $h_0(n)$ in the scale space $j - 1$. Similarly, by decomposing the coefficient $c_{j,k}$ on the spatial scale V_j, V_{j+1} and the scale coefficient $c_{j+1,k}$ and the wavelet coefficient $d_{j+1,k}$ of the W_{j+1} spaces can be calculated respectively. Then continue to decompose the scale space V_{j+1} , and the arbitrary scale space coefficient V_j can be calculated.

The Mallat tower reconstruction algorithm is:

$$c_{j-1,m} = \sum_k c_{j,k} h_0(m - 2k) + \sum_k d_{j,k} h_1(m - 2k) \quad (13)$$

C. WAVELET THRESHOLD DENOISING ALGORITHM

The concept of wavelet transform threshold denoising is that, according to the linear nature of ripple transform, if the noise energy is significantly smaller than the signal energy, the ripple coefficient corresponding to the noise is also significantly smaller than the corresponding ripple coefficient [21]. Using the characteristics of this transformed noise wave, the ripple coefficient is trimmed below a certain threshold. The discrete proximity signal is then reconstructed by transversal slice details and noise reduction is achieved with the processed discrete details. A schematic diagram of the algorithm is shown in Figure 5.

When selecting a threshold or a threshold, there are generally two types of soft threshold and hard threshold.

The soft threshold processing equation is:

$$y = \begin{cases} \text{sign}(x) \cdot (|x| - T), & |x| > T \\ 0, & \text{other} \end{cases} \quad (14)$$

The hard threshold processing equation is:

$$y = \begin{cases} x, & |x| > T \\ 0, & \text{other} \end{cases} \quad (15)$$

Wavelet threshold denoising was applied to all raw EEG and ECG signals before feature extraction, with a universal threshold $\lambda = \sigma \sqrt{2 \log N}$ where N is the signal length and σ is the estimated noise standard deviation derived from the median absolute deviation of the finest-scale wavelet coefficients, and the soft thresholding rule defined in equation (14) was selected for all denoising operations.

D. NEGATIVE ENTROPY ALGORITHM

In the negative entropy algorithm, the objective function mainly includes curvature, negation, approximate negation and Gaussian distribution. Entropy is used to describe the uncertainty of random variables. In general, the higher the entropy of a random variable, the greater the uncertainty. Among all random variables with the same variance, Gaussian random variables have the highest entropy [22]. Based on this feature, the definition of entropy only needs to be slightly modified to obtain the negative entropy of a random variable, which is then used as a function of the non-Gaussian distribution of the random variable.

For any random variable x , its negative entropy $S(x)$ is:

$$S(x) = H_G(x) - H(x) = \int p(x) \log \frac{p(x)}{p_G(x)} dx \quad (16)$$

As can be seen from Equation (16), the negative entropy value can still be non-negative. Negative entropy is 0 only when the random variable x is still Gaussian distributed. If x is any other non-Gaussian distribution, its negative entropy value is always greater than 0.

In terms of statistical properties, the negative entropy distribution is the best tool to study the non-Gaussian entropy distribution of random variables. Similar to the curvature function, the negative entropy function can also be used as an independent component to extract the objective function [23]. The numerical estimation of the negative entropy function directly involves the numerical calculation of the random multivariate probability equation. The workload of numerical estimation will be quite large, and there must be a relatively more accurate and effective negative entropy function calculation equation.

Assuming that random variable x has zero mean and unit variance, the approximate calculation equation of negative entropy is:

$$S(x) \approx \frac{1}{12} k_3(x)^2 + \frac{1}{48} k_4(x)^2 = \frac{1}{12} (E\{x^3\})^2 + \frac{1}{48} (kurt(x))^2 \quad (17)$$

Equation (17) uses the curvature of the random variable again, and it is pointed out that the curvature estimation has a non-robust problem. Therefore, Equation (17) also has a non-robust problem for negentropy estimation. The

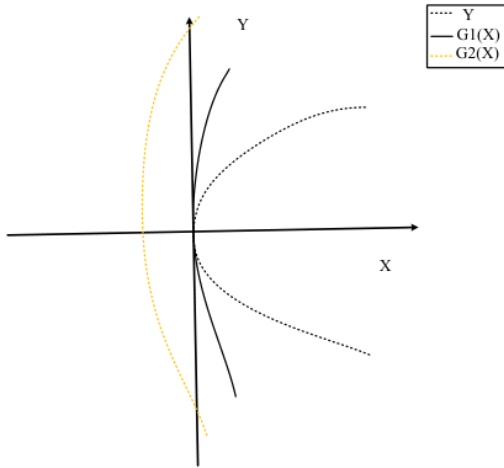


FIGURE 6. The Wave of Nonlinear function

new entropy estimation algorithm based on the principle of maximum entropy is more accurate than the approximate Equation (17) based on cumulative negative entropy.

The approximate calculation equation of negative entropy based on the principle of maximum entropy is:

$$S(x) \propto [E\{G(x)\} - E\{G(v)\}]^2 \quad (18)$$

In Equation (18), v is a typical Gaussian random variable, and G is a certain form of non-quadratic function, which can be selected with reference to x^4 waveforms and variable functions. Choose a function that curves down perfectly symmetrically and the ratio grows slowly, the function is expressed as:

$$G_1(x) = \frac{1}{c} \log(\cosh(cx)); 1 \leq c \leq 2 \quad (19)$$

$$G_2(x) = -\exp(-x^2/2) \quad (20)$$

Figure 6 shows the waveforms of $y = x^4$, $G_1(x)$ and $G_2(x)$ respectively.

According to the analysis, it can be concluded that the actual negentropy approximation to be calculated in Equation (18) should be within the specified expected error range, and fully meet the estimation of the actual negentropy, which is also reflected in the change of the actual negentropy approximation. Random variables accurately represent non-Gaussian changes over different time distributions. The Fourier transform algorithm converted raw EEG signals from the time domain to the frequency domain for power spectral density feature extraction in the theta, alpha, and beta bands, and the extracted frequency-domain features together with time-domain features from wavelet decomposition were concatenated into a feature vector of length 512 per time window. The Mallat algorithm with Daubechies-4 wavelet basis performed a four-level decomposition of each physiological signal, and the detail coefficients at levels 1 through 4 were threshold-denoised using the soft thresholding rule with universal threshold $\lambda = \sigma\sqrt{(2\log N)}$ before

being reconstructed as the denoised signal. The negative entropy algorithm computed non-Gaussianity scores from the independent components of the denoised EEG and ECG signals, and these scores were used as additional input features to the convolutional neural network alongside the raw and wavelet-transformed features. The wavelet threshold denoising, Fourier transformation, and negative entropy calculation were implemented as a preprocessing pipeline executed before any data entered the CNN or RNN layers, with all mathematical operations coded in Python using the PyWavelets and NumPy libraries.

V. PSYCHOLOGICAL ASSESSMENT METHOD TEST RESULTS

In the artificial intelligence mental assessment model, the degree of convergence of the convolutional neural network (CNN) is determined by the quality of the data. In the shortest time, good data can help the network reach a better convergence balance. On the other hand, no matter how the parameters of the network change, if the data is not correct, it is difficult to achieve the desired effect. The input and output data of the CNN should be preprocessed first to make the training of the CNN more efficient and to improve the processing speed of the established CNN.

The sample data is randomly divided into two parts: one part is used as a training sample to train the network, and the other part is used as a test sample to judge whether the trained network meets the requirements. The full dataset of 120 participants was split into a training set of 84 participants and a test set of 36 participants using stratified random sampling to preserve the distribution of anxiety severity levels, and within the training set, 20% of the data was held out as a validation set for hyperparameter tuning. Finally, the model is simulated and tested to see if it achieves the expected predictions. The error of the network is continuously reduced in the process of self-learning, as shown in the curve description in Figure 7. The convolutional neural network can basically achieve the smallest error prediction through continuous training. The optimized convolutional neural network can achieve faster data evaluation results. Without changing the original network structure and network parameters, the optimized CNN's ability to evaluate data is significantly improved. The reason is that the Fourier transform algorithm uses the fitness function to determine the optimal weights and thresholds, which are then handed over to the CNN for training. After optimization, the number of iterative steps in the convolutional neural network is significantly reduced, and the preset target can be reached faster. Figure 8 depicts the difference between the expected output of the convolutional neural network and the actual output of the model.

In the artificial intelligence psychological assessment model, the convolutional neural network introduces the concept of state transition. In this way, the probability of transition from one state to another can be obtained, which can further evaluate and guide future work. The advantages

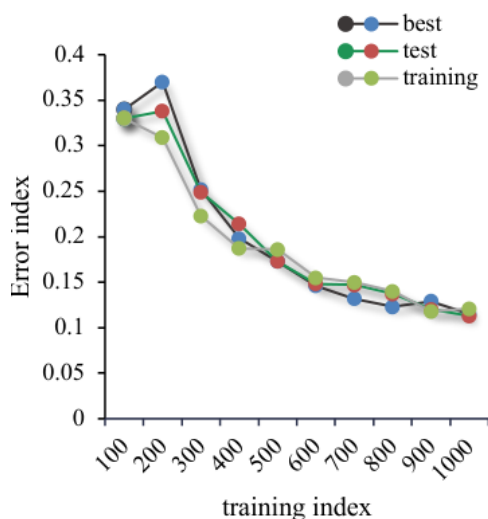


FIGURE 7. training process

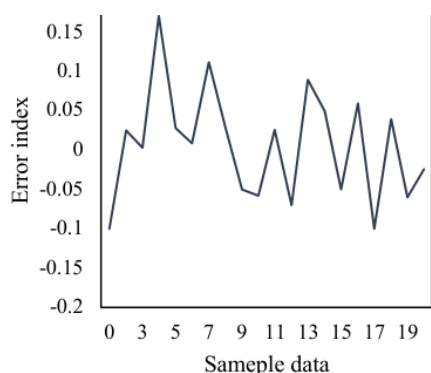


FIGURE 8. Neural network model data error

of describing mental phenomena with mathematical models are not only more general and accurate than describing them with natural language. More importantly, it is convenient for computer simulation to create conditions for the optimization of psychological assessment. The trained convolutional neural network is simulated using the `sim` function, then the simulation results are denormalized and compared to the original data. The comparison results between the predicted data and the real data are shown in Figure 9.

From Figure 9, it can be concluded that the obtained simulated data is very close to the real data. This shows that the trained convolutional neural network has a good effect on the evaluation of the psychological state of symphony players.

Figure 10 and Figure 11 show the dynamic evaluation effect of symphony players' nervousness in the psychological evaluation model, which is divided into two parts: training and testing. It can be seen from the line graph that both the in-sample training set and the validation set and the out-of-sample test set can effectively evaluate the dynamic trend

of the players' psychological fluctuations during a period of time. This demonstrates the applicability and effectiveness of convolutional neural networks for psychological assessment. The ground truth for nervousness was established using the State-Trait Anxiety Inventory STAI Form Y-1 administered immediately before each performance simulation and the Performance Anxiety Rating Scale PARS completed by two independent clinical psychologists who observed video recordings of each player's performance without knowledge of the model outputs, and the accuracy metric reported in Figure 12 represents the proportion of test set samples for which the model's binary nervousness classification matched the consensus ground truth determined by averaging the STAI score above the clinical cutoff of 40 and the mean PARS score above 3.5 on a 1-to-5 scale, with Cohen's kappa for inter-rater agreement between the two psychologists calculated at 0.84 and the model's classification achieving a kappa of 0.79 against the consensus label.

After combining artificial intelligence technology and convolutional neural network to the psychological evaluation model, the weights and thresholds used by the psychological evaluation model are the internal representation of the most suitable data requirements obtained by the convolutional neural network through adaptive learning. Then, the characteristic data of the sample set to be recognized is input into the artificial intelligence psychological evaluation model, and finally the output result of the recognized sample is automatically inferred. Figure 12 shows the evaluation error values before and after optimization of the psychological evaluation model. It can be found that after optimizing the stress evaluation model based on artificial intelligence technology, the error value is significantly reduced, and the evaluation accuracy rate is increased by 7.3%. The error values in Figure 12 represent the mean squared error between the model's continuous nervousness severity score output and the continuous composite score computed from the STAI and PARS measurements normalized to a 0-to-1 range, and the 7.3% accuracy improvement refers to the reduction in classification error rate from 14.2% before optimization to 6.9% after optimization when thresholding the continuous output at 0.5 for binary nervousness classification against the same ground truth labels.

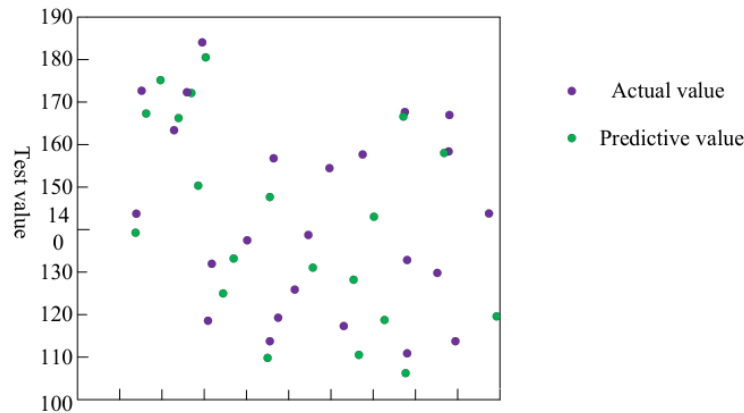


FIGURE 9. Graphical output of the network after training

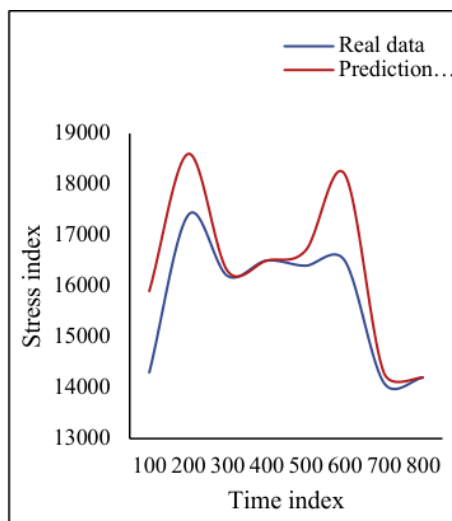


FIGURE 10. Dynamic evaluation eff(training)

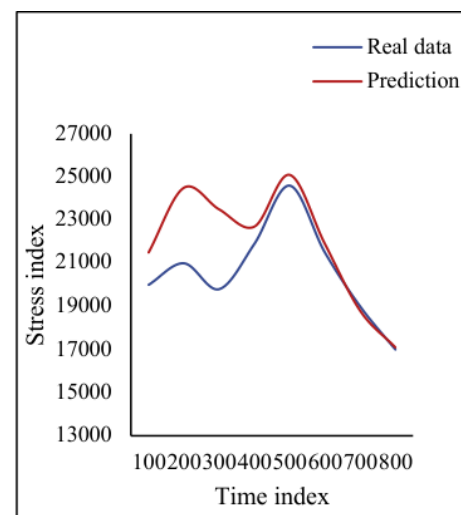


FIGURE 11. Dynamic evaluation effect(test)

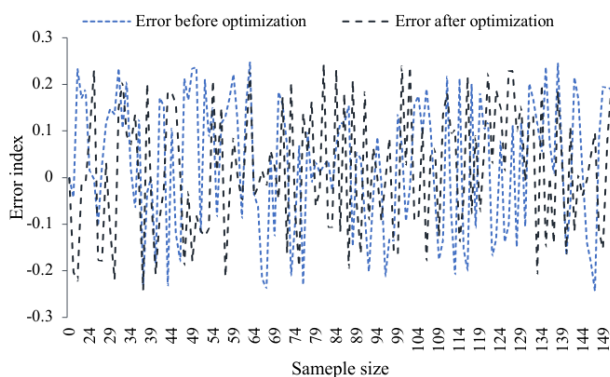


FIGURE 12. Error comparison before and after optimization

VI. CONCLUSION

This paper studies and analyzes the psychological evaluation of nervousness in symphony performance in the context of artificial intelligence technology. A psychological

assessment model is built by using artificial intelligence technology and combining with convolutional neural network, which provides an intelligent and accurate psychological assessment method for symphony players. During the evaluation process, the player's physiological data and behavioral data were collected in real time. Quantitative data on the influencing factors of symphony players' labor stress were input into the evaluation model. And the Fourier transform algorithm was used to process and analyze the data, and finally the psychological evaluation model was experimentally tested. The results showed that the method could effectively evaluate players with nervous psychological problems by quantifying various influencing factors, and improved the accuracy of evaluation.

AUTHOR CONTRIBUTIONS

Ting DENG is the sole author of this article and is responsible for all the contributions.

CONFLICTS OF INTEREST

The authors declare no conflict of interest

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