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Research Article

A Smart Detection Method of Sleep Quality Using EEG Signal and Long Short-Term Memory Model

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Sleep is the most important physiological process related to human health. The development of society has accelerated the pace of people's lives and has also increased people's life pressure. As a result, more and more people suffer from reduced sleep quality, and the resulting diseases are also increasing. In response to this problem, this study proposes a sleep quality detection and management method based on electroencephalogram (EEG). The detection of sleep quality is mainly achieved by staging sleep EEG signals. First, wavelet packet decomposition (WPD) preprocesses the collected original EEG to extract the four rhythm waves of EEG. Second, the relative energy characteristics and nonlinear characteristics of each rhythm wave are extracted. The multisample entropy (MSE) values of different scales are calculated as the main features, and the rest are auxiliary features. Finally, the long short-term memory (LSTM) model is applied to classify the extracted sleep features, and the final result is obtained. Experiments were conducted in the MIT-BIH public database. The experimental results show that the method used in this article has a high accuracy rate for sleep quality detection. For the detected sleep quality data, the data are managed in combination with the mobile terminal software. Management is mainly embodied in two aspects. One is to query and display historical sleep quality data. The second is that when there are periodic abnormalities in the detected sleep quality data, the user will be reminded so that the user can respond in time to ensure physical fitness.

1. Introduction

Sleep is an indispensable physiological process in people's daily life. Every day, most people spend about 30% of their time sleeping. After a day of study and work, the body and brain are in a state of fatigue. The ability to respond to nerves and the functioning of organs slow down during sleep. Heartbeat, blood pressure, and metabolic rate decrease, and muscle tissue becomes loose. At this time, sleep is the best way to eliminate fatigue from the body [1]. Good sleep helps to improve work efficiency and mental outlook. Inferior sleep can cause endocrine disorders, increase the risk of amnesia and other diseases, and cause inattention, which affects normal working and living conditions. Therefore, having good quality sleep is very important to people's lives. Studies have shown that in addition to poor physical conditions, people with insufficient sleep will age 4 to 5 times higher than those with healthy sleep. People who are affected by sleep for a long time will also decrease in intelligence, thus affecting normal life. Adequate sleep is one of the internationally recognized sleep health standards. In order to make people pay more attention to issues related to sleep quality, the International Mental Health and Neuroscience Fund in 2001 set the "World Sleep Day" as March 21, and launched a global sleep and health plan [2]. Nowadays, people all over the world have difficulty falling asleep or even insomnia. It is becoming more and more common, and there are more and more diseases derived from sleep problems. The problem of sleep quality is gradually getting people's attention, and the scientific inquiry related to sleep diseases has also received more attention from medical experts and scientists.

The main indicator for judging the quality of human sleep is whether the human brain is awake or not after waking up. Therefore, it is the best starting point to study sleep by studying the brain activity. EEG can accurately and quickly reflect the physiological changes of the human body; it belongs to an advanced biological signal. It provides important analytical reference information for neurology, medicine, and other disciplines. It can accurately reflect the activity of the brain, and its application in sleep research is gradually becoming common. Each person has different characteristics and amplitudes of EEG signals in different sleep states, which reflects the different and complex functions of the brain at different stages. People's sleep cycle can be roughly divided into three periods, namely, rapid eye movement (REM), nonrapid eye movement (NREM), and wake (W). According to a certain rule of classification of the characteristics of each stage, such a process is called sleep staging. If the result of sleep stage is similar to that of standard sleep classification, it means that the quality of sleep is good. Otherwise, the sleep effect is not good. The results of sleep stages can be used as the basis for judging sleep quality. Therefore, the higher the accuracy of sleep staging, the more accurate the feedback of sleep quality. Sleep staging has important clinical significance and broad application prospects for the treatment of sleep disorders.

In the 1820s, the German psychiatrist Berger discovered that the brain electrical activity of a person is different in the two states of waking and sleep. Since then, the study of sleep EEG has started. In the 1860s, Dumermuth et al. used fast Fourier transform to process EEG, which promoted its development in frequency domain analysis [3]. The American Academy of Sleep Medicine (AASM) formulated the current general AASM standard, which divided the sleep process into 5 stages [4]. When experts perform artificial sleep staging according to general staging standards, they need to observe sleep signals for a long time, which is time-consuming, heavy workload, and subjectively affected. Therefore, the automatic sleep staging method was born. At present, various statistics and pattern recognition methods [5–18] have been applied to sleep staging. The existing sleep staging methods have their own advantages and disadvantages. Considering that EEG data are time series data in order to establish a sleep quality detection model with high accuracy and fast calculation speed, this research proposes a detection method with higher accuracy and timeliness. The contributions of this research are summarized as follows:

(1) A more efficient sleep quality detection framework is used. The detection frame first performs denoising preprocessing and feature extraction on the raw data, inputs the extracted features into the classifier, and uses LSTM to classify sleep EEG signals. Experiments verify that the detection framework used has a higher detection accuracy for sleep quality.

(2) According to the results of sleep quality testing, a sleep quality monitoring system was designed. First of all, the system can collect sleep EEG signals and store the collected raw datasets on the cloud platform. Second, the used detection framework is used as the sleep quality detection module to classify and recognize the input original sleep EEG to obtain the final recognition result. The recognition result is stored in the cloud platform. Third, terminal devices such as mobile phones and tablet computers can access the cloud platform to obtain data and display the data on the terminal application. Users can view and query data through the application.

(3) The sleep detection cloud platform used in this article can collect sleep data of multiple users. These sleep data can provide data support for medical institutions and sleep-related enterprises. In addition to basic sleep data, the cloud platform can also collect the user's sleep quality diagnostic information. These diagnostic information can assist related companies to develop more accurate products for users.

2. Related Work

2.1. Introduction to EEG Signal and Sleep Quality. The brain is mainly responsible for controlling and regulating the thinking and consciousness activities of the human body. EEG is a random signal that reflects the electrical activity of brain tissue. The cerebral cortex is the highest center of the nervous system that regulates physical movement, responsible for the cognitive and emotional functions of the brain, and is also the most important part of the brain. Various activities and sensations of the human body can find corresponding areas in the cerebral cortex, and each area has its own specific role and function. The neuronal cells of the cerebral cortex are the reason why human beings have complex activities as advanced organisms. The condition that can produce complex activities is that each neuron cell can communicate through the connection of dendrites, making human activities have countless possibilities. The birth of EEG comes from the activity of neurons in the cerebral cortex. The signals generated by the potential activity of nerve cells can be obtained by adding electrodes on the scalp to obtain an EEG. The amplitude, frequency, and phase of the waveform contained in the EEG have certain characteristics. The bandwidth of EEG is 0.5~100 Hz, and only 0.5~30 Hz part of spontaneous EEG is considered in clinical medicine. According to frequency characteristics, it can be divided into four basic rhythm waves and nonbasic waves. During sleep, the rhythm waves appear regularly, and the irregular waves are nonfundamental waves. Figure 1 shows the basic characteristic wave of the EEG signal.

2.2. Sleep Staging. During sleep, the depth of sleep will cause changes in EEG. Therefore, as long as the sleep EEG numbers of people in different periods are grasped, it is possible to compare whether the EEG changes of the samples to be tested follow the standard change law. If the standard change rule is not followed, the sleep quality of the sample to be tested is determined to be poor. According to this

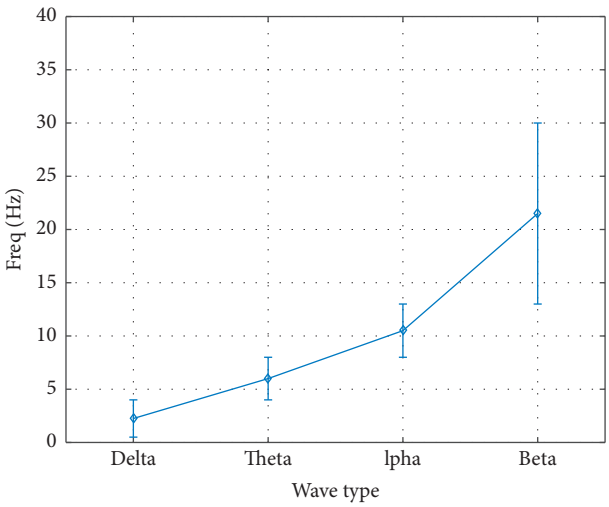

Figure 1: Basic characteristic wave of EEG.

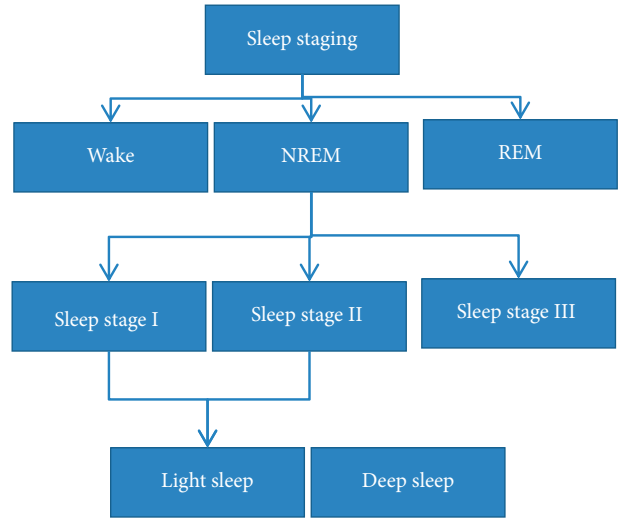

Figure 2: AASM sleep staging standard.

principle, it can be analyzed that to detect a person's sleep quality, it is necessary to perform a staged test of his sleep EEG. The most widely used sleep staging standard is the AASM standard, which is shown in Figure 2.

In different sleep states, EEG signals are different. The characteristics of EEG in various states are as follows:

W Period. The awake period is the preparation period for sleep. At this stage, the brain is in a conscious state that responds quickly to changes in the surrounding environment. At this time α wave and β wave are the main part. The alpha wave accounts for more than 50% to judge whether it is the awake period. This period is mostly awake, accompanied by blinking and rapid eye movements, and there will be a short W period during sleep.

S1 Stage. This period is the transitional stage from waking state to sleep state. At this stage, the eyeball moves slowly and with the appearance of spikes, the external environment hardly affects the sleep state. The proportion of alpha waves fell below 50%, with low amplitude theta waves dominating.

S2 Period. This period sleeps deeper than S1 period. At this stage, the amplitude of the EEG signal increases, and eye movement basically stops. Brain waves are dominated by low-amplitude and mixed-frequency spindle waves and K-complex waves, and delta waves account for less than 20%. If the duration of two consecutive spindle waves and K-complex waves is less than 3 minutes, it is judged as S2, and if the duration is longer than 3 minutes, it is judged as S1.

S3 Stage. This stage is a deep sleep state, also known as slow wave sleep. Low-frequency delta waves are the main signal, accounting for more than 20%. Generally, if the peak value exceeds 75 μV, a complex wave of spindle and K may appear, but it is mainly a delta waveform. There will be no large fluctuations in the amplitude of the brain waves, and the eyeballs and muscles will stop.

REM Period. This stage is accompanied by the rapid and autonomous rotation of the eyeball. Except that the spike wave is not obvious, everything else is the same as the waveform of the S1 period. REM is a lighter sleep process, during which people who wake up are sensitive to the surroundings. The proportion during sleep will gradually decrease with age. REM sleep function is higher, and the correlation between emotion regulation and memory function is higher.

2.3. Sleep Quality Management. Sleep quality management is mainly realized through the sleep quality management system. The architecture of the system is shown in Figure 3. First, collect the sleep EEG signal through a collector such as a worn watch, and send the collected data to a cloud platform for storage through a network such as WiFi. Second, the sleep quality detection module in the server obtains data from cloud platform and performs detection and identification to obtain sleep quality detection results. The server then sends the detection result to the cloud platform for storage. Third, use mobile phones, tablet personal computers, and other terminals to get sleep detection results and display them on the cloud platform. Fourth, the application on the terminal can not only display sleep detection data but also query and prompt the data.

This article focuses on the design of sleep quality management application. Sleep quality management application can detect human sleep data in real time, display sleep data for a certain period of time, and give sleep quality scores. This sleep quality score is obtained using the sleep quality test method in Section 3. The user can set the score threshold on the setting interface and promptly remind the user when the sleep quality score is lower than the set threshold. After the user receives the reminder, he can adjust the mechanical energy in time for his work and rest. In addition to the above basic functions, the following functions will be added to the APP designed in this study:

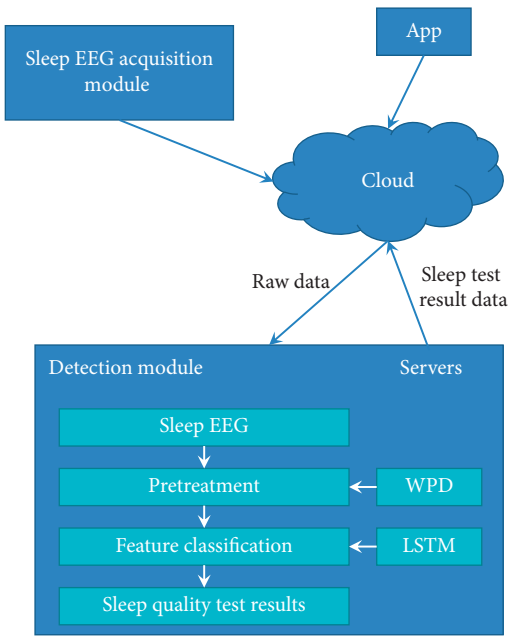

Figure 3: Architecture diagram of the sleep quality detection system.

(1) *Hypnotic Music*. When the user cannot sleep, the APP will combine sleep science and original sleep aid music to let the user fall asleep quickly. APP can intelligently recognize falling asleep and automatically stop the music after detecting that the user is asleep.

(2) *Gentle Wake Up*. The traditional alarm clock sounds loud, so the app's special music can gently wake up users and bid farewell to the awakening of traditional alarm clocks.

(3) *Record Sleep Talk and Snoring*. When the user talks about sleep and snoring at night, the APP will help the user to record it so that the user can discover the unknown self and share different fun.

(4) *Sleep Analysis Report*. The recognition algorithm in the APP has been tested and compared by a large number of professional sleep laboratories, and the sleep data are compared with professional EEG and ECG sleep monitoring equipment to ensure the accuracy of the sleep algorithm.

3. Sleep Quality Detection Based on EEG Signals

3.1. Sleep Quality Inspection Process. The detection of sleep quality is mainly realized by automatically staging sleep EEG signals. First, WPD is used [19, 20] to preprocess the collected original EEG to extract the four rhythm waves of EEG. Second, the relative energy characteristics and nonlinear characteristics of each rhythm wave are extracted, and the MSE values [21, 22] of different scales are calculated as the main characteristics, and the rest are auxiliary characteristics. Third, the sleep features after dimensionality reduction are sent to the LSTM model to return the final results. Figure 4 shows the sleep quality detection process.

3.2. Preprocessing of Sleep EEG Signals. Since the EEG signal is weak and noisy, it needs to be preprocessed. This study mainly uses wavelet threshold denoising. The wavelet threshold method is mainly divided into two types: soft threshold and hard threshold. According to the actual signal and requirements, choose one of the methods to filter out the Gaussian white noise in the noisy signal. The process of wavelet threshold denoising is shown in Figure 5.

The main steps of using the wavelet threshold method to preprocess EEG signals are as follows:

(1) Determine the optimal wavelet basis and the optimal decomposition layer, and iteratively select the optimal tree under the standard entropy, and then decompose the EEG signal in n layers.

(2) The decomposed coefficients are processed by using an appropriate threshold function. Each level of decomposition corresponds to a threshold, and the high-frequency coefficients are also thresholded.

(3) The discrete wavelet transform reconstructs the nonzero coefficient signal after processing in step (2), thus completing the threshold denoising process of EEG.

3.3. Feature Extraction of Sleep EEG Signal. Different sleep stages have different characteristic waves, so the rhythm waves of sleep EEG can be used as the basis for sleep staging. Different rhythm waves have different signal energy, and energy can be used as a parameter to distinguish the waveform. Energy is different in different sleep periods, so the change of energy has become an important basis for the study of sleep staging. Suppose the total energy of the signal is M, and the energy of each rhythm wave of EEG is $M_\alpha, M_\beta, M_\delta$, and M_θ. The total energy expression of signal $g(t)$ is

$$M_j = \int |g(t)|^2 dt = \sum_{i=1}^{n} |x_i|^2. \quad (1)$$

M_j represents the energy value after the signal $g(t)$ is repurchased. j represents different rhythm waves, and i represents the number of sampling points of signal samples, $i = 0, \ldots, m$. x_i represents the amplitude corresponding to the sampling point of the reconstructed signal. The total energy expression of each characteristic wave of sleep EEG is as follows:

$$M = \sum_{i=1}^{n} |x|^2. \quad (2)$$

The relative energy expression is

$$M_j = \frac{M_j}{M}. \quad (3)$$

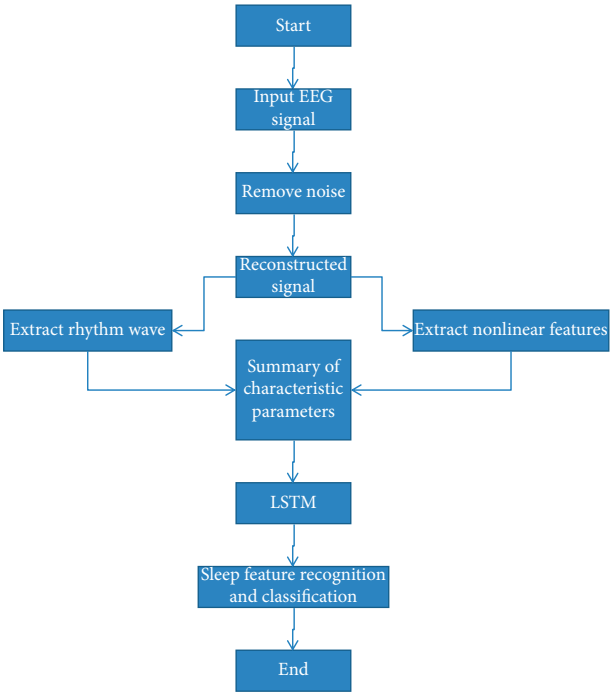

Figure 4: Sleep quality testing process.

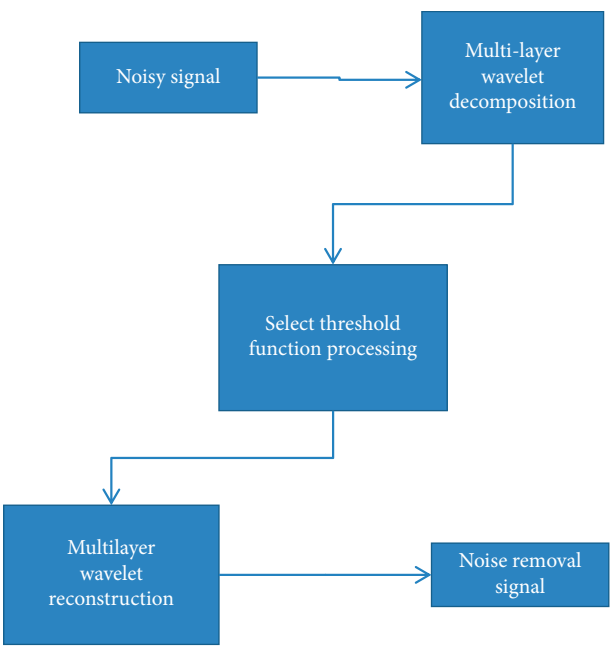

Figure 5: Wavelet threshold denoising flow chart.

3.4. Classification of Sleep EEG Signals. LSTM [23, 24] is a version of RNN [25, 26]. The difference between LSTM and general RNN is the way to update the status in the middle. It is characterized by a time cycle structure, which can well describe the sequence data with spatiotemporal correlation, including time series data, text, events, and so on. LSTM can be simply understood as an autoregressive model based on neural network. Suppose RNN is used to predict a text. When the interval between the relevant information and the current predicted position increases, RNN will lose the ability to learn the remote information. In theory, RNN can definitely deal with the problem of "long-term dependence." One can carefully select parameters to solve the most elementary form of such problems. However, in practice, RNN will not be able to learn these knowledge successfully. Based on this background, the LSTM model was proposed. Figure 6 gives the structure of the LSTM model.

In the figure, the large rounded rectangular block diagram represents a cell, the small right-angled rectangular block diagram represents a neural network layer, and the small circle represents dot multiplication. The cell state in the figure can be understood as a conveyor belt, which is the memory space of the entire model, which will change over time. The conveyor belt itself cannot control which information is memorized, but three control doors play a controlling role. The three gates are input gate, output gate, and memory gate.

The core idea of the LSTM model is to replace each hidden unit in the RNN with a cell with a memory function (as shown in Figure 7), and the other structures are the same as the RNN. In Figure 7, g_c represents input node, which has the same function as the RNN model. i_c represents input gate, which can control the input information. s_c represents internal state node, f_c represents forgetting gate, and o_c represents output gate.

Several cells form an LSTM layer, and the calculation formula of the LSTM layer is as follows:

$$\begin{aligned}
\mathbf{g}^{(t)} &= \phi\left(W_{gx}x^{(t)} + W_{gh}\mathbf{h}^{(t-1)} + \mathbf{b}_g\right),\\
\mathbf{i}^{(t)} &= \sigma\left(W_{ix}x^{(t)} + W_{gh}\mathbf{h}^{(t-1)} + \mathbf{b}_i\right),\\
\mathbf{f}^{(t)} &= \sigma\left(W_{fx}x^{(t)} + W_{fh}\mathbf{h}^{(t-1)} + \mathbf{b}_f\right),\\
\mathbf{o}^{(t)} &= \sigma\left(W_{ox}x^{(t)} + W_{oh}\mathbf{h}^{(t-1)} + \mathbf{b}_o\right),\\
\mathbf{s}^{(t)} &= \mathbf{g}^{(t)} \odot \mathbf{i}^{(i)} + \mathbf{s}^{(t-1)} \odot \mathbf{f}^{(t)},\\
\mathbf{h}^{(t)} &= \mathbf{s}^{(t)} \odot \mathbf{o}^{(t)}.
\end{aligned} \tag{4}$$

4. Experimental Data Analysis

The data used in this study are selected from the Sleep-EDF dataset in the MIT-BIH sleep database, which contains two files, SC and ST. The SC file contains the sleep data of 20 men and women with healthy sleep, and the ST file contains the sleep data of 22 men and women with different degrees of sleep disorders. In this study, the data of 4 subjects were selected from SC and ST for experiments. The 4 subjects with normal sleep were coded as SC01–SC04, and the 4 subjects with sleep disorders were coded as ST01–ST04. There were 800 pieces of sleep data for each participant, totaling 6,400 pieces of data. Select the data of SC01, SC02, ST01, and ST02 as the training set, and SC03, SC04, ST03, and ST04 as the test set. The training set samples are trained many times to avoid the chance of results. In this study, the model with the best training results was selected to classify the test set samples. The experimental software is Matlab2017. Since the manually marked staging results in the database use the R&K

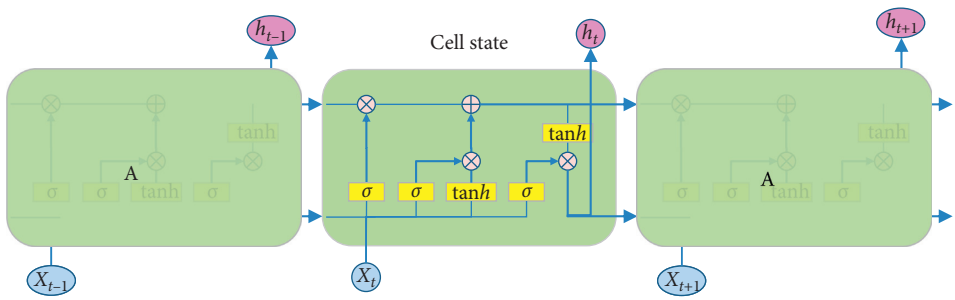

Figure 6: LSTM structure diagram.

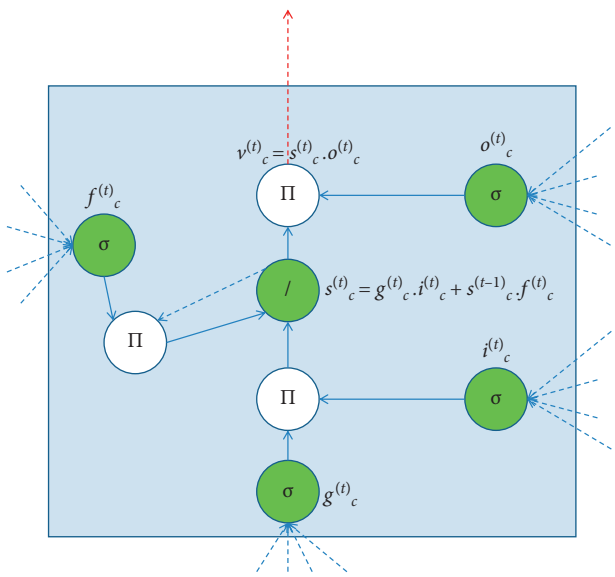

Figure 7: Schematic diagram of cell.

Table 1: Details of artificially labeled sleep stages.

Samples\sleep staging	W	S1	S2	S3	REM
SC01	247	60	250	220	123
SC02	88	61	485	57	209
SC03	197	56	409	136	102
SC04	50	87	403	162	198
ST01	57	52	282	298	211
ST02	24	40	562	109	165
ST03	49	67	338	284	162
ST04	21	66	462	132	219

Table 2: Sleep staging results of training samples.

Training sample	W	S1	S2	S3	REM	Accuracy
SC01	224	51	229	207	114	0.9081
SC02	75	49	476	48	198	0.8856
ST01	46	41	263	271	198	0.8752
ST02	20	32	523	95	148	0.8665

Table 3: Sleep staging results of test samples.

Test sample	W	S1	S2	S3	REM	Accuracy
SC03	180	52	367	119	87	0.8935
SC04	41	74	362	142	172	0.8628
ST03	41	56	299	249	140	0.8596
ST04	18	55	421	121	198	0.8845

staging standard, this study uses the AASM standard, so S4 is counted as S3 when the manual staging results are counted. The staging results marked by experts are shown in Table 1. Table 2 shows the results of the method proposed in this paper to perform sleep staging on the test set.

The data in Table 2 show that the accuracy of sleep staging for selected normal sleep samples and sleep disorder samples is higher than 86%. The accuracy of 5 different sleep periods is different, among which the accuracy of Wake period classification is higher and the accuracy of REM period is lower. The reason may be that there are eye movements during the rapid eye movement period. The EOG signal is more obvious than the EEG signal, so this period cannot be accurately divided.

Table 3 shows the results and accuracy of sleep staging for the test dataset. The experimental data in Table 3 demonstrate that the classification accuracy of the method used in this paper is lower than the training data, and the classification accuracy of the normal sleepers is not much different from the training data. The accuracy of sleep staging of the method used in this paper is slightly less than 90% and is generally between 85% and 89%. The accuracy rate in the awake period is higher, and it is lower in the REM period. The light sleep period is compared with the deep sleep period because the brain nerve activity is active in the light sleep period, and the characteristics are not obvious, and the deep sleep period enters the deep sleep stage, and the brain nerve cell activity is reduced, and the characteristics are obvious, so the classification accuracy rate of the light sleep period is less than deep sleep period.

In order to further verify the robustness of the method used in this paper, Gaussian noise with a mean value of 0 and a variance of 0.1, 0.2, 0.3, 0.4, and 0.5 was added to the abovementioned test dataset. The results of automatic sleep staging of the test samples are shown in Table 4. The experimental data in Table 4 show that with the increase in noise, the accuracy of sleep staging is gradually decreasing. This is consistent with the theory. On the whole, the sleep staging accuracy obtained by the 4 test samples is greater than 80%. This shows that even if there is a little noise, the sleep staging method of this paper is effective and feasible.

Table 4: Sleep staging results of the test dataset after adding noise.

Test sample	Noise	W	S1	S2	S3	REM	Accuracy
	(0,0.1)*	178	51	364	114	85	0.8752
	(0,0.2)	175	49	363	112	84	0.8596
SC03	(0,0.3)	173	47	360	110	82	0.8421
	(0,0.4)	171	44	359	108	80	0.8220
	(0,0.5)	168	42	357	107	76	0.8015
	(0,0.1)	40	73	360	140	171	0.8520
	(0,0.2)	39	71	359	138	170	0.8395
SC04	(0,0.3)	37	69	358	136	169	0.8229
	(0,0.4)	36	67	357	135	168	0.8116
	(0,0.5)	34	67	355	133	168	0.8001
	(0,0.1)	40	56	298	248	138	0.8518
	(0,0.2)	39	55	298	247	136	0.8415
ST03	(0,0.3)	39	54	297	246	136	0.8373
	(0,0.4)	38	54	294	245	135	0.8295
	(0,0.5)	37	52	293	244	134	0.8169
	(0,0.1)	17	54	420	121	197	0.8706
	(0,0.2)	17	53	419	119	196	0.8632
ST04	(0,0.3)	16	52	418	119	196	0.8502
	(0,0.4)	15	51	418	118	196	0.8361
	(0,0.5)	14	50	418	117	195	0.8212

*0 represents mean and 0.1 represents variance.

5. Conclusion

This article mainly studies from two aspects of sleep quality detection and management. For the detection of sleep quality, this article proposes a method of sleep staging detection. First, WPD preprocesses the collected original EEG to extract the four rhythm waves of EEG. Second, the relative energy characteristics and nonlinear characteristics of each rhythm wave are extracted. The MSE values of different scales are calculated as the main features, and the rest are auxiliary features. Finally, the sleep features use the LSTM model for classification, and the final result is obtained. This article uses the AASM standard to stage sleep. The experimental results demonstrate that the detection efficiency of this method is above 86%, which can meet the clinical detection requirements. For the management of sleep quality, this paper develops a piece of software based on the results of sleep detection. The software is used to display the results of sleep detection and remind users in time when the detection results are abnormal. This research has good practical value, and the feasibility of this research is further explained based on the test results. However, the accuracy of sleep detection in this study needs to be further improved. Subsequent research will focus on improving the classification algorithm, hoping to increase the classification accuracy to more than 90%. The sleep quality detection method based on EEG signal in this paper has been verified and can be applied in real life. Because sleep is an extremely complex process, it is difficult to achieve high accuracy in sleep staging. Therefore, this study can also consider the influence of other physiological parameters. As the sleep process is very complicated, physiological parameters such as ECG, EMG, EOG, and respiration have a certain influence on sleep. More physiological parameters should be introduced to study the sleep state to improve the accuracy of sleep quality detection.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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