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Research Article

Application of Virtual Reality Technology in the Recognition System for Overcoming Anxiety and Psychological Pressure of Family Elderly

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When the elderly enter the old age, their physical functions gradually decline; their physical strength, vision, and hearing are weakened; and their self-care ability gradually decreases with the increase of age. At the same time, it is accompanied by different degrees of anxiety and psychological problems. The rapid development of virtual reality technology in recent years provides a way to solve this problem, and high-performance computer and processing technology are the keys to directly affect the performance of the system. The existing research is more about the material and spiritual life of the elderly, but the research on their psychological status is relatively insufficient. From the perspective of mental health, this study makes a comprehensive and objective empirical study on the psychological status of family elderly. Based on virtual reality (VR), by extracting heart rate variability (HRV) features from the elderly, this paper establishes a model to identify the psychological pressure of family elderly, which solves the problem that the elderly have adverse effects on their body, mind, and life due to long-term psychological pressure. The paper analyzes the accuracy of KNN, CNN, and RFC models in identifying three psychological stress states: relaxation and low-pressure state, relaxation and medium-pressure state, and relaxation and high-pressure state. When the pressure is higher, the accuracy of the three models will be better than that of the lower pressure state. Under high pressure, the accuracy of CNN and RFC is close, but RFC is slightly better than CNN, and the accuracy of RFC model is as high as 95.02%.

1. Introduction

As China enters an aging society, the elderly group has attracted more and more attention. At the same time, aging of the population has brought changes to the family structure. Under normal circumstances, every elderly person belongs to a specific family. On the one hand, the aging population has increased the number of the elderly in the composition of family members. With the increasingly serious problem of population aging, the problems of the elderly are emerging one after another, including physical and psychological problems. The research on the stress and psychological stress of the elderly is also increasing. Aging is an irresistible natural law. People will move from a living state to aging. In this process, if we do not give more understanding and attention to various factors, it will lead to many problems, such as decline in health status, physiological dysfunction, and psychological imbalance. To sum up, the mental health of the elderly deserves more attention. Psychological stress is an important factor affecting human health. When the pressure in the human body exceeds the psychological load, it will lead to depression, anxiety, and other serious mental diseases, threatening health.

With the rapid growth of the population, psychological research is also gradually increasing. Xu made a preliminary discussion on the causes of psychological pressure of football referees. He found out the internal and external factors of the psychological pressure of football referees and explored the ways to reduce this psychological pressure in order to alleviate it [1]. Bühren's field experiment analyzed the impact of psychological pressure on the performance of sequential games [2]. The purpose of Benrabah's research was to understand the level of group cohesion of emerging football players under the age of 17 and the type of relationship between them and psychological stress and control center [3]. Galvin investigated the stressors involved in prequalification clinical psychology reported by the sample of clinical psychologists in the UK and also discussed the main coping strategies reported by trainees [4]. Chen expected to more readily comprehend the connection among College Students' downturn and life occasions, social help, mental pressure, and adapting style [5]. However, although various studies have carried out some psychological exploration on many people from different angles, there are few studies on the identification of psychological stress of the elderly under the background of population aging.

The development of VR has greatly changed various industries. Aliyu discussed the recent application of VR in educational environment and chemistry self-learning [6]. Maples searched in the current writing on the viability of integrating VR into the treatment of different mental sicknesses and directed a methodical writing search to decide the execution of VR-based research in the therapy of tension or other mental infections [7]. Based on VR, Zhang further studied two key problems in real-time rendering to realize and improve the modeling speed of virtual roaming [8]. Lai briefly introduced the application of VR from two aspects: the application in theoretical teaching and VR surgical system [9]. Zeming presented the plan and execution of Korean instructing framework. He worked on the effectiveness of showing cycle and increment understudies' advantage; the framework applies augmented reality (AR) innovation [10]. Although these algorithms make the problem simpler and easier to solve to a certain extent, their accuracy still needs to be improved.

In this paper, through the accuracy of identifying three psychological stress states of the three models, we can get the conclusion that KNN has lower accuracy than the other two models in identifying relaxation and different psychological stress, while CNN and RFC have closer accuracy, and RFC is slightly better than CNN. The innovation of this paper is the combination of VR and elderly psychological stress recognition. This paper introduces the theory and related methods of high-performance computing and feature extraction.

2. Pressure Identification Method Based on VR

2.1. Overview of VR. With the accelerated pace of society, the impact of psychological stress on personal life is becoming more and more obvious. The assessment and identification of personal psychological stress has received extensive attention from scholars from all walks of life. The problem of population aging in China is becoming more and more serious, and elderly care services are constantly being researched and improved. The application of VR technology in the elderly will bring new experiences that are different from the existing ones and become one of the new directions of future development trends.

VR technology can also be transformed into immersive and intelligent technology. It is a comprehensive information technology developed at the end of the twentieth century. It provides users with a charming virtual interactive environment. It is a 3D interactive environment with computer technology as the core. Wearing necessary wearable auxiliary devices, users can experience the virtual environment in a very natural way, such as vision, hearing, smell, touch, pain, and so on. It can also interact with other objects in the virtual environment, allowing users to enjoy an immersive and real experience in the environment [11, 12]. Figure 1 describes the whole process of VR.

It can be seen from Figure 1 that physical virtualization mainly includes six key technologies (basic model construction, scene model organization, spatial tracking, sound localization, visual tracking, and viewpoint sensing) shown in the figure. These technologies can create a real virtual world, detect user functions in the virtual environment, and obtain operation data. VR is the key technology to ensure that users can obtain visual, auditory, and other sensory knowledge. Force and touch in virtual environment is the main research content of virtual object implementation. It includes visual perception, auditory perception, and power and tactile perception [13, 14].

VR is a modern high-tech with computer technology as the core, and in it, high-performance computing and processing technology are the keys that directly affect the performance of the system. For the research of high-performance computing, on the one hand, it is beneficial to improve the performance of the elderly stress recognition system, and on the other hand, it makes the recognition system more fluent. High-performance computing clusters are mainly used to deal with complex computing problems and are widely used in the fields of meteorology, environment, and computer-aided engineering. High-performance scientific computers usually use multiple processors or computing systems, as well as a multicomputer environment organized into a complex system. In order to improve the efficiency of computing, the cluster architecture design is generally adopted as a whole to provide strong computing power, and high-speed network transmission is used for internal data communication [15]. The architecture of high-performance scientific computing cluster is shown in Figure 2.

As shown in Figure 2, the high-performance scientific computing cluster system is composed of parallel computing nodes, parallel computing control nodes (management and login nodes), parallel storage system, InfiniBand computing network, Gigabit management network, cluster software system, and other auxiliary equipment. After the job is submitted, it is queued, distributed by the management node, and distributed to the computing node for processing. At present, high-performance computing usually adopts blade server, which refers to the server platform with high availability, high density, and low cost [16]. Blade server refers to a standard-height rack-type chassis that can be plugged into multiple card-type server units.

2.2. High-Performance Computing and Processing Technology. Parallel computer research greatly simplifies the process of stress recognition programs in older adults, as well as the process of distributing recognition tasks across the system.

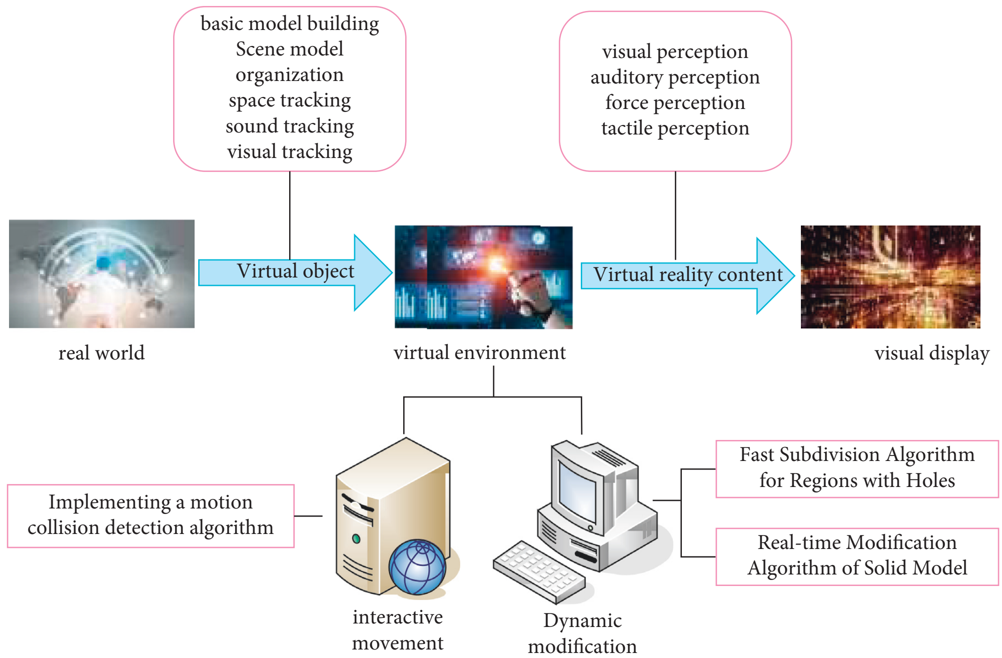

Figure 1: The whole process of VR.

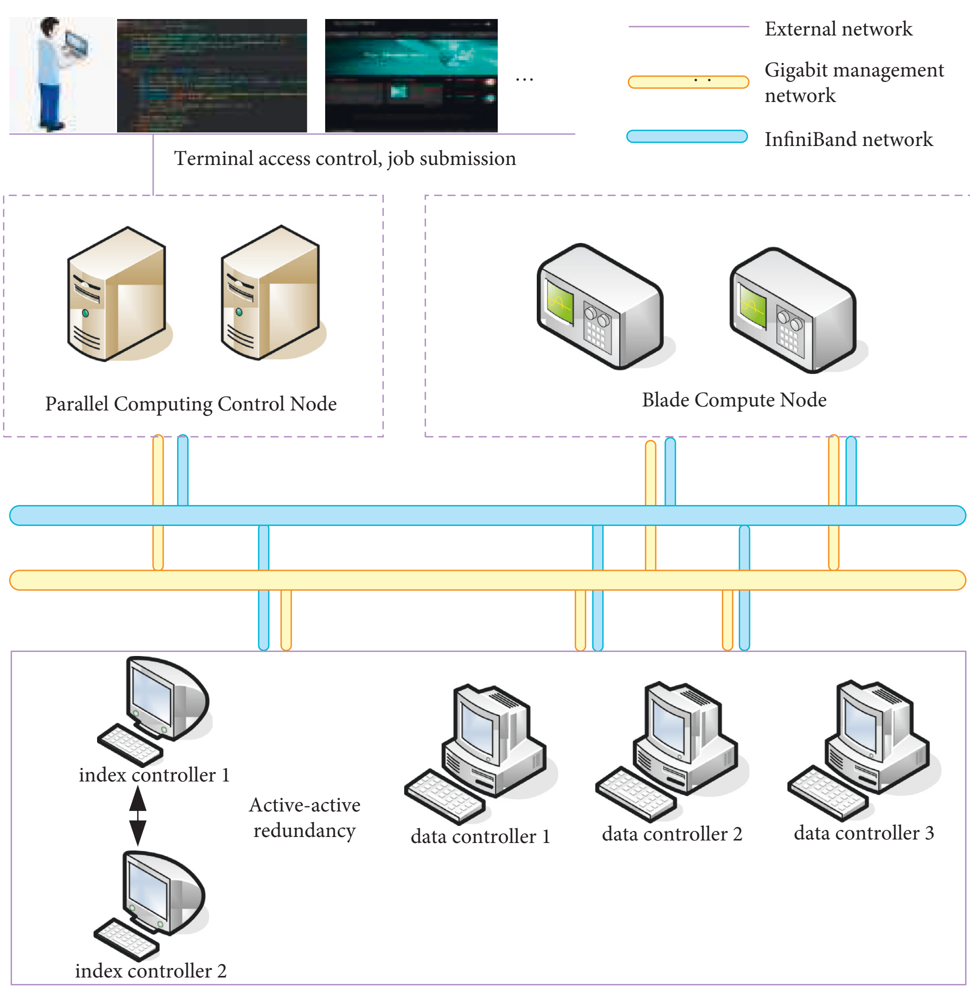

Figure 2: Architecture diagram of high-performance scientific computing cluster.

Parallel computing is the homonym of supercomputing and high-performance computing. It is one of the significant bearings of the improvement of PC innovation. Figure 3 shows the parallel solution process of the problem.

Parallel computing is a method and step of solving a problem by multiple processors. Firstly, the problem to be solved is decomposed into as many independent subproblems as possible, and then multiple computers are used to solve the problem at the same time, so as to finally obtain the original problem.

When measuring the performance of multiprocessor system, the commonly used index is called acceleration coefficient. The acceleration factor is defined as

$$W(h) = \frac{\mathrm{d}_1}{\mathrm{d}_h}, \tag{1}$$

d_1 represents the serial algorithm with the best time to execute serial programs using a single processor. Sometimes, it also represents the execution time of parallel algorithms on a single processor. The two representations are still different. d_h indicates the execution time required for parallel program execution with h processors.

A parallel program can generally be divided into serial part and parallel part. If the second representation method above is adopted, it can be expressed as follows:

$$\begin{aligned} d_1 &= f\bullet d_1 + (1-f)\bullet d_1, \\ d_h &= f\bullet d_1 + (1-f)\bullet \frac{\mathrm{d}_1}{h}. \end{aligned} \tag{2}$$

According to

$$\begin{aligned} W(h) &= \frac{1}{(f + ((1-f)/h))}, \\ \frac{1}{(f + ((1-f)/h))} &= \frac{h}{f\bullet h + 1 - f}. \end{aligned} \tag{3}$$

Then,

$$W(h) = \frac{h}{f\bullet h + 1 - f}. \tag{4}$$

We have

$$\frac{h}{f\bullet h + 1 - f} \leq \frac{1}{f}. \tag{5}$$

So,

$$W(h) \leq \frac{1}{f}. \tag{6}$$

If the serial part of a parallel program accounts for 10%; that is, $f = 0.10$, according to this formula, no matter how many processors are used, the acceleration coefficient will be less than 10, which is the famous Amdahl formula.

$$Effp = \frac{Wh}{h}. \tag{7}$$

Wh is the acceleration coefficient expressed in (1), h is the number of processor cores, and *Effp* is the performance cost ratio obtained by using h processors or kernel parallel processing, which is generally less than 1. Value is an international criterion for measuring the floating-point performance of high-performance computer systems. The floating-point performance of high-performance computers is evaluated by the test of the ability to solve linear algebraic equations.

2.3. Feature Extraction Algorithm. In order to study the problem of using biological signals to detect psychological stress in the elderly, the quality of data collection and preprocessing has an important impact on stress detection. Next, we will describe how to extract the HRV features of the elderly.

2.3.1. Fundamental Frequency and Jitter. Pitch refers to the frequency generated by vocal cord vibration in the process of phonation, and pitch frequency refers to the frequency string of vocal cord vibration, referred to as fundamental frequency [17]. The commonly used fundamental frequency extraction methods mainly include autocorrelation method, cepstrum method, and wavelet transform method. In this paper, the cepstrum method is used to extract the fundamental frequency. When the noise doped in the speech signal is low, the effect of cepstrum method is particularly prominent.

Speech signal is a convolution signal rather than an additive signal. The convolution homomorphism system can be used to process it first, so that the speech signal can be analyzed by the linear system. After the convolution homomorphism system processing, the output pseudo time domain sequence is called the complex cepstrum of the original sequence, and its expression is

$$\widehat{c}(m) = IDFT|\mathrm{In}[DFT|x(m)|]|. \tag{8}$$

The expression of cepstrum is

$$\widehat{c}(m) = IDFT|\mathrm{In}|DFT[x(m)]||. \tag{9}$$

DFT represents different Fourier transform and *IDFT* represents inverse discrete Fourier transform. The specific implementation process is shown in Figure 4:

(1) It uses a window function (such as Hamming window) to multiply the original speech signal to obtain the signal after framing. (2) After DFT, take the modulus and then calculate the logarithm. (3) The complex cepstrum of the signal is obtained by IDFT. (4) It detects the pitch period. Because the voiced signal is periodic, the complex cepstrum is also the same as the voiced signal period. Therefore, the interval between two impulses in the detection cepstrum is the pitch period. The reciprocal of the pitch period is the pitch frequency [18].

Jitter refers to the disturbance of vocal cord vibration, which originates from the periodic change of fundamental frequency. The general explanation of disturbance is the deviation from stability or law. Research shows that the calculation of jitter can be analyzed by using 20 pitch cycles. Suppose X_a is a periodic parameter (amplitude or pitch period), where a represents the ath period. The arithmetic

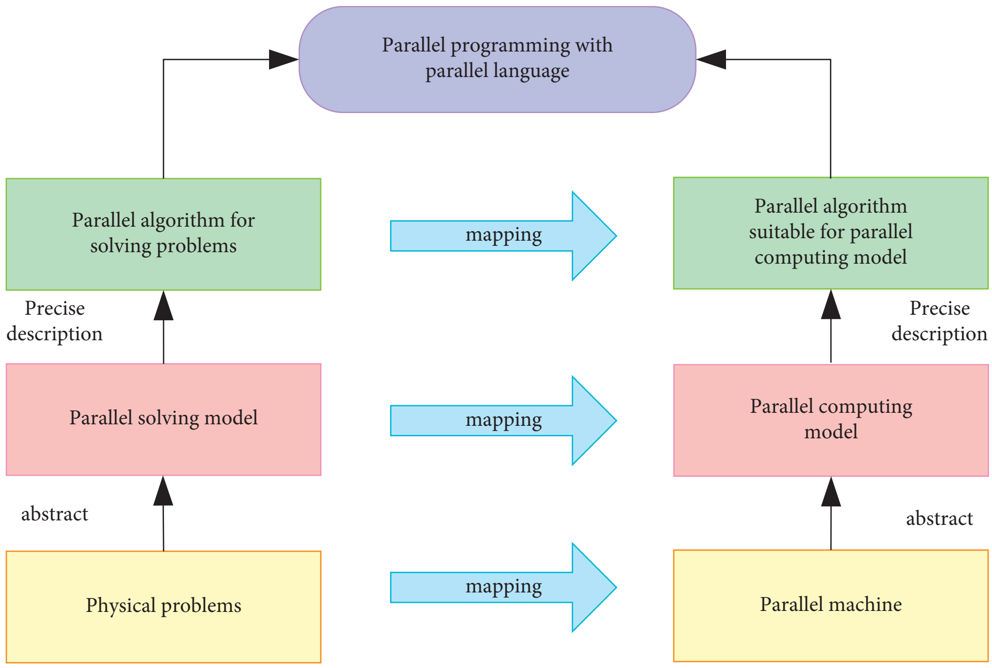

FIGURE 3: Parallel solution process diagram.

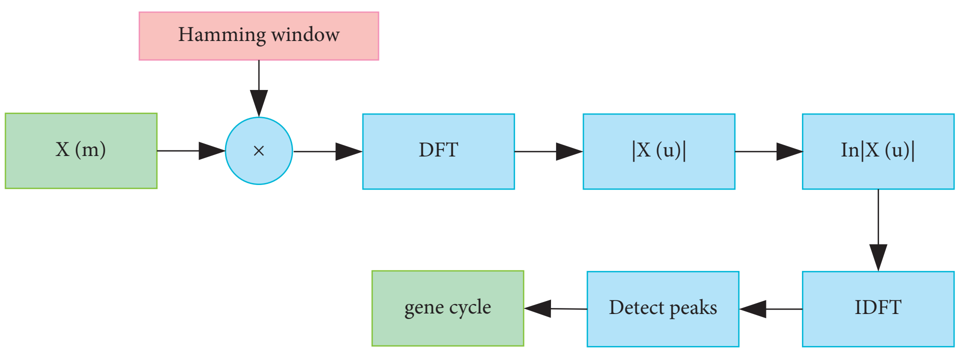

FIGURE 4: Schematic diagram of pitch detection by cepstrum method.

average of M cycles can represent the stable value of the parameter:

$$\overline{X} = \frac{1}{M} \sum_{a=1}^{M} X_a. \tag{10}$$

Then the 0-order disturbance function can be expressed as

$$J_a^0 = X_a - \overline{X}, \quad a = 1, \ldots, M. \tag{11}$$

Superscript of J_a^0 represents the order of the disturbance function. The higher-order disturbance function is defined as the difference between the preceding and subsequent terms of the lower first-order disturbance function. The first-order disturbance function is

$$J_a^1 = J_a^0 - J_{a-1}^0, \quad a = 1, \ldots, M. \tag{12}$$

The fundamental frequency disturbance can be determined by the first-order disturbance function, and its formula is as follows:

$$\text{jitter} = \frac{100}{(M-1)\overline{X}} \sum_{a=2}^{M} \left| X_a - X_{a-1} \right|. \tag{13}$$

2.3.2. Normalized Subband Energy Ratio. The normalized subband energy ratio is a feature based on frame analysis, and the calculation process of this feature is described in Figure 5.

By time-sharing windowing of the voiced segment with a frame length of 51.2 ms and then analyzing the ratio of the energy in the four subbands to the energy on 0–2000 Hz through traditional spectrum analysis such as Welch's power spectrum estimation, the four eigenvalues on each frame are obtained.

2.3.3. Formant Detection. The vocal tract can be regarded as a sound tube with uneven cross section, which plays the role of echo in the process of sound production. When an almost periodic pulse is stimulated in the vocal tract, it will produce

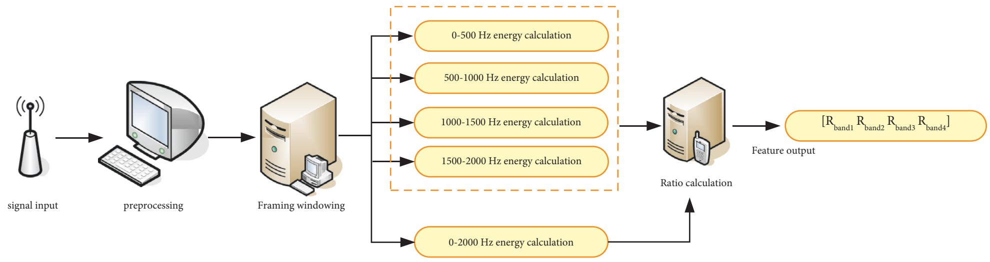

FIGURE 5: Calculation steps of normalized self-carried energy.

resonance characteristics, resulting in a set of resonance frequencies, called formation frequency or short formation frequency. There are many methods to estimate the form of speech signal. The more effective ones are linear prediction coefficient (LPC), all-pole model root method, and spectrum method. LPC root seeking method is to establish an all-pole model $Q(z)$ for the LPC prediction coefficient of speech signal and solve the denominator polynomial root of the model to calculate the formant center frequency and bandwidth. Its characteristic is that it can accurately calculate the center frequency and bandwidth of formant, but the calculation amount of solving polynomial complex root is too large [19–21]. Assuming P-order LPC analysis of signal X(m), there are

$$X(m) = \sum_{u=1}^{p} a_u X(m-u) + Hv(m). \tag{14}$$

$v(m)$ is the excitation function, H is the gain, and a_u is the LPC. If $Q(z)$ is obtained by Z transformation of (14), there are

$$\begin{aligned} Q(z) &= \frac{X(z)}{Hv(z)} \\ &= \frac{1}{1-\sum_{u=1}^{p} a_u z^{-u}} \end{aligned} \tag{15}$$

$z_i = s_i e^{j\varphi i}$ is the complex root of $Q(z)$ denominator polynomial and g_X is the signal sampling rate.

Then the formant center frequency gc_i and bandwidth D_i are, respectively,

$$\begin{aligned} gc_i &= \frac{\varphi_i}{2\pi} g_X, \\ D_i &= -\frac{lms_i}{2\pi} g_X. \end{aligned} \tag{16}$$

The most common spectrum method is LPC model power spectrum peak detection method. Since the poles of $Q(z)$ are in the unit circle of the z plane, the power spectrum of $Q(z)$ can be expressed as

$$\begin{aligned} p(w) &= |Q(z)|^2_{z=e^{jw}} \\ &= \frac{1}{\left|1-\sum_{u=1}^{p} a_u e^{-jw}\right|^2}. \end{aligned} \tag{17}$$

After calculating the power spectrum curve from (17), the center frequency and bandwidth of the formant are obtained by detecting its peak value. Figure 6 shows an example of formant detection for a frame signal and compares it with the power spectrum estimated by Welch method. It can be seen that LPC spectrum eliminates the influence of fundamental frequency and can well estimate formant.

3. Experiment of Psychological Stress Recognition System for the Elderly

3.1. Basic Characteristics of the Elderly

3.1.1. Demographic Characteristics of the Elderly. A total of 1468 elderly people over the age of 60 were recorded in this review. There were more elderly people aged 75 to 90, a total of 648, accounting for 44.14%. There are 996 elderly people without spouses, accounting for 67.85%, more than those with spouses. The elderly living alone are more than those not living alone. There are 1014 elderly living alone, accounting for 69.07%. The elderly who think they are in poor health are the most, with a total of 816, accounting for 55.59%. There are 1145 old people close to their children, accounting for 77.80%. There are 858 elderly people with high contact frequency with their children, accounting for 58.45%. There are 1056 elderly people with high neighborhood support, accounting for 71.93%, as displayed in Table 1 for details.

3.1.2. Characteristics of Social and Economic Status of the Elderly. Among the 1468 elderly included in the study, the elderly living in rural areas are more than those living in cities and towns. There are 868 elderly living in rural areas, accounting for 59.13%. There are more elderly people with 0 years of education, a total of 978, accounting for 66.62%. There are more elderly people without pension than those with pension. There are 1238 elderly people without pension, accounting for 84.33%, as shown in Table 2.

3.1.3. Physiological Health Characteristics of the Elderly. Among the six indicators of the activity of daily living (ADL), the proportion of the elderly with impaired bathing ability was 30.45% (447/1468), the proportion of the elderly with impaired self-toilet ability was 16.76% (246/1468), and the proportion of the elderly with impaired dressing ability was 16.28% (239/1468). The proportion of the elderly with impaired indoor activity ability was 14.78% (217/1468), the proportion of the elderly with impaired autonomous eating

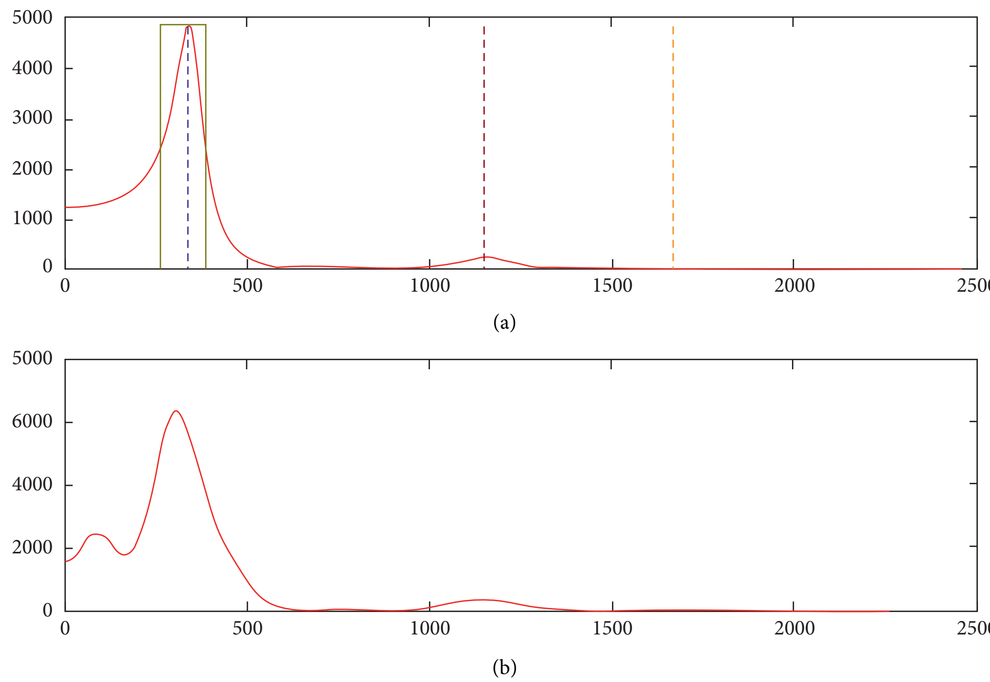

Figure 6: Example of LPC spectrum considering formant frequency and central broadband. (a) Formant estimation of LPC spectrum detection. (b) Pwelch spectrum estimation.

Table 1: Demographic characteristics of the elderly.

Variable	Category	Number of people (person)	Proportion (%)
Age	60–75 years old	612	41.69
	75–90 years old	648	44.14
	90+	208	14.17
Marital status	Married	472	32.15
	No spouse	996	67.85
Way of living	Living alone	1014	69.07
	Not living alone	454	30.93
Self-assessed health	It is good	94	6.40
	Generally	558	38.01
	Not good	816	55.59
Relationship with children	Close	1145	77.80
	Generally	220	14.99
	Not close	103	7.02
Frequency of contact with children	High	858	58.45
	Generally	412	28.07
	Low	198	13.49
Degree of neighborhood support	High	1056	71.93
	Generally	365	24.86
	Low	47	3.20

Table 2: Demographic characteristics of the elderly.

Variable	Category	Number of people (person)	Proportion (%)
Place of residence	Rural	868	59.13
	Town	600	40.87
Years of education	0 years	978	66.62
	1–6 years	389	26.50
	7+ years	101	6.88
Pension status	Have a pension	1238	84.33
	No pension	230	15.67

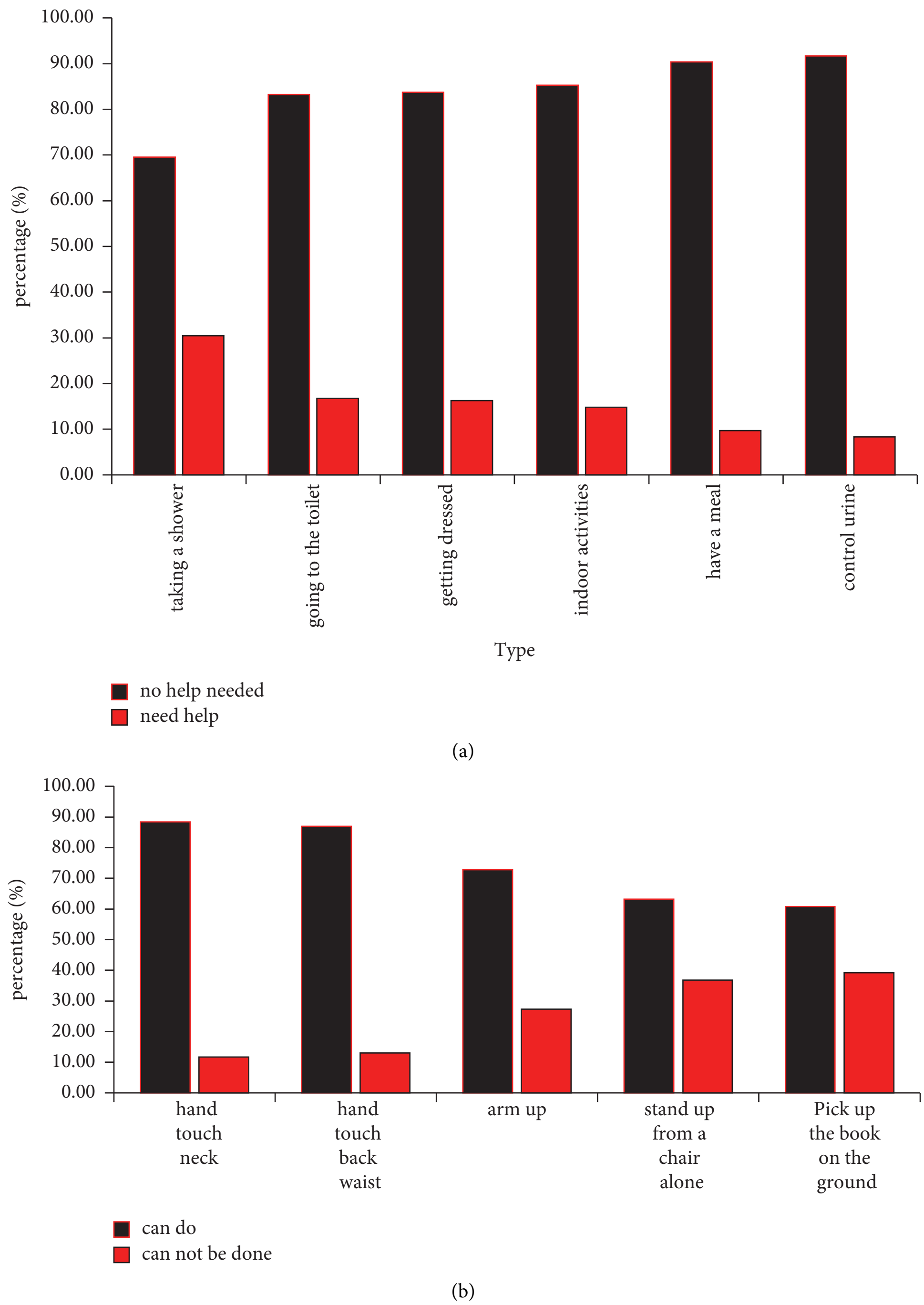

FIGURE 7: Physiological health characteristics of the elderly. (a) Activities of daily living of the elderly. (b) Functional limitation of the elderly.

ability was 9.67% (142/1468), and the proportion of the elderly with impaired defecation control ability was 8.31% (122/3729), as shown in Figure 7(a).

Among the five indicators of the limited function (Loa) scale, the proportion of the elderly with limited function of touching the cervical root by hand was 11.65% (171/1468), and the proportion of the elderly with limited function of touching the back waist by hand was 13.08% (192/1468). The proportion of the elderly with limited arm lifting function was 27.25% (400/1468), the proportion of the elderly with limited ability to stand up from the chair alone was 36.78% (540/1468), and the proportion of the elderly with limited ability to pick up books on the ground was 39.17% (575/1468), as shown in Figure 7(b).

3.1.4. Lifestyle Characteristics of the Elderly. Among the 1468 elderly people, 45.23% (664/1468) now smoke and 51.98% (763/1468) drink. The proportion of the elderly who exercise is 22.41% (329/1468), and the proportion of the elderly with diet score <15 is 86.24% (1266/1468), as shown in Table 3 for the lifestyle characteristics.

Table 3: Lifestyle characteristics of the elderly.

Variable	Category	Number of people (person)	Proportion (%)
Smoking	Smoke	664	45.23
	Do not smoke	804	54.77
Drinking	Drink	763	51.98
	Do not drink alcohol	705	48.02
Exercise	Exercise	329	22.41
	Not exercising	1139	77.59
Diet score	<15 points	1266	86.24
	≥15 points	202	13.76

3.2. Psychological Stress Identification. Compared with other methods, physiological signals are regulated and controlled by human autonomic nervous system and not dominated by individual consciousness. They can reflect the real stress state of human body and even detect and evaluate stress without human consciousness. Therefore, it is more advantageous to use physiological signals to detect psychological stress.

The experimental design of this paper is shown in Figure 8. In the process of stress induction, the ECG data of subjects are obtained through ECG signal acquisition equipment, the HRV features are extracted, and the relaxation and different degrees of stress states are identified by classification model using HRV features.

It can be seen that the whole experimental design mainly includes five parts: data acquisition, pressure induction, ECG data processing, HRV feature extraction, and pressure recognition. The degree of pressure induction, ECG data, and HRV features are synchronized in the same time period. This change, that is, the induction mode of regulating pressure, can not only cause the change of subjects' pressure level, but also obtain the synchronous change of HRV characteristics from ECG signal.

3.2.1. Poincare of HRV Quantitative Feature Extraction of Scattergram. Poincare scatter plot, also known as Lorenz scatter plot or RR interval scatter plot, shows the change characteristics of RR interval in the form of coordinates by recording the RR interval over a period of time.

Poincare scatter diagram is a point distribution diagram marking the positions of all adjacent RR interval points in rectangular coordinate system. It is simple and intuitive and can reflect the overall characteristics of HRV. It can also reflect the instantaneous change of beat-by-beat heart rate, so as to reveal the nonlinear law of HRV. It is a commonly used nonlinear analysis method in clinical and experimental research. In this paper, Poincare scatter diagram is used to analyze and extract the features of HRV.

The drawing of the Poincare scatter plot is to use the value of the first RR interval as the abscissa in the rectangular coordinate system after recording the RR interval for a period of time, and the value of the second RR interval should be used as the ordinate to determine the first RR interval point. Then the second RR interval value is used as the abscissa, and the third RR interval value is used as the ordinate to determine the second point, and so on.

In this paper, the Poincare scatter diagram of HRV of the elderly under different degrees of stress is drawn. It is found that 80% of the subjects show a change trend from concentration to dispersion under high pressure, medium pressure, low pressure, and relaxation, as shown in Figure 9.

It can be seen that the Poincare scatter diagram of HRV has a large proportion in different psychological stress, showing regular changes. In order to automatically identify the state of psychological stress through the feature set of HRV, this paper quantifies the graphics presented by Poincare scatter diagram into two common indicators: vector angle index and vector length index.

Vector angle index (VAI): it is used to measure the dispersion degree of Poincare scatter diagram on the 45° line. The specific formula is as follows:

$$VAI = \frac{\sum_{a=1}^{M} \left|\theta_a - 45\right|}{M}, \tag{18}$$

M represents the number of points in Poincare scatter diagram, and θ_a represents the included angle between the line between scatter point and coordinate origin and X axis.

Vector length index (VLI) is used to measure the dispersion degree of Poincare scatter diagram in the length direction. The formula is as follows:

$$VLI = \sqrt{\frac{\sum_{a=1}^{M} \left(k_a - \overline{K}\right)^2}{M-1}}, \tag{19}$$

k_a is the vector length of point a and $\overline{K}$ is the average of M vector lengths.

3.2.2. Model ROC Curve and Classification Accuracy Analysis. In order to study the performance of random forest model in identifying pressure state through HRV, this paper uses KNN, CNN, and RFC model used in most relevant studies for comparative analysis. The parameters of the model are adjusted through five cross validations; that is, the data are randomly divided into five copies: four copies of the data are used as the training set and one copy is used as the test set. We utilize three models to recognize loose and low-level pressure states, loose and medium-level pressure states, and loose and undeniable level pressure states. For every acknowledgment, the typical precision of ROC bend and multiple times of 50 overlay cross approval test are utilized as the assessment record of model execution.

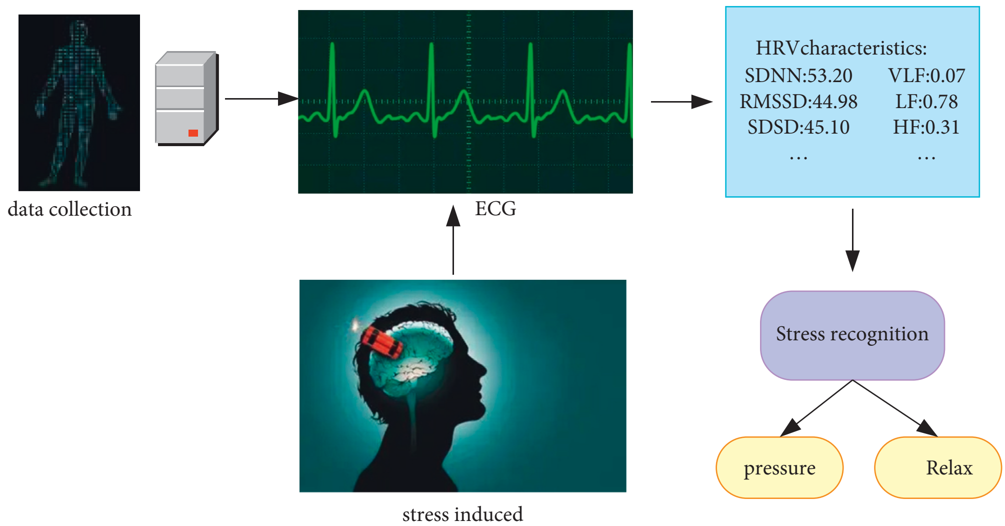

Figure 8: Experimental design architecture.

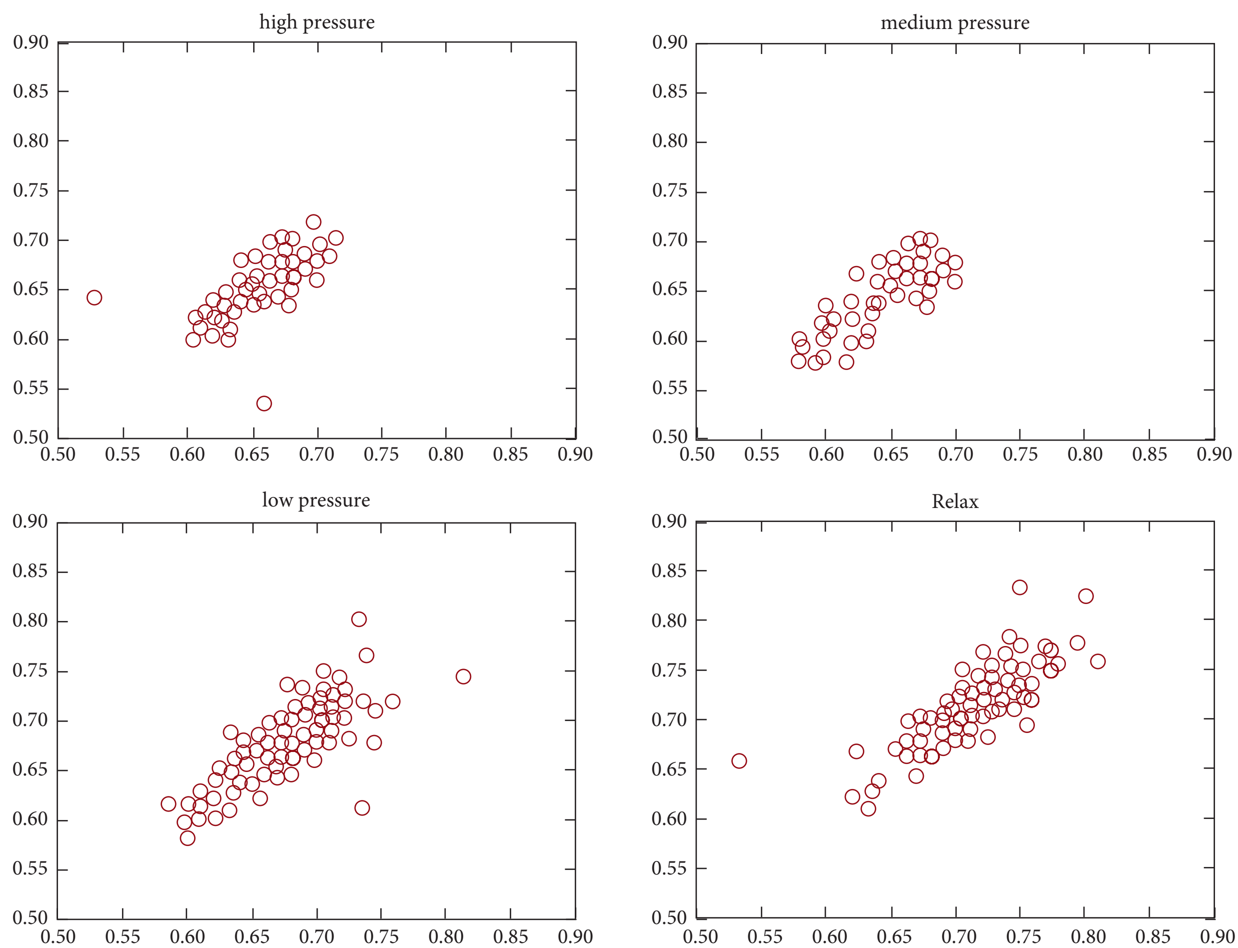

Figure 9: Poincare scatter diagram of HRV under different pressure levels.

The ROC curve and AUC value of the three models to identify different psychological stress states are shown in Figure 10, in which the diagonal dotted line represents the result of random guess, and its AUC is 0.5.

The nearer the ROC bend is to the upper left corner, the bigger the encompassing region of its lower part is, showing better exhibition of the model. The nearer the ROC bend is to the slanting dabbed line, the nearer the AUC is to 0.5, and

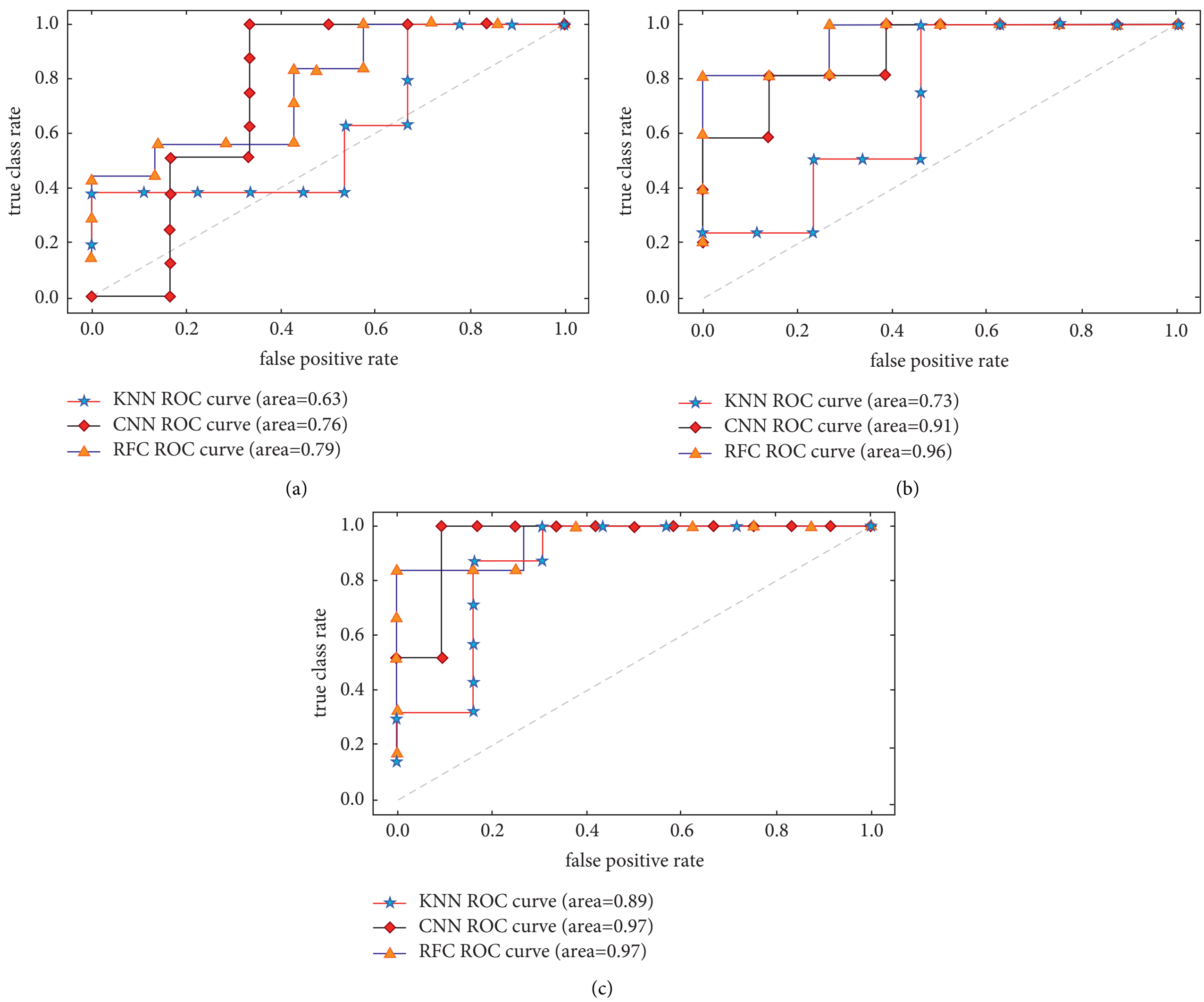

Figure 10: Three types of models identify the ROC curves of three types of states respectively. (a) Models KNN, CNN, and RFC identify ROC curves in relaxed and low-pressure states. (b) Models KNN, CNN, and RFC identify ROC curves in relaxed and medium-pressure states. (c) Models KNN, CNN, and RFC identify ROC curves in relaxed and high-pressure states.

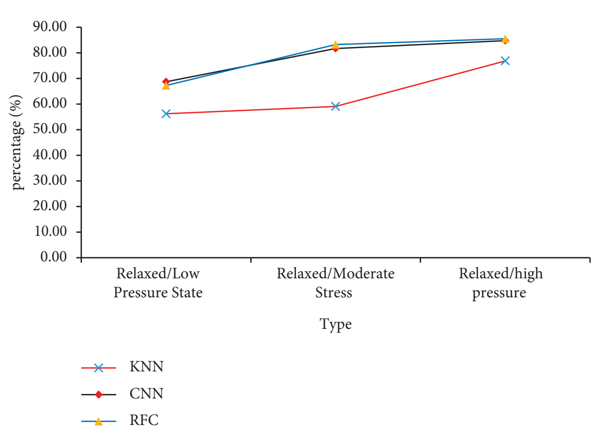

Figure 11: Comparison of classification accuracy of the three classifiers under relaxation and different pressure states.

the nearer the presentation of the model is to the irregular outcome. As shown in Figure 10(a), while distinguishing loose and low tension expresses, the AUCs of KNN, LR, and RFC are 0.63, 0.76, and 0.77 individually. The presentation of CNN and RFC is close, while the exhibition of KNN is somewhat poor. The overall recognition effect of the three models is poor. When identifying the relaxed and medium-pressure states in Figure 10(b), the AUCs of KNN, CNN, and RFC are 0.73, 0.91, and 0.96, respectively. At this time, RFC achieves better recognition performance, CNN is slightly lower, while KNN recognition performance is still poor. Figure 10(c) shows that the AUCs of KNN, CNN, and RFC are 0.89, 0.97, and 0.97, respectively, when identifying relaxed and high-pressure states. At this time, the three models

Table 4: General situation of anxiety and stress in the elderly.

Anxiety level	Number of people	Proportion (%)
No anxiety	1012	68.94
Mild anxiety	275	18.73
Moderate anxiety	106	7.22
Severe anxiety	75	5.11

Table 5: Logistic multiple regression analysis of the effects of anxiety and stress on the elderly.

	Dependent variable	B	χ	P	OR	95% IC
Anxiety	Family relationship satisfaction	0.454	7.430	0.005	2.204	1.210–3.380
	The source of life	−0.290	4.189	0.040	0.833	0.694–0.995
	Medical insurance	−0.304	3.897	0.046	0.843	0.710–0.999
	Interpersonal communication	0.580	7.837	0.005	2.092	1.240–3.530
	Healthy body	−0.198	4.041	0.044	0.838	0.699–0.997

achieve good recognition performance. It may be seen that the performance of the three models to identify pressure increases with the increase of pressure. Compared with KNN, RFC and CNN have better identification effect.

Figure 11 shows the acknowledgment exactness of the three models for recognizing loose and low-level pressure states, loose and medium-level pressure states, and loose and significant level pressure states.

As can be seen from Figure 11 above, the recognition accuracy of the three models in identifying relaxation and different pressure states is consistent with the ROC curve and AUC in Figure 10. When the pressure is low, the recognition accuracy of the three models is low. Only when the pressure state reaches the medium strength pressure or above, the model CNN and RFC identification can achieve good results. At the same time, comparing the recognition accuracy of the three models, it is found that KNN has a lower accuracy in identifying relaxation and different psychological pressures than the other two models, while CNN is closer to RFC, and RFC is slightly better than CNN.

3.3. Overcoming Stress Research. In the survey sample, the statistical results show that 74.18% of the elderly do not have anxiety stress; 18.73% of the elderly have mild anxiety disorder; 7.22% of the elderly have moderate anxiety and stress; 5.11% of the elderly have severe anxiety and stress. The overall detection rate of anxiety disorders among the elderly in the study was 31.06%, as shown in Table 4.

Using anxiety stress as the dependent variable and general situation as the independent variable, logistic regression analysis was performed on the elderly who moved with the community. The data showed that the effective predictors of elderly anxiety were family relationship satisfaction ($P = 0.005$), source of life ($P = 0.040$).), medical security ($P = 0.046$), interpersonal communication ($P = 0.005$), and physical health ($P = 0.0044$) ($P < 0.05$). Among them, when the predictor is the source of life, β is -0.290; when the predictor is medical security, β is −0.304; when the predictor is physical health, β is −0.198, indicating that the source of life, medical security, and physical health are causing anxiety for the elderly. There was a significant negative predictive effect of stress disorder, as shown in Table 5.

Before the intervention, there was no statistical difference between the intervention group and the control group; $P > 0.05$. After the intervention, the GDS score of the intervention group decreased significantly at the 5th and 10th weekends compared with before the intervention, and there was a statistical difference compared with the control group ($P < 0.05$). The GDS score of the control group also decreased after the intervention, but the decrease was not as obvious as that of the intervention group; see Table 6.

Table 6: Comparison of before and after intervention for the elderly in mild anxiety and stress group (SAS).

Project	Before intervention	5 weekends	10 weekends
Intervention group(138)	14.60 ± 3.29	10.12 ± 3.98	9.09 ± 4.03
Control group(137)	14.90 ± 3.45	13.58 ± 3.64	12.14 ± 3.21
P	0.198	0.013	0.012

4. Conclusion

With the acceleration of social rhythm and the increasing pressure of life, psychological pressure has gradually become one of the important factors affecting human physical and mental health and quality of life. Biological HRV is a common assessment method to detect and identify psychological stress, which can reflect the state of psychological stress without subjective consciousness. HRV has random and irregular chaotic characteristics. This paper uses the method of nonlinear analysis to mine the pressure characteristics of HRV and compares the Poincare scatter diagrams of HRV under different pressures. It was found that the RR interval scatter diagram of different people showed a regular change from divergence to aggregation to a certain extent in the process of increasing psychological pressure, and two quantitative indexes VAI and VLI of Poincare scatter diagram were extracted. Aiming at the problem of psychological stress identification of family elderly, this paper establishes a psychological stress identification model. By extracting and identifying the pressure features of the HRV of the elderly, coupled with the use of high-performance computing, the efficiency of the identification system is improved and the process is simpler. Through the comparative experiment of the three classifiers, it is found that when HRV is used to judge the state of psychological stress, RFC and CNN have better recognition effect than KNN, and the recognition effect is similar. When the pressure is high, the RFC model generally has good recognition performance, and the recognition rate can reach 95.02% under high pressure. After ten weeks of intervention between the intervention group and the control group, the GDS scores of the intervention group were significantly decreased at the end of 10 weeks compared with those before the intervention, and there was a statistical difference compared with the control group ($P < 0.05$). The decrease in the control group was not as obvious as that in the intervention group. Due to the limited space of the article, it is unable to conduct a more in-depth study of all the contents, and the research data are not rich enough, which is also presenting the limitation of this paper. In the future, the author looks forward to using more real data for further research.

Data Availability

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

Conflicts of Interest

The author declares no conflicts of interest.

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