

Elderly Health Status Monitoring Using WNN and PSO

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Abstract: With the global population aging, monitoring the health status of elderly people has become a key research focus. However, the lack of data format interoperability among medical platforms reduces the accuracy of monitoring results. Therefore, this study proposes a health status monitoring model that integrates the Wavelet Neural Network (WNN) and the Particle Swarm Optimization (PSO) algorithm. The model extracts and learns physiological features and data variations by integrating the Wavelet Neural Network with the Particle Swarm Optimization algorithm, enabling health status monitoring. Experimental results show that the proposed model achieves a prediction consistency of 0.946 and a monitoring accuracy of 96.18% on a self-constructed dataset. In addition, the proposed model's monitoring F1 score exceeds 94%, and its accuracy in identifying chronic disease types reaches 98.74%. These results demonstrate that the model can accurately and efficiently assess the health status of elderly people and capture subtle variations, providing reliable technical support for building adaptive, high-precision health-monitoring systems.

Keywords: Wavelet Neural Network(WNN); Particle Swarm Optimization(PSO); health status monitoring; elderly.

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1. Introduction

With the continued acceleration of global population aging, advancing age is accompanied by a gradual decline in physiological functions and a higher incidence of chronic diseases, leading to a significant reduction in physical abilities and quality of life among elderly people. At the same time, the demand for health status monitoring is rising (Mulyasari et al., 2023). Currently, governments and society have combined artificial intelligence and Internet of Things (IoT) sensors to improve the feasibility of health monitoring (Ugah et al., 2025). However, traditional health status monitoring methods struggle to address continuity issues associated with chronic diseases among elderly people, and frequent medical examinations further increase their economic and psychological burdens (Gudivaka et al., 2024). Existing detection methods rely on machine learning models and time-series analysis algorithms, but these approaches have limitations, including poor interpretability and difficulty processing complex nonlinear data on resource-constrained edge devices (Alsadoon et al., 2024). The Wavelet Neural Network (WNN) is the first neural network using wavelet activation functions. It can effectively adapt to time-frequency local feature transformations and autonomously learn from historical data, showing strong capability in handling nonlinear data (Eduru et al., 2024). In addition, the Particle Swarm Optimization (PSO) algorithm optimizes the positions and velocities of targets by tracking extreme values, thereby enhancing information sharing and cooperative performance among targets (Nayak et al., 2023). The core issues addressed by this study include improving feature extraction for complex nonlinear physiological signals in elderly health monitoring and enhancing the model's real-time tracking performance on dynamic time-series data. Therefore, this study integrates WNN and PSO to form the WNN-PSO algorithm. Based on this algorithm, a health-status monitoring model is proposed for the elderly population. The model addresses the issue that the traditional approach tends to fall into local optima with high-dimensional data, thereby optimizing the accuracy and efficiency of health detection and further improving the quality of life and health management for the elderly. The innovations and contributions of this study can be summarized in three aspects. Firstly, it proposes a health-monitoring algorithm that combines WNN and PSO, providing an accurate and reliable basis. Secondly, it proposes a health-monitoring model for the elderly and addresses issues such as low computational efficiency in health data analysis. Thirdly, the proposed algorithm and model achieve promising monitoring performance in validation experiments and can offer technical support for elderly health monitoring. Compared with current deep sequence models, the proposed fusion model combines the feature extraction and global optimization capabilities of WNN-PSO, thereby reducing the need for data annotation and improving the accuracy of processing nonlinear dynamic data. Additionally, the study introduces an Adaptive Extended Kalman Filter

(AEKF) for adaptive noise suppression and state correction, enabling the research model to track dynamic health data more effectively in real time than traditional hybrid models.

2. Literature Review

The WNN algorithm has attracted significant research interest due to its strong capability to handle non-stationary data and to enhance the interpretability of signal-processing results. Singh et al. (2023) designed a hybrid soft-computing approach that uses a WNN to estimate groundwater contaminant concentrations. This study used the multi-stage techniques of WNN and ARIMA to identify potential sources of groundwater contamination and ultimately measured groundwater contaminant concentrations. Furthermore, a WNN-based dynamic management model was proposed to handle marine plastic waste. This method processed waste plastics and marine debris, recovered fragments using WNN and limited-memory algorithms, and developed a meshless algorithm to dynamically manage marine waste. PSO algorithms have demonstrated unique value in engineering applications due to their efficient convergence speed, attracting research efforts from numerous domestic and international scholars. Pirozmand et al. (2023) proposed an improved PSO algorithm to determine the ideal schedule for resource allocation. This algorithm defined particles through PSO and multi-adaptive learning, reduced the probability of falling into local optima, and efficiently allocated schedulable resources. Yang et al. (2023) proposed a stochastic contrast interaction strategy based on PSO for movement in vast solution spaces. This strategy constructed random interaction topologies for each particle and introduced a dynamic adjustment scheme for topology size to gradually expand the interaction topology, thereby enabling focused search and exploitation of optimal regions.

Monitoring the health status of elderly people can improve their quality of life and family happiness, prompting research by numerous domestic and international scholars. Hosseinzadeh et al. (2023) proposed an IoT-based health monitoring system for elderly care. This system monitored and evaluated elderly people's behavioral activities and biological parameters through IoT devices for data analysis. Experimental results showed that this method achieved 99% prediction accuracy. Ghosh et al. (2023) proposed an end-to-end, interconnected smart home healthcare system for remote monitoring of the health status of elderly people. This method collected information through IoT sensors, combined novel federated learning for health data analysis and finally utilized a collaborative framework to collect, store and share medical recommendations. Yang et al. (2023) proposed a customized physical health monitoring system to comprehensively detect the physical condition of elderly people. This system uses smart sensing technology to understand elderly people's physical data and track physiological characteristics and physical health in real time. Experimental results showed that the system accurately monitored 197 steps of the target. Park et al. proposed a knowledge graph-based intelligent care system for elderly people. This system organized and collected elderly people's information and care knowledge into a dynamic knowledge graph. Experimental results showed that the system achieved a score of 8 points for basic information evaluation (Park et al., 2024).

In summary, research in society today has made some advances in monitoring the health status of the elderly, but there is still room for improvement in the ability to process dynamic data changes and in the sensitivity to noise interference in the monitoring results. Therefore, this study proposes an elderly health status monitoring model based on WNN and PSO algorithms, aiming to track real-time changes in physical condition and provide a more accurate, intelligent solution for monitoring elderly health.

3. Construction of Elderly Health Monitoring Model Based on WNN-PSO Algorithm

3.1. Design of Health Monitoring Algorithm Integrating WNN and PSO

Most elderly people currently collect physiological signals using wearable smart devices to monitor their physical condition. However, during signal acquisition, motion artifacts, environmental interference, and device loosening can easily occur, leading to unstable health-monitoring data (Mohan et al., 2024; Dermody et al., 2024). Traditional health monitoring methods also suffer from limitations such as data silos and a lack of standardization, making it difficult to achieve multi-source data sharing and process complex nonlinear data (Su et al., 2024; Mahato et al., 2024). The WNN algorithm shows strong capability in non-stationary signal processing. It accurately captures subtle changes in original signals and health conditions, effectively suppresses background noise interference, and improves monitoring accuracy (Wu et al., 2023). Therefore, this study applies to the WNN algorithm to monitor the health status of the elderly, thereby enhancing robustness and recognition accuracy. The health monitoring process is shown in Fig. 1.

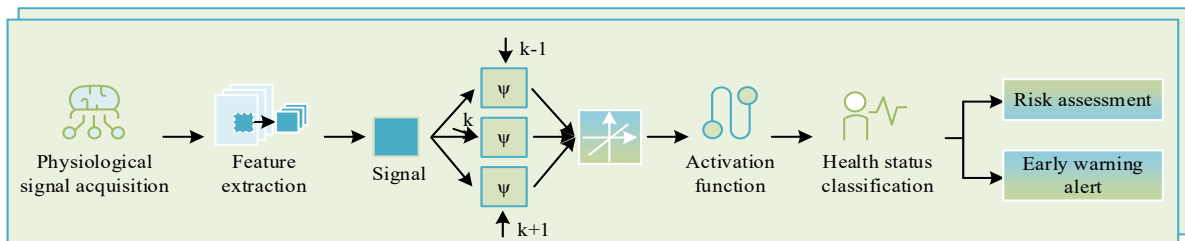


Fig. 1. Workflow of health status monitoring based on WNN

In Fig.1, the WNN algorithm preprocesses physiological data collected by sensors, such as blood pressure and blood oxygen levels operations are performed on the data. After the data is preprocessed, the next operation is feature extraction. In the WNN algorithm, the data is divided into different frequency bands. Time-domain, frequency-domain, and time-frequency joint features are extracted from the data. The signals to be analyzed will pass through the wavelet layer to capture

multi-resolution features, then proceed to the neural network layer. The WNN algorithm will then provide categories based on health status and predictions of physiological values, such as trends in blood pressure changes. The functionality of the WNN algorithm for semantic images with varying resolutions is given in Eq. (1).

$$\begin{cases} \phi(x) = \sum_k h_k \phi(2x - k) \\ \psi(x) = \sum_k g_k \phi(2x - k) \end{cases} \quad (1)$$

In Eq. (1), $\phi(x)$ represents the monitoring semantic image scale function, h_k represents the monitoring semantic image scale filter, k represents the position of filter coefficients, $\psi(x)$ represents the wavelet function, and g_k represents the wavelet filter. The input-output relationship for monitoring semantic neurons in the WNN algorithm is expressed in Eq. (2).

$$S_{out} = \phi\left(\sum_m W_m S_{in,m} + T\right) \quad (2)$$

In Eq. (2), W_m represents the monitoring semantic weight, $S_{in,m}$ represents the m -th input, T represents the threshold, and ϕ represents the nonlinear activation function. The hidden-layer output of the WNN algorithm is given by Eq. (3).

$$f_N(x) = \sum_{k=-K}^K c_k \psi(2^J x - k) \quad (3)$$

In Eq. (3), $f_N(x)$ represents the weighted sum of hidden layer monitoring semantic outputs, x represents the input layer, 2^J represents the monitoring semantic weight of the input layer, and k represents the neuron. During health status monitoring, rapid and real-time responses to abnormal conditions are required. However, WNN hyperparameter selection is difficult and lacks adaptability, which affects state recognition accuracy (Wang et al., 2023). The PSO algorithm uses a parallel structure and global optimization capability to avoid falling into local optima. Therefore, this study integrates the PSO and WNN algorithms to improve adaptability and computational efficiency (Luo et al., 2024). The process of health monitoring improvement using the PSO algorithm is shown in Fig. 2.

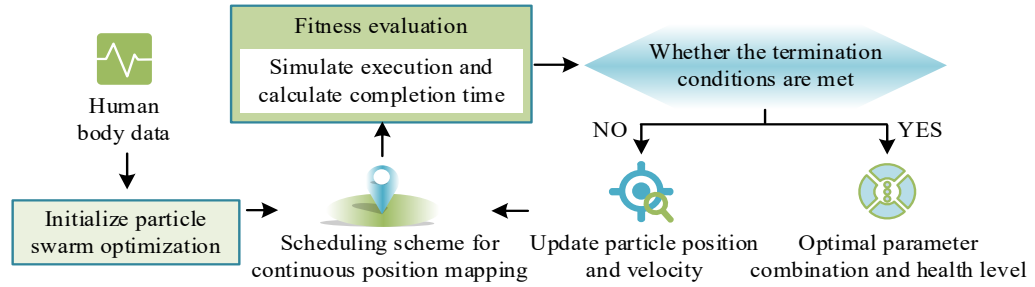


Fig. 2. Workflow of PSO-based health status monitoring

As shown in Fig. 2, the PSO algorithm receives previously collected physical data from elderly individuals and generates particles representing combinations of health states. The PSO algorithm encodes particles' positions and velocities to determine task sequences. The PSO algorithm then updates the particles' positions and evaluates the health risks using the fitness function and the constraint conditions, taking into account differences among the target individuals. The system then checks if the maximum termination condition is met. If not, the particles are updated, and the global optimal particle is searched. If the iteration requirement is satisfied, the optimal solution containing health risk levels is output. The position and velocity representation of the i -th monitoring information particle in the PSO algorithm is shown in Eq. (4).

$$\begin{cases} p_i = (p_{i,1}, p_{i,2}, \dots, p_{i,D}) \\ v_i = (v_{i,1}, v_{i,2}, \dots, v_{i,D}) \end{cases} \quad (4)$$

In Eq. (4), p_i represents the particle position, v_i represents the particle velocity, and D represents the particle dimension. The representation is shown in Eq. (5).

$$\{(p_1, v_1), \dots, (p_i, v_i), \dots, (p_n, v_n)\} \quad (5)$$

The PSO algorithm calculates the fitness values of monitoring information particles using the objective function and updates the particles' best positions and the global optimal position at each iteration, as expressed in Eq. (6).

$$\begin{cases} p_{i,best} = (p_{i,1,best}, p_{i,2,best}, \dots, p_{i,D,best}) \\ G_{best} = (g_{1,best}, g_{2,best}, \dots, g_{D,best}) \end{cases} \quad (6)$$

In Eq. (6), $p_{i,best}$ represents the best position of the i -th particle, and G_{best} is the global optimal position of the particles. By integrating the WNN algorithm's signal-capturing capability with the PSO algorithm's global optimization performance, the WNN-PSO health monitoring algorithm achieves efficient signal processing and robust performance to data noise. The health monitoring process of the WNN-PSO algorithm is shown in Fig. 3.

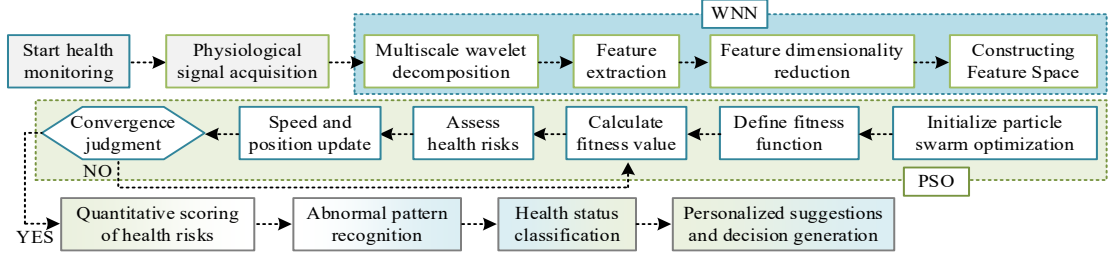


Fig. 3. Workflow of health status monitoring with WNN-PSO model

As shown in Fig. 3, the WNN-PSO algorithm accepts the collected physiological signals and initiates health detection. The WNN algorithm performs multi-scale wavelet decomposition on the input data, reduces feature dimensions, and fuses features to construct a feature vector space. In the PSO module, feature space vectors are converted into particle swarms. Particle fitness values and health risks are evaluated using the fitness function, and particle velocities and positions are updated. When the WNN-PSO algorithm reaches the maximum number of iterations, the monitoring results are output. The WNN algorithm employs a scale factor of 8, with training batches and epochs set at 32 and 100, respectively. It features 64 hidden layer nodes, a learning rate of 0.001, a Sigmoid activation function, and a Mexican wavelet basis function. The PSO algorithm parameters include a particle swarm size of 50, with individual and global learning factors set to $c_1=2.0$ and $c_2=2.0$, respectively, and inertia weights decreasing linearly from 0.9 to 0.4. The fitness function uses mean squared error, with particle positions constrained to $[0,1]$ and velocities to $[-0.5,0.5]$. Convergence is determined by a change in fitness function values below $1e-6$ over 20 consecutive generations. The particle velocity and position update process for monitoring data in the WNN-PSO algorithm is given by Eq. (7).

$$\begin{cases} v_{i,j}(t+1) = \omega \cdot v_{i,j}(t) + c_1 \cdot r_1 \cdot (p_{i,j,beat}(t) - p_{i,j}(t)) + c_2 \cdot r_2 \cdot (g_{j,beat}(t) - p_{i,j}(t)) \\ p_{i,j}(t+1) = p_{i,j}(t) + v_{i,j}(t+1) \end{cases} \quad (7)$$

In Eq. (7), $v_{i,j}(t+1)$ represents the velocity of particle i in the j -th dimension, $p_{i,j}(t+1)$ represents the position, t represents the current iteration number and inertia weight parameter, c_1 represents the global learning capability parameter, and c_2 represents the particle's self-learning capability parameter.

3.2. Establishment of Health Monitoring Model with Adaptive Extended Kalman filter

During health status monitoring, most data and information remain dynamic and time-varying. For example, blood glucose concentration changes with time and diet, and blood pressure fluctuates with emotional states (Khan et al., 2024). However, the WNN-PSO algorithm is better suited to static mapping relationships and has limited capability for tracking dynamic sequences, which may lead to unstable outputs. The AEKF predicts dynamic target data in real time using an optimal recursive state structure, thereby improving adaptability and robustness during online estimation and parameter adjustment (Abdolahi et al., 2023; Zhang et al., 2024). Therefore, this study demonstrates the robustness of the AEKF in optimizing the WNN-PSO algorithm, thereby enhancing the real-time performance and estimation accuracy of the monitoring system. The process for optimizing health status monitoring using the AEKF is shown in Fig. 4.

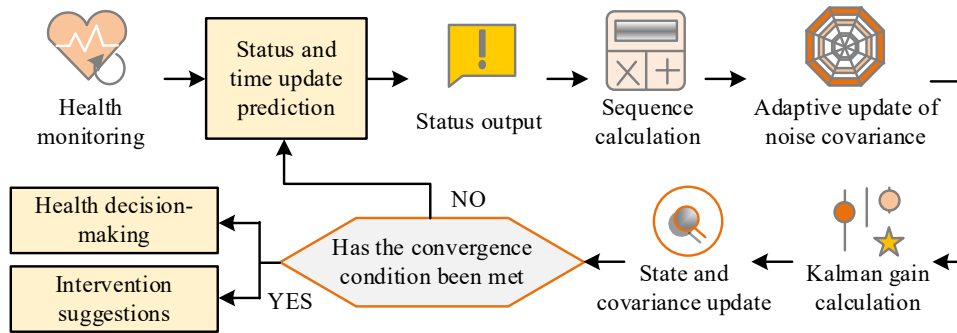


Fig. 4. Workflow of health status monitoring optimized by AEKF

As shown in Fig. 4, the AEKF takes in collected physiological parameters such as heart rate and systolic blood pressure, defines them as state vectors, and sets the covariance matrix. The AEKF completes adaptive parameter adjustment through state and covariance prediction, innovation sequence and Kalman gain calculation, estimation of noise statistical characteristics, and parameter update. Then, the updated state and covariance measurements are used to correct and update

the health status classification, followed by a risk assessment. The system determines whether the state estimation satisfies the iteration condition. If the condition is satisfied, real-time state estimation results are output. If not, the state and covariance matrix are re-predicted, and the process repeats until the condition is met, after which the final monitoring intervention decision is output. The AEKF algorithm is implemented as follows: The system noise covariance matrix Q is initialized as $\text{diag}([0.01, 0.01, 0.01, 0.01])$, and the measurement noise covariance matrix R is initialized as $\text{diag}([0.02, 0.02, 0.02, 0.02])$. State initialization incorporates process and observation noise covariance matrices, which are adjusted based on physiological parameter ranges of fluctuation and sensor accuracy. Adaptive noise estimation employs a sliding window method with a window width of 10, while the forgetting factor ranges from 0.99 to 0.85. The state estimation process of monitoring data in the AEKF algorithm mainly includes five steps. The first step is to linearize nonlinear monitoring data by computing the Jacobian matrix, as expressed in Eq. (8).

$$\hat{x}_{n|n-1} = \phi_{n|n-1} \hat{x}_{n-1|n-1} \quad (8)$$

In Eq. (8), $\hat{x}_{n-1|n-1}$ represents the estimated monitoring data value at the $n-1$ -th step, $\phi_{n|n-1}$ represents the system transition matrix, and $\hat{x}_{n|n-1}$ represents the prior estimate at the n -th step. The second step calculates the error covariance matrix for the monitoring data, as expressed in Eq. (9).

$$P_{n|n-1} = \phi_{n|n-1} P_{n-1|n-1} \phi_{n|n-1}^T + Q \quad (9)$$

In Eq. (9), $P_{n|n-1}$ represents the error covariance matrix of the prior estimate, and Q represents the covariance matrix of system noise. The third step calculates the Kalman gain, as expressed in Eq. (10).

$$K_{n|n-1} = P_{n|n-1} C^T (C P_{n|n-1} C^T + R)^{-1} \quad (10)$$

In Eq. (10), $K_{n|n-1}$ represents the Kalman gain, R represents the covariance matrix of measurement error in monitoring data, and C represents the measurement matrix. The fourth step corrects the estimated value, as expressed in Eq. (11).

$$\hat{x}_{n|n} = \hat{x}_{n|n-1} + K_{n|n-1} (Y_n - C \hat{x}_{n|n-1}) \quad (11)$$

In Eq. (11), $\hat{x}_{n|n}$ represents the posterior estimate, and Y_n represents the measurement value. The fifth step computes the covariance matrix for estimating monitoring data at the next time step, as expressed in Eq. (12).

$$\begin{cases} P_{n|n} = (I - K_{n|n-1} C) P_{n|n-1} \\ x_n = \phi_{n|n-1} x_{n-1|n-1} + W_{n-1} \\ Y_n = C x_n + V_n \end{cases} \quad (12)$$

In Eq. (12), $P_{n|n}$ represents the covariance estimate at the next time step, and W_{n-1} and V_n represent system noise and measurement noise during monitoring, respectively. This study combines the dynamic data-tracking advantage of the AEKF with the WNN-PSO algorithm to form the AEKF-WNN-PSO elderly health monitoring model, referred to as the AWP model, thereby achieving multi-scale monitoring and integrated management. The health status monitoring process of the AWP model for elderly people is shown in Fig. 5.

In Fig. 5, the AWP model takes the data as input and converts it into data streams. The data streams are then updated based on the parameters. The updated data streams are then input into the WNN module for wavelet decomposition on multiple scales. The time-frequency features are then fused using the neural network to obtain the output features. The features are then input into the PSO module for optimization. The fitness values are then calculated based on the fitness function. The optimal position and velocity are then updated to obtain optimal weight values. The weight values are then input into the AEKF module for state estimation and covariance prediction. Adaptive noise is then estimated based on innovation calculation. Finally, the AWP model outputs health status classification results, quantified risk scores, and trend predictions to complete health status monitoring. The noise-estimation variation rate process in the AWP model is given by Eq. (13).

$$\gamma = \frac{\left| \sum_{i=k-2N}^k N_i - \sum_{i=k-2N}^{k-N} N_i \right|}{\sum_{i=k-2N}^k N_i} \quad (13)$$

In Eq. (13), γ represents the estimated value of the observation noise variation rate, $2N$ represents the time window width, and k represents the current time step. The process of adjusting the forgetting factor based on the rate of variation in observation noise is given by Eq. (14).

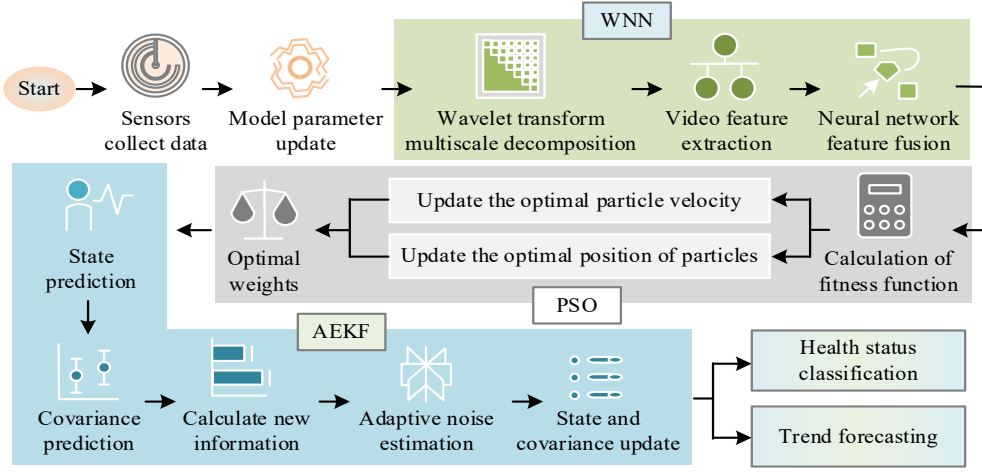


Fig. 5. Workflow of health status monitoring using the AWP model

$$b = b_{\max} - \gamma^4(b_{\max} - b_{\min}) \quad (14)$$

In Eq. (14), b represents the value of the forgetting factor at the current time step, $b_{\max}$ represents the maximum value of the forgetting factor, and $b_{\min}$ represents the minimum value of the forgetting factor. The computational complexity of the AWP model is as follows: the computational complexity of WNN is NMS , where N , M , and S represent the number of samples, the number of hidden layer nodes, and the number of scales, respectively; the computational complexity of PSO is TPD , where T , P , and D represent the number of iterations, the number of particles, and the dimensionality of particles, respectively; the computational complexity of AEKF is D^3 , where D is the dimensionality of the state vector; the overall computational complexity of the AWP fusion model is $NMS + TPD + D^3$.

4. Performance Evaluation of Health Monitoring Model Integrating WNN and PSO

4.1. Verification of Health Monitoring Performance of WNN-PSO Algorithm

To confirm the superiority of the proposed WNN-PSO algorithm's health status monitoring performance, comparative experiments were conducted against three health algorithms: the Normalized Least Mean Square Algorithm (NLMS), the Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and the Short-Time Fourier Transform (STFT). The experimental parameters were set as follows: the operating system was Windows 11, the CPU was Intel Core i7-12700K, the RAM was 32 GB DDR4 3200 MHz, the GPU was NVIDIA RTX 3060 12 GB, the learning framework was PyTorch 1.11.0, and the number of iterations was 100. The datasets in the experiment were the National Health and Nutrition Examination Survey dataset and the English Longitudinal Study of Aging dataset. The National Health and Nutrition Examination Survey dataset was used for periodic health status monitoring of 5000 individuals, including health detection information of elderly individuals. The English Longitudinal Study of Aging dataset recruited over 12000 elderly individuals for health status monitoring. The ELSA and NHANES datasets map monitoring indicators such as heart rate, systolic blood pressure, and body mass index to the AWP model's input variables, and map health status types and chronic disease types to the model's output variables. The queue selects the elderly population aged 65 and above, removes samples with a data-missing rate exceeding 30%, and retains 10240 and 4560 samples from the ELSA and NHANES datasets, respectively. The study uses Z-scores to normalize physiological indicators and then applies median filtering to eliminate sensor noise. Missing values are filled using K-nearest-neighbor interpolation for continuous variables, with a 15-minute time window. Non-synchronously collected physiological data is interpolated and aligned to ensure temporal consistency. To further verify the superiority of the WNN-PSO algorithm's monitoring performance, this study conducted experiments with it and the three comparative algorithms on the ELSA and NHANES datasets, using Area Under the Receiver Operating Characteristic Curve (AUC) to assess the algorithms' ability to distinguish states. AUC refers to the area under the receiver operating characteristic curve, representing the probability of randomly selecting one positive and one negative sample, with a value range between 0.5 and 1.0. A higher AUC value closer to 1 indicates stronger classification capability of the model, reflecting its ability to distinguish between healthy and unhealthy states in elderly populations. The experimental results are shown in Fig. 6.

As shown in Fig. 6(a), the AUC value of the WNN-PSO algorithm reached 0.956, which was larger than those of the other three comparative algorithms. Compared to the DBSCAN algorithm, the AUC value increased by 0.077. In Fig. 6(b), the AUC value tested by the WNN-PSO algorithm was 0.948, also higher than the three comparative algorithms, representing an improvement of 0.043 compared to the NLMS algorithm. The above results showed that the AUC values obtained by the WNN-PSO algorithm across different datasets were high. This was because the structure of the WNN algorithm effectively improved the accuracy of feature extraction and the discrimination between normal and abnormal features. To further confirm the advantages of the WNN-PSO algorithm in the health monitoring field, the ELSA dataset was tested by the WNN-PSO algorithm and the three comparative algorithms, and the False Positive Rate (FPR) and False Negative Rate (FNR) were used to assess the health monitoring and warning abilities of the algorithms. FPR is the proportion of misclassifying healthy samples as abnormal samples, and FNR is the proportion of misclassifying abnormal samples as healthy samples. Choosing FPR and FNR as evaluation indicators can balance the risks of missed diagnosis and misdiagnosis.

If FNR is too high, it can cause abnormal samples to go unrecognized, threatening the lives and health of the elderly. If FPR is too high, it can lead to misdiagnosis and increase the manpower and material costs of elderly care institutions. The test results are shown in Fig. 7.

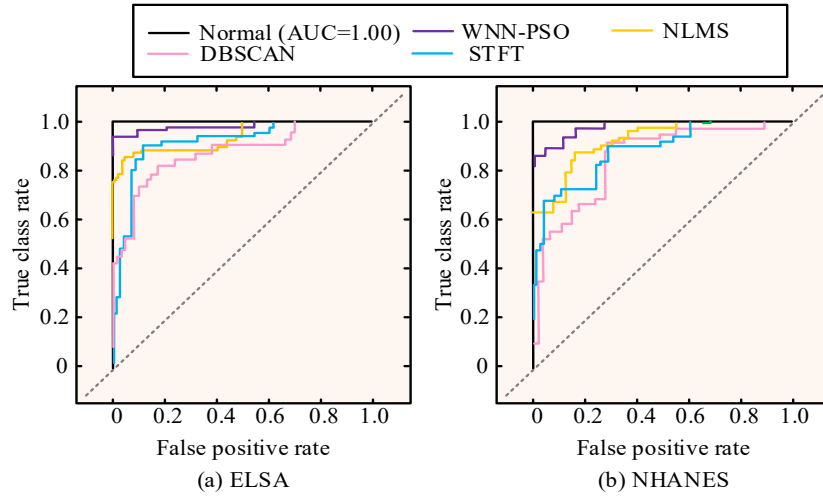


Fig. 6. AUC comparison of ELSA and NHANES datasets

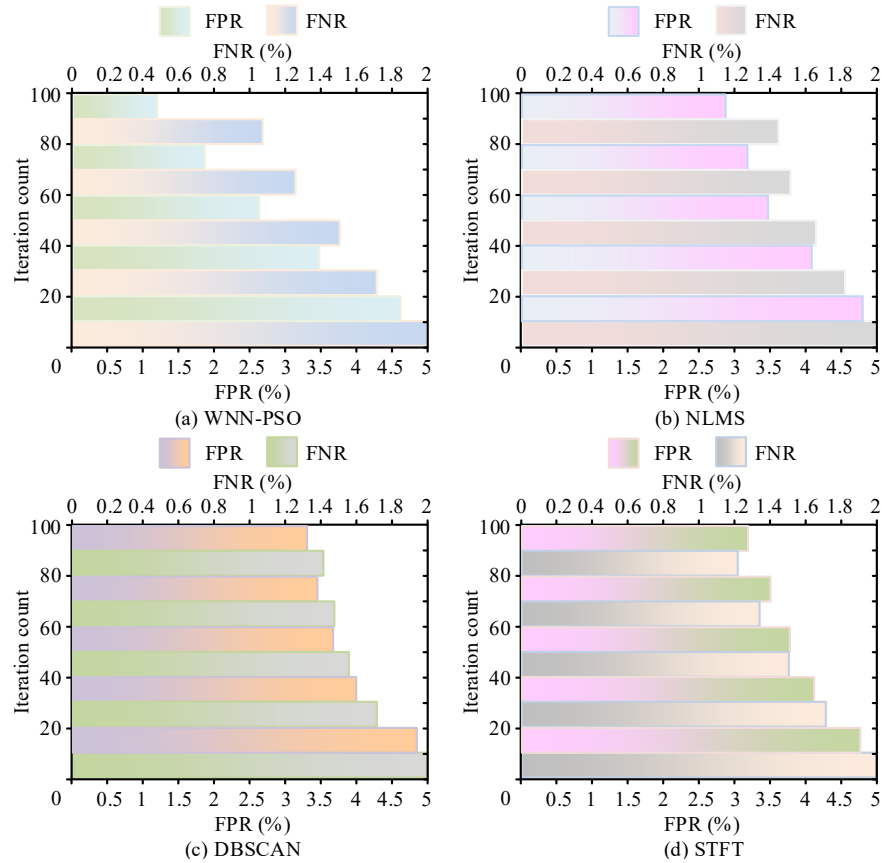


Fig. 7. Comparison of different FPR and FNR algorithms with ELSA dataset

As shown in Fig. 7(a), the FPR result of the WNN-PSO algorithm was 1.21%, and the FNR result was 1.07%. In Figures 7(b), (c), and (d), the FPR and FNR of the other three algorithms were all higher than those of the WNN-PSO algorithm. Compared to the NLMS algorithm, FNR decreased by 0.37%, and compared to DBSCAN, FPR decreased by 2.08%. The above results indicated that the WNN-PSO algorithm could effectively balance the trade-off between false positives and false negatives, demonstrating excellent discriminative power and the ability to control error types. This was related to the particle search mechanism in the optimization process of the WNN-PSO algorithm, which enabled the algorithm as a whole to adjust adaptability and obtain decision boundaries with better discrimination thresholds.

4.2. Performance Evaluation of AWP Health Status Monitoring Model

After verifying the advantages of the monitoring performance of the WNN-PSO algorithm, this study also verified the monitoring performance of the AWP model in human health status monitoring and conducted comparative experiments with three different human health status monitoring models, namely Logistic Regression (LR), Cox Proportional Hazards Model (Cox), and Framingham Risk Score (FRS). In the experiment, the experimental environment parameters were set to match those used to verify the WNN-PSO algorithm's monitoring performance. In the experiment, the datasets used were the ELSA dataset and a custom-made dataset. The parameters of the self-made dataset are shown in Table 1.

As shown in Table 1, the study recruited 50 elderly volunteers aged 65 years or older and collected data using smart sensors combined with electrocardiogram (ECG) acquisition devices. The schematic diagram of the smart sensors and ECG acquisition devices is shown in Fig. 8.

The study collected electrocardiogram (ECG) signals at 250 Hz, pulse waves at 100 Hz, and blood pressure, heart rate, blood oxygen saturation, and sleep activity data every 15 minutes. Meanwhile, this study labeled four chronic diseases among the elderly (hypertension, diabetes, coronary heart disease, and arthritis) as A, B, C, and D, respectively. The training set, validation set, and test set were divided in a 7:2:1 ratio to ensure a balanced distribution of samples across disease types. The rationality of the sample size of the self-built dataset is achieved by selecting elderly individuals aged 65 and above who have been diagnosed with chronic diseases. The model's monitoring performance is verified using 5-fold cross-validation and guided resampling (resampling times = 1000). This is done to minimize bias from small sample sizes. After guided resampling, the monitoring accuracy of the AWP model on the self-built dataset is within the 95% confidence interval [94.25%, 97.86%], and the accuracy of chronic disease recognition is within the 95% confidence interval [97.12%, 99.58%]. The learning curve of the AWP model on the self-built dataset is shown in Fig. 9.

Table 1. Parameter settings for self-constructed dataset

Type	Parameter	Label
Age	65-85	-
Sex	25 males, 25 females	-
Height	140-185cm	-
Major chronic diseases	Hypertension	A
	Glycuresis	B
	Coronary disease	C
	Arthritis	D

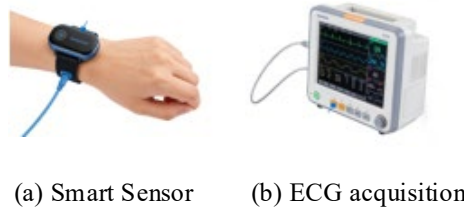


Fig. 8. Intelligent sensor and ECG acquisition device diagram

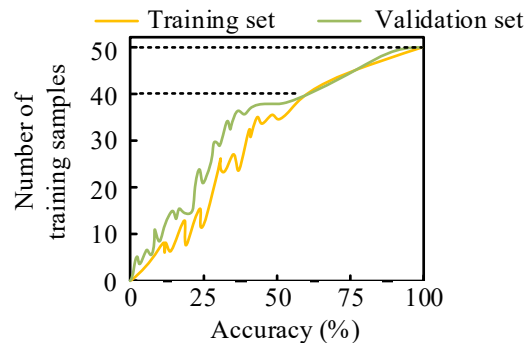


Fig. 9. Self-built dataset learning curve

As shown in Fig.9, when the number of training samples reaches 40, the accuracy of the training and validation sets of the AWP model tends to stabilize, indicating that a sample size of 50 can meet the training requirements of the AWP model. The four models were applied through variable selection and weighted adjustment during data loading and cleaning. The experiments for this study were conducted on the AWP model and three other comparative models, using the ELSA dataset to evaluate agreement in prediction performance for heart rate trends. The results are shown in Fig. 10.

The study collected electrocardiogram (ECG) signals at 250 Hz, pulse waves at 100 Hz, and blood pressure, heart rate, blood oxygen saturation, and sleep activity data every 15 minutes. Meanwhile, this study labeled four chronic diseases among the elderly (hypertension, diabetes, coronary heart disease, and arthritis) as A, B, C, and D, respectively. The training set, validation set, and test set were divided in a 7:2:1 ratio to ensure a balanced distribution of samples across disease types. The rationality of the sample size of the self-built dataset is achieved by selecting elderly individuals aged 65 and above who have been diagnosed with chronic diseases. The model's monitoring performance is verified using 5-fold cross-validation and guided resampling (resampling times = 1000). This is done to minimize bias from small sample sizes. After guided resampling, the monitoring accuracy of the AWP model on the self-built dataset is within the 95% confidence interval [94.25%, 97.86%], and the accuracy of chronic disease recognition is within the 95% confidence interval [97.12%, 99.58%]. The learning curve of the AWP model on the self-built dataset is shown in Fig. 9.

In Table 2, the accuracy of the AWP model on the ELSA and self-constructed datasets reached 95.84% and 96.18%, respectively. The RMSE values were both below 4%, and the F1 scores exceeded 94%, significantly outperforming the comparative models. Compared with the FRS model, the AWP model achieved a 6.76% higher F1 score on the ELSA dataset. From the above experimental results, the AWP model exhibits excellent monitoring performance and effectively extracts physical signals and characteristics. This was because the AWP model used the WNN-PSO component for adaptive optimization and correctly recognized the state, correcting errors using the AEKF algorithm. Finally, to further verify the dynamic monitoring performance of the AWP model, experiments were conducted on the self-built dataset using the AWP model and its three comparative models. Based on recognition results of various chronic diseases, this study evaluated its ability to recognize and alert to the dynamic monitoring of senior citizens. The experimental results are shown in Fig. 11.

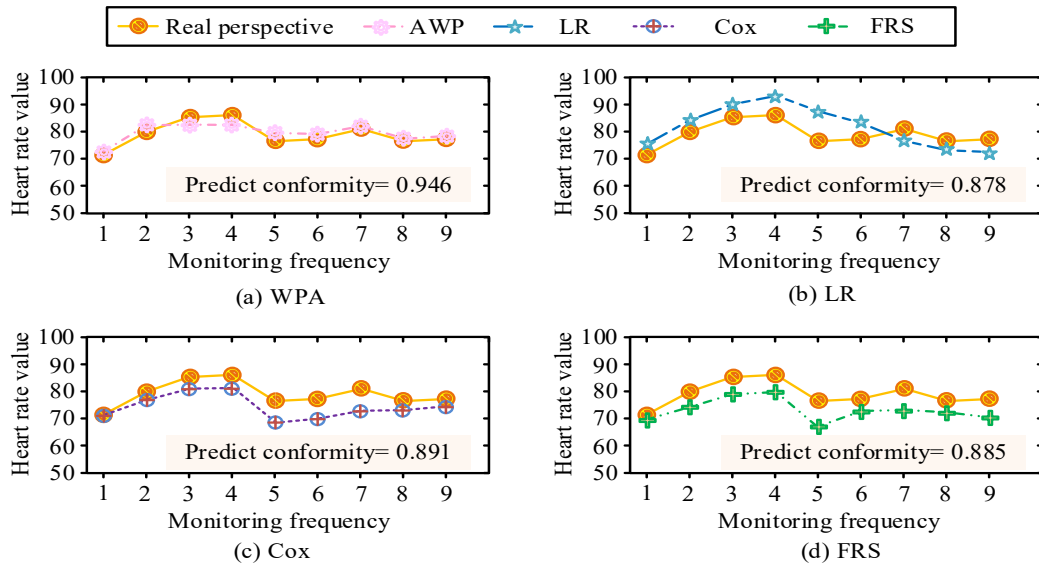


Fig. 10. Comparison of heart rate prediction performance and ELSA dataset

Table 2. Performance comparison of different models

Dataset	Model	Accuracy (%)	RMSE (%)	F1 (%)
ELSA	AWP	95.84	3.12	94.68
	LR	91.13	5.59	90.32
	Cox	85.25	9.74	83.88
	FRS	89.36	6.23	87.92
Self-made	AWP	96.18	2.91	95.43
	LR	90.25	6.12	89.51
	Cox	86.04	9.36	85.66
	FRS	89.58	6.48	88.14

As shown in Fig. 11(a), the AWP model accurately identified different types of chronic diseases, with fewer instances of missed recognition and incorrect recognition. In Fig. 11(b), (c), and (d), the recognition effects of the other three comparative models were all lower than those of the AWP model. They all showed cross-recognition among types and had more false negatives and false positives than the AWP model. The results above indicated that the AWP model exhibited excellent classification and recognition capabilities. This was related to the WNN-PSO module performing deep learning and discriminative feature extraction, and the AEKF module's state estimation further improved the stability of classification

decisions, thereby minimizing errors. To demonstrate each component's contribution to the model's monitoring performance, the study validated the model via ablation experiments on a custom dataset. The experimental results are shown in Table 3.

In Table 3, the complete AWP model achieved the highest accuracy and F1 score. The AEKF module alone yields weaker results while having the lowest response time, demonstrating that relying on filtering alone cannot extract complex physiological features. Although WNN has certain nonlinear mapping capabilities, the lack of parameter optimization means accuracy cannot be guaranteed. Compared with relying on WNN alone, using WNN+PSO can increase accuracy and F1 score by 5.22% and 5.62%, respectively, demonstrating the effectiveness of PSO-based parameter optimization for the WNN network. Although there is a slight increase in response time for the complete AWP model, it still meets the response-time requirement. From the above results, it can be seen that WNN, PSO, and AEKF are used together for feature extraction, parameter optimization, and tracking, respectively. In addition, in order to evaluate the impact of training sample size on model performance, the study chose to validate its monitoring stability on a larger cohort, selecting a sample survey from the National Center for Health Statistics in the United States, which included health monitoring data from 4560 elderly people over 65 years old. Samples with missing data rates exceeding 30% were excluded, and monitoring accuracy and average F1 score were used to assess performance and to conduct statistical significance tests. Each experiment was repeated three times, and the experimental results are shown in Table 4.

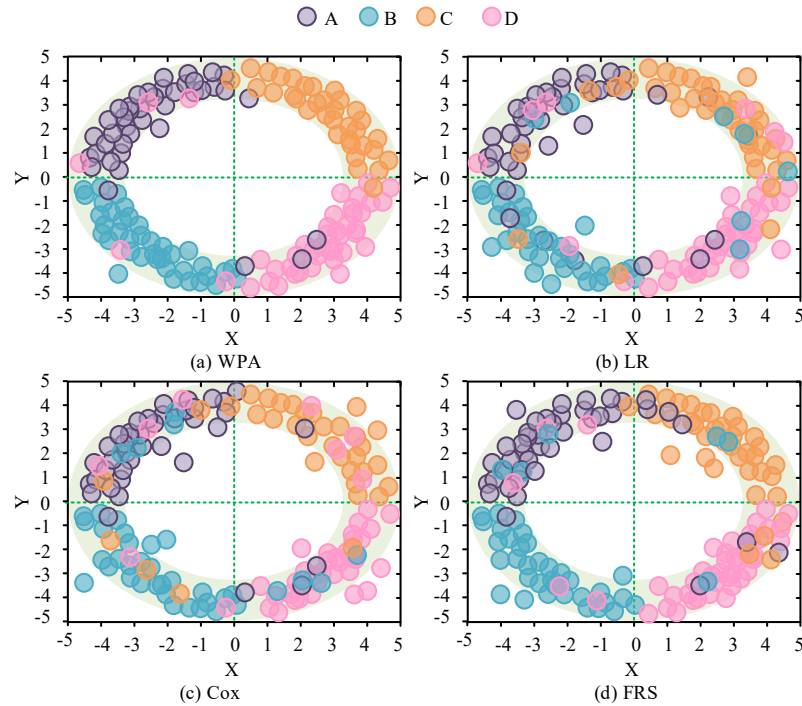


Fig. 11. Performance comparison of different models

Table 3. Comparison of ablation experiment results

Model Configuration	Accuracy (%)	F1 score (%)	Response time (ms)
WNN only	87.32	85.61	28.69
WNN+PSO	92.54	91.23	42.38
AEKF only	84.16	82.94	12.45
Full model	96.18	95.43	45.71

Table 4. Experimental results of large-scale model data

Dataset	Model	Accuracy (%)	F1 score (%)
National Center for Health Statistics, United States	AWP	95.84 $\pm$ 0.23	94.68 $\pm$ 0.31
	LR	91.13 $\pm$ 0.42*	90.32 $\pm$ 0.48*
	Cox	85.25 $\pm$ 0.56**	83.88 $\pm$ 0.62**
	FRS	89.36 $\pm$ 0.38**	87.92 $\pm$ 0.44**

Note: * indicates significant differences between LR, Cox, FRS models and AWP model, * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$.

As indicated in Table 4, the paired t-test showed that the differences between the AWP model and the three comparative models were significant. In the large-scale cohort validation, the AWP model achieved 95.84% monitoring accuracy and 94.68% F1 score, both higher than those of the three comparative models. From the above results, it can be concluded that the improved performance of the AWP model on the large-scale cohort was not caused by random factors and was reliable.

5. Decision-Making Significance and Practical Application Solutions

The AWP model offers administrators of monitoring institutions, such as nursing homes and community health centers, four decision-making optimization strategies: real-time abnormal tagging and threshold adjustment, priority triage in remote monitoring centers, individualized tracking of physiological indicator trends, and optimization of resource allocation. Real-time anomaly tagging is performed using the model's risk scores. If the risk score is below 0.3, it can be regarded as a low-risk sample. If the risk score is between 0.3 and 0.7, it can be regarded as a medium-risk sample. If the risk score is above 0.7, it can be regarded as a high-risk sample. The aforementioned workflow successfully achieves automated anomaly tagging. Priority triage in the remote monitoring center can be conducted by medical staff for high-risk samples, by nurses for medium-risk samples, and through routine monitoring for low-risk samples. Personalized physiological index trend-tracking monitors changes in indices, such as heart rate, in patients with chronic diseases, such as hypertension and diabetes, in real time. When the trend is abnormal, nurses will initiate a follow-up visit. Resource allocation optimization is based on the model's computational complexity and real-time requirements, ensuring appropriate battery resource allocation. Monitoring devices for high-risk patients use high-bandwidth, high-endurance configurations, while those for low-risk patients use conventional configurations. The model sets the cost-weight coefficients, with the missed-cost weight set to 5 and the false-positive cost weight set to 1. The calibration chart and decision curve analysis of the model are shown in Fig. 12.

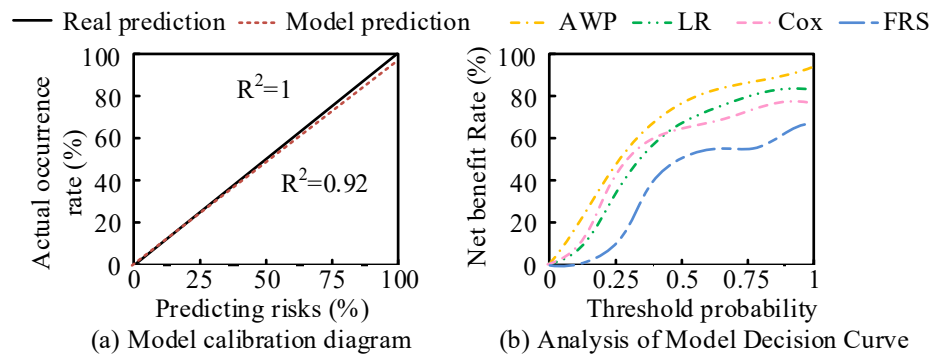


Fig. 12. Calibration chart and decision curve analysis of model

As shown in Figs. 12(a) and (b), the consistency between the predicted risk and the actual occurrence risk of the model is $R^2=0.92$, and the net benefit of the AWP model is higher than that of the LR, Cox, and FRS models. From this, it can be seen that the AWP model's risk prediction has good calibration and greater practical value in clinical decision-making.

6. Conclusion

Health status monitoring plays a vital role in extending healthy life expectancy and enhancing the quality of life for older adults. The timely detection of illnesses and implementation of corresponding interventions can also be achieved. However, due to limitations in traditional techniques for the timely and accurate detection of dynamic physiological parameters, the reliability of current monitoring results remains insufficient. Hence, this study proposed developing a health status model for seniors based on WNN-PSO. The model extracted deep features using WNN and then applied AEKF after optimizing the monitoring-related parameters using PSO. The research was conducted based on the following assumptions: physiological parameters of the monitored subjects can be collected reliably, and the training data distribution aligns with real-world application scenarios. Experimental results showed that the WNN-PSO algorithm's monitoring response time was 0.74 s, the AUC was above 0.94, the FPR was 1.21%, and the FNR was 1.07%. The AWP model's predicted trend agreement reached 0.946. The monitoring accuracy on the ELSA dataset and the self-made dataset reached 95.84% and 96.18%, respectively; the F1 score exceeded 94%; and the accuracy of identifying chronic disease types reached 98.74%. All the above indicators outperformed those of the three comparative methods. In summary, the AWP model demonstrated significant advantages in dynamic health monitoring of elderly people, could track data changes in real time, and accurately captured physiological data features, demonstrating excellent generalization. Based on the above risk assessment framework, managers of health monitoring institutions can adjust their current management processes in the following decision-making stages. For real-time anomaly tagging, administrators can dynamically adjust monitoring thresholds based on model-generated risk scores, appropriately reduce the monitoring frequency of low-risk cohorts to conserve resources, and trigger immediate warnings and manual reviews for high-risk cases. For prioritized triage within remote monitoring centers, administrators can reassign response duties to medical staff based on risk levels, ensuring that high-risk cases receive immediate, professional intervention. For personalized trend tracking, administrators can establish tailored follow-up protocols for patients with chronic diseases by leveraging model-based dynamic predictions of key indicators, such as heart rate and blood pressure. Although the AWP model has shown great potential for recognition and monitoring, its long-term applicability still needs to be assessed. Future research directions for the development of the AWP model for elderly health monitoring include two aspects: combining wearable sensors, imaging and genetic information to improve the model's disease-identification capability and applying a lightweight model development strategy by pruning and quantizing the AWP model.

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Institutional Review Board Statement

Not applicable. The datasets in the experiment were the National Health and Nutrition Examination Survey dataset and the English Longitudinal Study of Aging dataset.

Declaration of Artificial Intelligence (AI) Tools

The author used ChatGPT solely for language editing and formatting assistance. The author reviewed and takes full responsibility for all content.

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