Digital Twin-Based Multimodal Data Fusion for Health Monitoring in Smart Elderly Care Platforms

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In the smart elderly care mobile service platform, multimodal sensor data is redundant due to differences in format, accuracy, etc., and the lack of effective analysis makes it difficult to extract feature components, which affects the fusion effect. A new method is proposed for this: first, real-time health data is collected through platform integrated sensors such as electrocardiograms, and then the raw data is redundantly processed to generate standardized datasets in a unified format. Next, a digital twin model is constructed, and feature component extraction techniques are used to analyze the data distribution structure. The dynamic correlation of the quantified data is calculated by associating distribution features to complete the fusion. The experiments have proved that under the application of this method, when the elderly are in a state of hypertension, the blood pressure fusion value significantly increases to nearly 1. When the heart rate is too fast, the pulse fusion value and electrocardiogram fusion value reach approximately 0.8 and 0.7 respectively. The average accuracy rate of identifying various abnormal health conditions is over 85%. The overall standard deviation is 0.004, indicating that the degree of dispersion of the fused data is smaller. In terms of data fusion error, it is below 0.15% under all data volume conditions, which is conducive to promoting the development of the elderly care industry.

Povzetek: Študija predstavlja metodo za natančnejšo analizo in združevanje zdravstvenih podatkov starejših z uporabo digitalnega dvojčka in senzorjev.

1 Introduction

The smart elderly care mobile service platform uses multiple sensors to collect real-time health data such as heart rate and blood pressure of the elderly and upload it. It can analyze it in real time, issue timely warnings in case of abnormalities, and achieve dynamic health monitoring and management. Due to multiple sensors and heterogeneous sources of health data in monitoring. By utilizing multimodal data from the platform, we can comprehensively understand the condition of the elderly, accurately reflect their health and potential risks, and improve the level of personalized elderly care services [1, 2].

In recent years, the academic community has proposed a variety of solutions to the key technical bottlenecks of multimodal data fusion in smart elderly care. Alsamhi et al. [3] introduced blockchain to provide a transparent and immutable ledger, and realized the integration and sharing of decentralized data in smart elderly care and healthcare through federated learning. They combined blockchain and federated learning to achieve collaborative processing and built a secure sharing framework for multimodal data in smart elderly care and healthcare. By utilizing federated learning technology, it is possible to prevent the leakage of data sources for smart elderly care and healthcare, achieving cross platform and institutional multimodal data joint modeling. The distributed ledger feature of blockchain can ensure transparent, immutable, and traceable transmission and storage of multimodal data, safeguarding data sharing. The combination of the two effectively enhances the accuracy and reliability of multimodal data fusion in elderly care service models. However, this method lacks a standardized preprocessing mechanism for multimodal data, and the problem of raw data redundancy still exists, which in turn affects the effect of the final multimodal data fusion. Al-Qudah et al. [4] built a deep learning model for vibration data of elderly care facilities, and accurately located the potential damage position of the facility by analyzing the characteristics of vibration signals. The defect classification model is established by using the optical image data of the elderly care facilities. The model classifies and identifies defects such as cracks and deformations on the surface of the facilities through image recognition technology. The vibration data model and the optical image model are organically integrated to form a new method for structural health monitoring based on multimodal data. The multimodal data fusion results are further verified by the vibration signals and real structural images of the elderly care facilities actually collected. Deep learning models are often used to extract vibration and image data features, but there is no cross modal correlation analysis method, making it difficult to effectively capture dynamic correlation features such as heart rate variability and blood pressure fluctuations, resulting in poor multimodal data fusion performance. Josey et al. [5] in the smart elderly care mobile service platform, different sources of elderly care data weights can be adjusted by generating balanced weights to solve the problems of confounding factors and sampling bias in multimodal data fusion, ensuring the representativeness and accuracy of data fusion, and more effectively estimating the average effect of elderly people receiving services, achieving effective integration. However, the effectiveness of this method relies on precise identification and quantification of confounding factors and sampling bias. However, the platform's elderly care data is complex and diverse, with confusing factors that are difficult to identify and quantify, which cannot completely eliminate data bias and affect the accuracy of fusion. Kulkarni et al. [6] a medical system framework based on the Internet of Things has been constructed, with multiple sensors deployed in elderly care communities to collect and transmit real-time health data of the elderly. The disease prediction strategy is specifically designed for smart elderly care scenarios, using theoretical modeling to integrate elderly health history, lifestyle habits, and community environmental factors to construct a prediction model. Using principal component analysis to reduce dimensionality of multimodal data, extract key features, and eliminate redundancy; Preliminary classification of data through cluster analysis; Using artificial bee colony algorithm to optimize the parameters of nonlinear support vector machine classifier, generate efficient classifier pairs, and accurately classify disease risks. Feature-level fusion analysis is performed on the processed and classified multimodal data. The feature information of different data sources is integrated to form a more comprehensive and accurate feature representation. However, the principal component analysis technology in this method may not be able to fully explore the potential information in the data when processing complex multimodal data, resulting in the omission of important features and affecting the multimodal data fusion results.

The smart elderly care mobile service platform has a wide range of multimodal data sources, diverse formats, and heterogeneity issues [7, 8]. Based on the digital twin model, a digital model corresponding to the real elderly and their environment can be constructed in the virtual space. Data in different formats can be uniformly modeled and processed in the virtual space to achieve data standardization and normalization, and solve the fusion problem caused by data heterogeneity [9]. With the help of digital twin models, smart elderly care data associations can be visually presented, potential associations can be explored using data analysis algorithms, and the effectiveness of multimodal data fusion can be improved. Based on this, a multimodal data fusion method for an smart elderly care mobile service platform is proposed, which can achieve good integration of platform data and enhance elderly care safety and reliability. The relevant work summary table, technical gaps and the elaboration of the contributions of this article are specifically shown in Table 1.

Table 1: Relevant work summary table

Author	Method	Data type	Limitations
Alsamhi et al.	Blockchain - Federated Learning	Multimodal health data	The lack of a standardized preprocessing mechanism has not solved the problem of redundant raw data
Al-Qudah et al.	Deep learning	Vibration signals, optical images	The lack of cross-modal correlation analysis makes it difficult to capture dynamic correlation features
Josey et al.	Balanced weight generation	Multi-source pension data	Relying on the precise identification and quantification of confounding factors, it is difficult to completely eliminate biases in complex data
Kulkarni et al.	PCA dimensionality reduction - Clustering - Artificial bee Colony Optimization SVM	Multimodal health and environmental data	PCA omits important features, affecting the integrity of fusion
This paper	Digital twin modeling - Feature component extraction - Dynamic association fusion	Multimodal sensor data such as electrocardiogram, body temperature, blood pressure, blood oxygen, and pulse	Focus on heterogeneous data standardization, redundancy elimination and cross-modal dynamic association modeling

This study aims to address the issues of multi-modal data redundancy, heterogeneity and insufficient fusion accuracy caused by differences in sensor types, formats and accuracies in the mobile service platform for smart elderly care. Develop a method that integrates preprocessing, feature modeling and dynamic correlation analysis to significantly reduce the error and dispersion of multimodal health data fusion and improve the accuracy of identifying abnormal health conditions in the elderly. To achieve this goal, this study is dedicated to addressing the following research questions. How to eliminate redundancy and format inconsistency in the raw data of multi-source sensors; How to construct a digital twin model that can represent and quantify the dynamic correlations among multimodal health data to go beyond the traditional static or single-modal feature fusion; Can the proposed method achieve significant improvements in fusion accuracy and abnormal state recognition accuracy compared with the existing mainstream methods? Based on the above problems, this paper proposes the following research hypotheses. Redundancy processing using a generalized data model and state-time triples can effectively improve data quality. Feature extraction and distribution structure analysis based on digital twin models can effectively capture and quantify the dynamic correlations and spatio-temporal distribution characteristics among multimodal data. The complete fusion process proposed in this paper will outperform the comparison methods under multi-index evaluation, specifically manifested as follows: the data fusion error is less than 0.15%, the overall standard deviation is significantly reduced, and the recognition accuracy of abnormal states such as hypertension and rapid heart rate is improved.

This study systematically expounds and verifies the above-mentioned goals, problems and hypotheses through the method design in sections 2-3 and the experimental analysis in Section 4.

2 Multimodal data fusion of smart elderly care mobile service platform

2.1 Smart elderly care mobile service platform

In the field of smart elderly care, multimodal data fusion faces the challenge of data heterogeneity caused by different sensor types. Therefore, this study focuses on standardized collection and preprocessing techniques for multi-source health data.

The smart elderly care mobile service platform integrates multiple sensors such as electrocardiogram, body temperature, and blood pressure to collect real-time health data of the elderly [10], including electrocardiogram, body temperature, blood pressure, and other basic data [11]. The structure is shown in Figure 1.

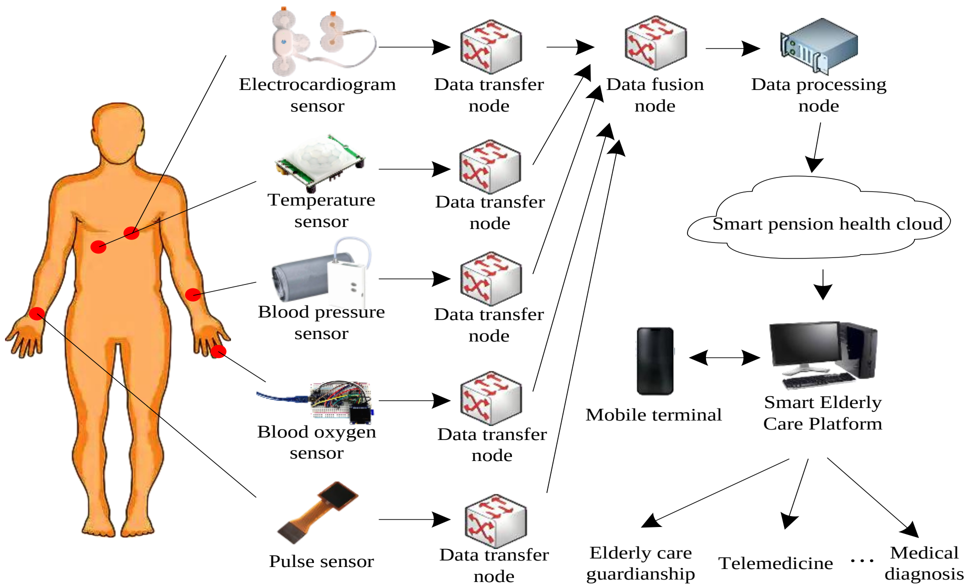

Figure 1: Structure of smart pension mobile service platform

As shown in Figure 1, with the help of electrocardiogram, body temperature, blood pressure, blood oxygen, pulse sensors, basic data such as electrocardiogram, body temperature, blood pressure, blood oxygen saturation, heart rate, etc. of the elderly are collected separately. The collected health data is transmitted through the data transmission node, and the multimodal data is integrated and processed by the data fusion node to construct an smart elderly care health cloud. It is stored on the smart elderly care platform and interacts with mobile terminals. Finally, based on the fused data, elderly care monitoring, remote medical care, medical diagnosis, etc. are achieved [12]. The details of the acquired health data of the elderly are shown in Table 2.

Table 2: Detailed contents of elderly health data

Information of the elderly	Indicator	Detailed information
Electrocardiogram data x_1	Date of electrocardiogram recording x_{11}	The specific date of electrocardiogram data collection
	The electrocardiogram records the time x_{12}	The specific time for collecting electrocardiogram data
	R value x_{13}	Changes in ventricular depolarization potential
	P value x_{14}	Changes in atrial depolarization potential
	ST value x_{15}	The potential changes of the ventricular muscle from the end of depolarization to the beginning of repolarization
Body temperature data x_2	Date of body temperature record x_{21}	The specific date for collecting body temperature data
	Temperature recording time x_{22}	The specific time for collecting body temperature data
Blood pressure data x_3	Blood pressure recording date x_{31}	The specific date of blood pressure record collection
	Blood pressure recording time x_{32}	The specific time for collecting blood pressure records
	High voltage value x_{33}	High blood pressure condition
	Low pressure value x_{34}	Low blood pressure condition
Blood oxygen data x_4	Blood oxygen recording date x_{41}	The specific date of blood oxygen data collection
	Blood oxygen recording time x_{42}	The specific time for collecting blood oxygen data
Pulse data x_5	Pulse recording date x_{51}	The specific date of pulse data collection
	Pulse recording time x_{52}	The specific time for pulse data collection
Name x_6	/	Name of the elderly person under guardianship
Gender x_7	/	Gender of the elderly person under guardianship
Age x_8	/	Age of the elderly person under guardianship
Contact number x_9	/	Contact number of the elderly person under guardianship

As shown in Table 1, the smart elderly care mobile service platform can collect various types of information from the elderly and obtain identity and health data. By utilizing effective multimodal data fusion, smart elderly care monitoring can be achieved, providing high-quality medical and diagnostic services for abnormal physical conditions of the elderly and ensuring their safety.

2.2 Redundant processing of multimodal data in smart elderly care

In the smart elderly care system, the sampling frequency, data format, and measurement accuracy of various sensors naturally differ [13], highlighting the problem of heterogeneous raw data sets. For example, the ECG sensor may collect signals at a higher frequency, the data format is a specific analog-to-digital conversion code, and the measurement accuracy reaches the millivolt level; while the temperature sensor has a lower sampling frequency, a simple numerical data format, and a measurement accuracy of degrees Celsius. This inconsistency at the data level will have a negative impact on the accuracy of subsequent feature extraction and model training [14]. Therefore, it is necessary to eliminate the systematic differences between sensors through standardization processing to provide a consistent data basis for multimodal fusion.

According to the structure of the smart elderly care mobile service platform in Section 2.1, integrating multiple sensors can obtain multimodal data, which is presented in the form of data streams and can be represented as:

$$X = \langle \eta, N, A, T \rangle \quad (1)$$

Among them, X represents the multi-mode data stream of the smart elderly care mobile service platform, η is its data stream encoding value, N is the sensor number value of the mobile service platform, A is the obtained elderly care dataset, and T represents the reading time of the elderly care data.

To unify the processing of multimodal data for smart elderly care, a generalized data model is introduced, where S_t uniformly identifies state information and uniformly identifies time information T_i. The sensor outputs of each smart elderly care mobile service platform are represented by triplets, as shown in formula (2).

$$X = \langle \eta, S_t, T_i \rangle \quad (2)$$

According to formula (2), the original smart elderly care data can be simplified. If the continuous data generated by the sensors of the smart elderly care mobile service platform remains unchanged during time period $t \sim t+1$, all information except for the beginning and end time data is considered redundant. When making a judgment, use the data retrieval function to locate the current state S_t, compare it with the previous state S_{t-1}, and combine the timestamp difference to make a judgment. Assuming the minimum time collection granularity is ΔT_{min}, satisfy any of the following conditions:

$$S_t = S_{t-1} \quad (3)$$

$$T_t - T_{t-1} < \Delta T_{min} \quad (4)$$

Afterwards, if it is determined to be redundant, the smart elderly care data will be deleted; On the contrary, update the records and retain the new status information.

After this processing, assuming the original multimodal dataset has a data volume of M, and after removing redundancy, it becomes M'. The calculation formula for the redundancy data elimination rate R is:

$$R = \frac{X(M - M')}{M} \times 100\% \quad (5)$$

This method effectively eliminates redundant information from multimodal data of smart elderly care, improves platform data quality, reduces data processing pressure, and enhances the accuracy and efficiency of subsequent data analysis [15].

2.3 Multimodal data fusion of smart elderly care mobile service platform based on digital twin model

Although data standardization processing has addressed the issues of heterogeneity and redundancy, due to the complex spatiotemporal characteristics and dynamic correlations of elderly health data, it is necessary to deeply explore the intrinsic connections of multimodal data through digital twin modeling. Specifically, this method builds a virtualized sensor integration digital twin model based on the standardized dataset processed in Section 2.2. The core is to analyze the patterns of various modal data using feature extraction technology and achieve multi-source data fusion by quantifying the dynamic relationships among health parameters [16].

Figure 2 shows the digital twin model of multimodal data fusion for the smart elderly care mobile service platform.

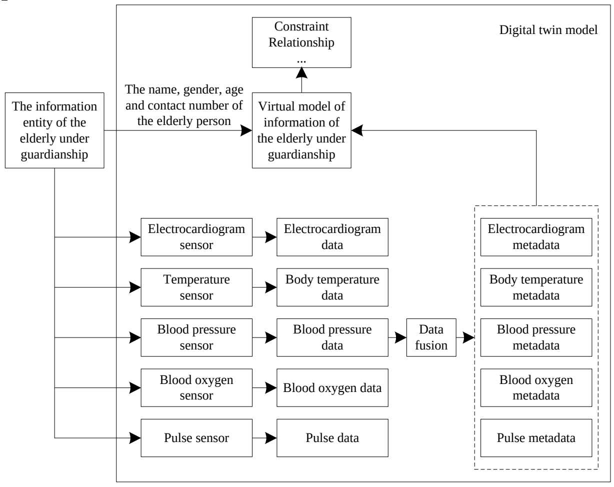

Figure 2: Digital twin model of multi-modal data fusion of smart pension mobile service platform

In smart elderly care, the multimodal health data of the elderly are scattered and have different formats and semantics. Digital twin modeling can uniformly present physiological states and provide accurate references. The metadata digital model is constructed by multimodal data of smart elderly care mobile service platform after redundancy processing in Section 2.2. This model is a virtualized sensor device integration model, which corresponds to the actual sensor physical model. The digital twin technology can extract the feature components of multimodal data from smart elderly care platform c, which can be expressed as follows:

$$c = \mu R\left[\beta(X) - \min\beta(X)\right] / \left[\max\beta(X) - \min\beta(X)\right] \quad (6)$$

μ is the standard deviation of multimodal data for the smart elderly care mobile service platform; $\beta(X)$ is its gain; $\max\beta(X)$. $\min\beta(X)$ represents the maximum and minimum values of the data gain, respectively.

To accurately measure the multimodal data integration degree of the smart elderly care mobile service platform, it is necessary to conduct multimodal data distribution structure analysis based on feature components. The multimodal data distribution structure can describe the distribution characteristics of data from multiple dimensions, including the distribution of data between different health monitoring device data sources, the distribution between different data types, and the distribution at different time and space scales [17]. By combining the feature components and distribution structure of multimodal data, a more comprehensive and in-depth evaluation of its integrated state can be achieved. The multi-modal data distribution structure calculation of the smart elderly care platform is as follows:

$$\alpha = c\left|c_0 - c'\right| \quad (7)$$

c_0 is the initial value of the multimodal data feature component, and c' is the ideal value.

Based on equation (7), the multimodal data distribution structure of the intelligent elderly mobile service platform is calculated, and its similarity and variability are analyzed using standard deviation to reveal the similarities and differences in information distribution [18]. Calculate the probability density ρ of multimodal data similarity using distribution structure α , as follows:

$$\rho = \alpha\kappa \quad (8)$$

κ represents the similarity changes of multimodal data in the smart elderly care mobile service platform.

Calculate the probability density value ρ of multi-modal data similarity for the intelligent elderly mobile service platform according to formula (8), and convert the original data into structured time series data. Based on probability density ρ , the platform multimodal data two-component λ can be obtained as follows:

$$\lambda = \rho D_i \chi \quad (9)$$

D_i represents the physical model of the information sensor of the i -th smart elderly care mobile service platform, and χ represents the metadata of the platform's information.

Based on the multimodal data of the smart elderly care mobile service platform, a dual component λ is used to construct its multimodal metadata model $E(X)$, which is expressed as follows:

$$E(X) = \lambda(\kappa + \varphi) \quad (10)$$

κ represents the relationship between multimodal data of smart elderly care mobile service platforms, and φ represents the constraints of multimodal data of smart elderly care related platforms. By utilizing the constructed information metadata model, smart elderly care multimodal data fusion can be achieved, which essentially involves deep data mining to obtain probabilistic decisions [19].

Firstly, it is necessary to extract the relevant distribution characteristics of multimodal data for smart elderly care using relevant distribution coefficients, which can quantitatively represent the relationships between various elements. Due to the different structures and formats of multi-source data, but with potential correlations [20], the correlation distribution coefficient can reveal hidden relationships.

Secondly, in smart elderly care, the internal connections and impacts of various platform elements should be considered. In the information metadata model, elements interact with each other, and a change in one element can trigger a chain reaction, which are key factors in data fusion.

To effectively integrate multimodal data and calculate its correlation and distribution characteristics h , the formula is as follows:

$$h = \xi\left[\iota E(X)\right] \quad (11)$$

ξ is the correlation distribution coefficient of multimodal data fusion for the smart elderly care mobile service platform, and ι is the variable.

By combining equation (11), the multi-modal data correlation distribution feature h can be obtained. Extracting the platform information envelope feature quantity, the multi-modal data reliability component η can be calculated, and the formula is as follows:

$$\eta = hE(X) + \eta\varpi \quad (12)$$

Where, ϖ represents the analytical factor.

By utilizing the extracted multimodal data reliability components of the smart elderly care mobile service platform, a subset of reliability features is constructed and screened to obtain a value function that reflects the inherent attributes of the data and reveals potential relationships [21]. By using fuzzy information fusion technology to integrate information, the multimodal data fusion result Y is finally obtained, and the formula is as follows:

$$Y = \eta\theta\psi \quad (13)$$

Where, θ represents the value function, ψ represents the fuzzy rule.

According to the above process, the specific steps for achieving multimodal data fusion on the smart elderly care mobile service platform based on the digital twin model are shown in Figure 3.

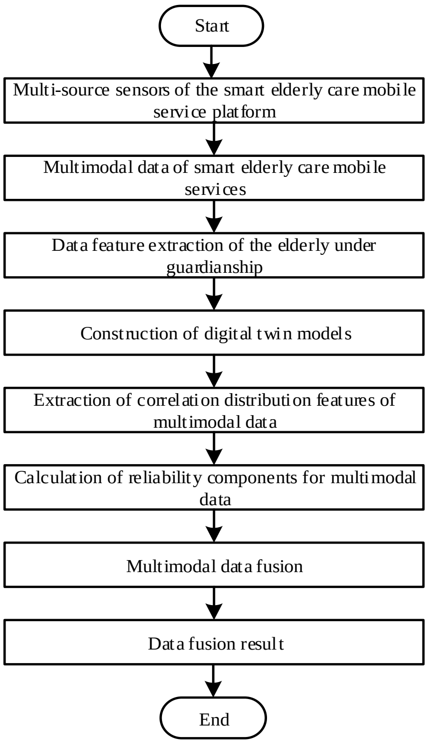

Figure 3: Multi-mode data fusion process of smart pension mobile service platform

As shown in Figure 3, the data fusion of the smart elderly care platform can provide data support for elderly medical care.

This paper adopts fuzzy logic for the final decision fusion, mainly because it can effectively handle the fuzziness of health states, dynamically integrate multimodal information and fuse knowledge. It is achieved through a trainable adaptive neural fuzzy reasoning system: fuzzing the data of each sensor into semantic labels such as "normal" and "high"; The system reasons based on a sparse rule base initialized by expert experience and optimized through data-driven methods. During this process, the reliability components of each mode are dynamically integrated to adjust their weights in decision-making. The system outputs a comprehensive health score through deblurring. This fuzzy system learns the optimal parameters through end-to-end training instead of using static rules, thereby ensuring the robustness, interpretability of the fusion results and fair comparison with contrast methods. The pseudo-code of the article is as follows:

Initialize sensor_data_streams = [ECG, temp, BP, SpO2, pulse] # Raw data collection

standardized_data = apply_z_score_normalization(sensor_data_streams) # Standardization

filtered_data = remove_redundant_records(standardized_data, time_threshold=T) # Redundancy removal

digital_twin_model = create_virtual_sensor_model(filtered_data) # Digital twin initialization

feature_components = extract_features(digital_twin_model) # Feature extraction

correlation_matrix = calculate_correlation(feature_components) # Relationship analysis

fused_output = fuzzy_fusion(correlation_matrix) # Final data fusion

3 Experimental analysis

To verify the multimodal data fusion method of the smart elderly care mobile service platform in this article, experiments were conducted on the nursing home platform as the real scene. In an environment that simulates the daily activities of the elderly, MATLAB Simulink is used to simulate and optimize data collection parameters. Multiple sensors are used to collect health data of the elderly, which is then imported into the processing module and fused according to the method described in this article. This includes removing redundancy, unifying data, modeling features, quantifying correlations, etc. The results are presented/visualized on the interface, with the actual experimental setup depicted in Figure 4.

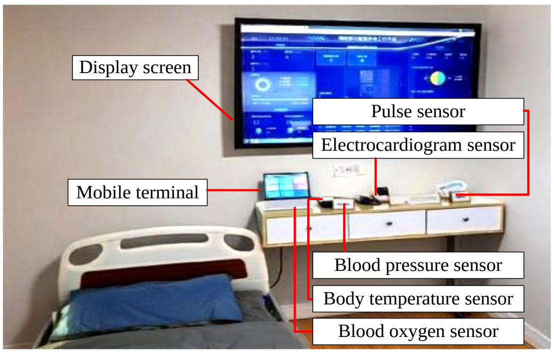

Figure 4: Real scene of smart pension mobile service platform

As shown in Figure 4, the smart elderly care mobile service platform collects elderly health data using numerous sensors and conducts statistical analysis on the parameters of each sensor. The results are shown in Table 3.

According to the sensor parameters in Table 2, the elderly's health data was obtained. The method proposed in this paper was used to fuse multimodal data on the intelligent elderly mobile service platform, and the effect was good.

From the multimodal data page of the smart elderly care mobile service platform in Figure 5, it can be seen that the integrated data includes detailed personal information such as the elderly's name and gender, as well as precise health information such as body temperature and pulse. The accuracy and completeness of these data have been significantly improved, and the associations between different modal data have been effectively mined and integrated. For example, analyzing the correlation between electrocardiogram and pulse data can accurately determine the heart health of the elderly; Joint display of temperature and blood pressure data can help medical staff quickly identify potential changes in the elderly's body. Multimodal data fusion can provide multidimensional and reliable support for elderly care monitoring and medical diagnosis, reflecting the health of the elderly more comprehensively than single monitoring, and helping to improve the level of smart elderly care. Its practical application has been verified to be effective and practical.

All the elderly volunteers participating in the experiment signed a written informed consent form before the experiment. During the research process, the rights, safety and privacy of the participants were fully protected. All the collected personal identity information has been desensitized and is only used for the purpose of this study. The simulation data section does not involve any individual privacy information.

The fusion results are displayed on the page, and the multimodal data page is shown in Figure 5.

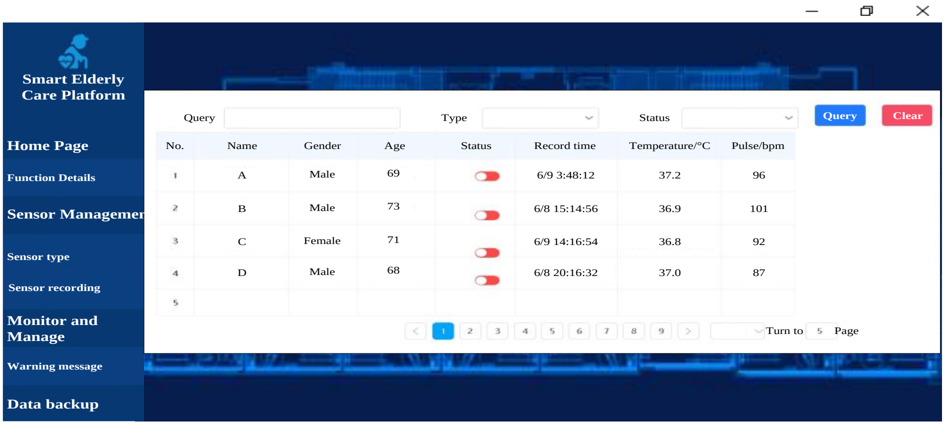

Figure 5: Smart pension mobile service platform page

Table 3: Related parameters of the sensor

Sensor type	Parameters	Specific value
	Specific model	ECG-1000
	Measurement range/Hz	0.5~100
Electrocardiogram sensor	Accuracy/mV	±0.1
	Sampling rate/Hz	500
	Resolution	12 bits
	Specific model	TMP36GT9Z
	Measurement range/°C	-40~125
Body temperature sensor	Accuracy/°C	±0.5
	Sampling rate/Hz	/
	Resolution	10mV/°C
	Specific model	BP-200
	Measurement range/mmHg	Systolic blood pressure:0~300； Diastolic blood pressure:0~200
Blood pressure sensor	Accuracy/mmHg	Systolic blood pressure:±3； Diastolic blood pressure:±2
	Sampling rate/Hz	/
	Resolution	/
	Specific model	MAX30102
	Measurement range/%	70~100
Blood oxygen sensor	Accuracy/%	±2
	Sampling rate/Hz	100
	Resolution	16 bits

Pulse sensor	Specific model	PULSE-500
	Measurement range/bpm	30~250
	Accuracy/bpm	±2
	Sampling rate/Hz	100
	Resolution	/

To verify the effectiveness of the multimodal data fusion method proposed in this paper for the smart elderly care mobile service platform, an experiment was conducted in a cooperative scenario of a certain nursing home. A total of 42 elderly volunteers aged 65 to 85 were recruited for the experiment, and data collection was conducted in an environment that simulated daily activities such as sitting still, walking, and light activities. Using the sensors of the models listed in Table 2, each subject was continuously monitored for 5 days, with 8 hours of monitoring each day, to collect the original physiological data such as electrocardiogram, body temperature, blood pressure, blood oxygen and pulse. The data acquisition frequency of each sensor is strictly based on its specifications: the electrocardiogram sensor is 500 Hz, the blood oxygen and pulse sensors are 100 Hz, and the body temperature and blood pressure sensors record according to preset instructions or events. Meanwhile, to expand the data volume and verify the robustness of the algorithm, based on the distribution characteristics of the collected real data, a high-fidelity sensor model was constructed using MATLAB Simulink to simulate multimodal data streams under different health conditions such as sudden arrhythmia and sudden increase in blood pressure. Eventually, a comprehensive data set containing more than 500 hours of records was formed. All the collected physiological data were independently reviewed and labeled by two senior nursing experts and one physician, serving as the benchmark true value for evaluating the performance of the algorithm. The marked content not only includes discrete health status labels such as "normal", "hypertension", and "rapid heart rate", but also precise start and end time markers for specific abnormal events. To comprehensively evaluate the performance of the fusion method, the overall standard deviation and the data fusion error are adopted as comparison indicators. Among them, the overall standard deviation measures the consistency among multiple fusion results, and the lower the value, the more stable the fusion process is. The data fusion error is normalized to the interval [0, 1].

This method can effectively integrate multimodal data from intelligent elderly mobile service platforms to evaluate the health status of the elderly. Based on the fusion results, evaluate the abnormal health status of different elderly people, as shown in Figure 6 for details.

From the quantitative evaluation results in Figure 6, under normal health conditions (Figure 6 a), the fusion values of multimodal data such as blood pressure, ECG, pulse, blood oxygen, and body temperature are relatively balanced and at a low level, reflecting that the physical indicators of the elderly are normal and stable. When the elderly are in a state of hypertension (Figure 6b), the blood pressure fusion value significantly increases to close to 1 (expressed as a normalized dimensionless value), while other modal data fluctuate but the relative change amplitude is small relative to blood pressure, indicating that blood pressure indicators dominate the judgment of hypertension. In the state of too fast heart rate (Figure 6c), the pulse fusion value and ECG fusion value increase significantly, reaching about 0.8 and 0.7 respectively, highlighting the key role of pulse and ECG data in identifying abnormal heart rate. In the fever state (Figure 6d), the body temperature fusion value rises to about 0.9, and other modal data also fluctuate to a certain extent, indicating that body temperature is the core indicator for judging fever and other physiological indicators of the body will be affected by it. In the state of low blood oxygen level (Figure 6e), the blood oxygen fusion value is significantly reduced to about 0.2, which becomes a significant sign of this abnormal state. In terms of heart disease status (Figure 6f), the electrocardiogram fusion value is about 0.9, highlighting its importance in evaluating heart disease. Overall, multimodal data fusion can accurately identify the normal and abnormal health states of the elderly, such as hypertension, fever, and heart disease, and provide early warnings. According to statistics, the average accuracy of identifying abnormal states exceeds 85%, which is beneficial for the health recovery of the elderly and provides them with strong data and decision support.

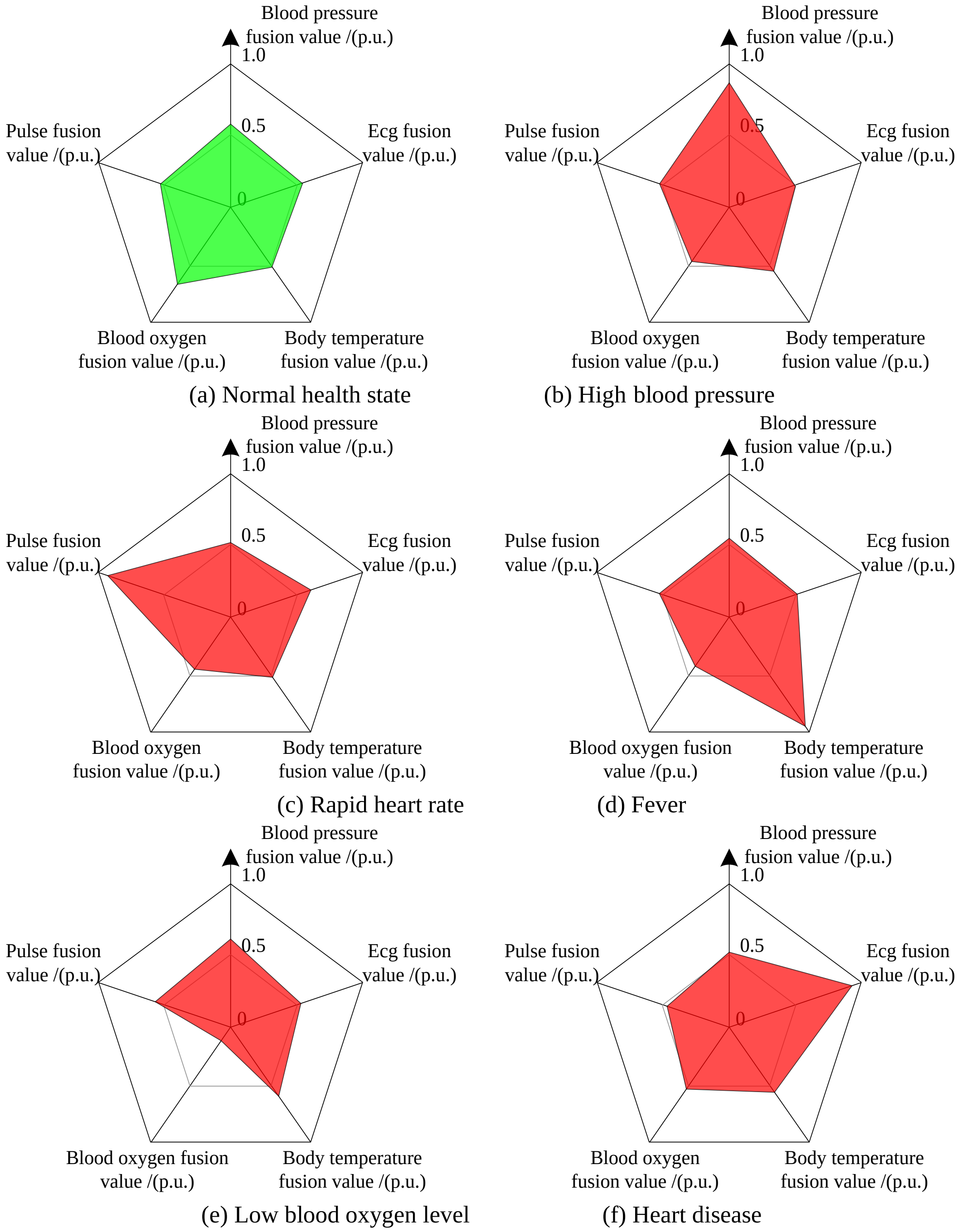

Figure 6: Assessment results of abnormal health status of the elderly

Using the method described in this article, integrate multimodal data from the smart elderly care mobile service platform, and statistically analyze the overall standard deviation and error of the fusion. Meanwhile, the data fusion performance of our method on this platform was compared with the performance of federated learning, deep learning, and support vector machine methods. To conduct a fair and rigorous comparison, three representative baseline methods were reproduced and tested based on the same dataset.

Federated learning method: Each sensor data source is regarded as a client, with a total of 5 clients set up, corresponding to electrocardiogram, body temperature, blood pressure, blood oxygen, and pulse. The server model is a three-layer fully connected neural network, with an input layer of 256 dimensions, a hidden layer of 128 dimensions, and an output layer representing fused features. Set the local training cycle to 5 and the batch size to 32.

Deep learning method: Constructing dual-branch deep neural networks. One branch processes electrocardiogram and pulse timing signal data, using a one-dimensional convolutional layer with a convolutional kernel size of 5, 64 channels, and 128 hidden units in the LSTM layer. Another branch processes relatively static data such as body temperature, blood pressure and blood oxygen levels, using a fully connected layer. After the features of the two branches are concatenated, they are fused through two fully connected layers with dimensions of 64 and 32 respectively.

Support vector machine method: Utilizing principal component analysis to reduce the original multimodal features to 50 dimensions. Support vector machines with radial basis functions as kernel functions are used for classification and regression.

To prevent overfitting of the model and objectively assess its generalization ability, this study adopts a strategy combining hierarchical time series partitioning with cross-validation. The time series data of all 42 subjects were divided into a training set, a validation set and an independent test set in a ratio of 7:1.5:1.5. When dividing, ensure that the data does not overlap in both the subject and time dimensions, that is: the training set is used for parameter learning and training of different methods; The validation set is used for hyperparameter tuning, model selection, and early stopping during training to monitor overfitting. Within the training set, to further optimize the hyperparameters and stabilize the performance estimation, a 5-fold time series cross-validation was adopted. The training set data is divided into five consecutive segments in chronological order. One segment is used as the internal validation fold in sequence, and the other four are used as training folds. This process is repeated in a cycle. The final hyperparameter setting takes a 50% discount to verify the combination with the best average performance. In addition to the above data division, the early stop method was adopted in model training. Training was halted when the validation set loss did not decline for 10 consecutive cycles, and Dropout and L2 regularization were applied to the deep learning model. All comparison methods follow exactly the same data partitioning and validation process to ensure the fairness of the comparison. The results are shown in Table 4.

Table 4 shows that the proposed method's multimodal data fusion performance on the smart elderly care mobile service platform is compared with joint learning, deep learning, and support vector machine methods under different data sizes (2GB~10GB). In terms of overall standard deviation, the methods proposed for each data size were significantly lower than the other three methods. When using 2GB of data, the overall standard deviation of the proposed method is 0.004, federated learning is 0.054, deep learning is 0.05%, and support vector machine is 0.733, indicating that the proposed method has low data fusion dispersion and strong consistency. In terms of data fusion error, the proposed method is lower than 0.15% under all data volume conditions, while the errors of the other three methods at different data volumes are higher than the proposed method. For example, when the data volume is 2GB, the data fusion error of the federated learning method is 0.147%, the deep learning method is 0.354%, and the support vector machine method is 8.903%. The overall standard deviation of the fusion results of the proposed method is extremely low, which strongly proves the accuracy of its multimodal data fusion; The small error of smart elderly care data fusion highlights the reliability of this method in integrating multimodal data, which can provide accurate and reliable data for elderly care monitoring, medical diagnosis, etc., ensuring the safety and health of the elderly.

To verify the statistical significance of performance improvement, a one-way analysis of variance was conducted on a total of 20 sets of fusion error data under five data scales for the four methods. The analysis results show that there are extremely significant differences in the fusion errors among different methods, $F(3, 16) = 185.42$, $p < 0.001$. Further Tukey HSD post hoc tests indicated that the fusion error of the method proposed in this paper was significantly lower than that of the federated learning method ($p = 0.003$), the deep learning method ($p < 0.001$), and the support vector machine method ($p < 0.001$), with confidence intervals of 95% for all. The overall standard deviation index also presented a similar significant difference pattern ANOVA, $F(3, 16) = 102.37$, $p < 0.001$.

Table 4: Comparison of multimodal data fusion effects

Amount of data/GB	**Usage method**	**Overall standard deviation**	**Data fusion error/%**
2	Method of text	0.004	0.023
	Federated learning method	0.054	0.147
	Deep learning method	0.052	0.354
	Support vector machine	0.733	8.903
4	Method of text	0.008	0.083
	Federated learning method	0.027	0.27
	Deep learning method	0.058	0.324
	Support vector machine	0.885	5.051
6	Method of text	0.002	0.027
	Federated learning method	0.038	0.646
	Deep learning method	0.055	0.587
	Support vector machine	0.795	0.704
8	Method of text	0.004	0.134
	Federated learning method	0.309	0.247

	Deep learning method	0.226	0.532
	Support vector machine	0.881	6.969
10	Method of text	0.009	0.034
	Federated learning method	0.385	0.886
	Deep learning method	0.447	0.578
	Support vector machine	0.859	6.871

4 Discussion

The multimodal data fusion method based on the digital twin model proposed in this study has demonstrated significant performance improvements in the health monitoring scenario of the smart elderly care mobile service platform. The following compares and analyzes the experimental results with the existing methods, explores the intrinsic reasons for the performance advantages, and clarifies the novelty of this method in the technical path.

(1) Performance comparison and quantitative improvement with existing methods

Compared with the federated learning method of Alsahmi et Al. [3], the deep learning method of Al-Qudah et al. [4], and the support vector machine method of Kulkarni et al. [6], the method proposed in this paper achieves the lowest overall standard deviation and fusion error under different data scales. Under an 8GB data volume, the fusion error of this method, 0.134%, is approximately 45.7%, 74.8%, and 98.1% lower than that of federated learning at 0.247%, deep learning at 0.532%, and support vector machine at 6.969%, respectively. The overall standard deviation also shows an advantage of an order of magnitude, indicating that the consistency and stability of the fusion results have significantly improved.

(2) Core innovation of digital twin models

The core innovation of the method proposed in this paper lies in the construction of a digital twin model with state mapping and association mining capabilities, achieving an improvement from data cleaning and alignment to virtual mapping and dynamic fusion. Unlike Josey et al. [5] who handled data bias through static weight adjustment or isolated feature extraction using traditional methods, digital twin models can continuously simulate and quantify the dynamic correlations among multimodal data streams by constructing virtual sensor integration models and information metadata models. Not only can the synchronous increase of electrocardiogram and pulse data under the state of rapid heart rate be identified, but also the coupling strength and pattern can be quantified through the correlation distribution coefficient.

(3) Practical significance and limitations

The high-precision and low-error fusion results of this method provide a reliable data foundation for the precise monitoring and early warning of smart elderly care. However, this study also has limitations. Firstly, the experiment was conducted in simulated and specific nursing home scenarios. In the future, it needs to be verified in a broader and dynamic home-based elderly care environment. Secondly, the construction and calculation of digital twin models have certain requirements for platform computing power, and the deployment strategy on resource-constrained edge devices is worthy of further study. Finally, the current model mainly integrates physiological sensor data. In the future, it can be expanded to integrate multi-source data such as behavior and environment to build a more comprehensive digital twin for the elderly.

5 Conclusion

The multimodal data fusion method proposed in this article for the intelligent elderly mobile service platform solves the redundancy and feature extraction problems caused by sensor differences in traditional methods. By constructing standardized datasets and digital twin models, the system can accurately analyze multi-source heterogeneous data such as electrocardiograms and calculate dynamic correlations. The experiment shows that this method can accurately identify the health status of the elderly, and the fusion error is always below 0.15% under 2GB~10GB data. Compared with traditional methods such as federated learning, it has significant advantages in indicators such as overall standard deviation (minimum 0.002), providing reliable data for smart elderly care monitoring and diagnosis. The research has verified the effectiveness of this technology in health monitoring, providing a feasible solution for the intelligent and precise development of the elderly care industry, with both theoretical and clinical value.

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Competing interests

The authors have no relevant financial or non-financial interests to disclose.

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