Journal of Information Security Research

Print ISSN: 0976-4143
Online ISSN: 0976-4151

DLINE JOURNALS

JISR 2024;15 (4)
https://doi.org/10.6025/jisr/2024/15/4/148-154

Research on AI-based Integrated Monitoring System for Elderly Safety

Ming Sun, Hao Wang
Xinxiang Vocational and Technical College
453006, Xinxiang, Henan, China
sunming@xxvtc.edu.cn

Received: 3 July 2024
Revised: 20 August 2024
Accepted: 4 September 2024

ABSTRACT

In today's ageing society, elderly safety has become a major concern in China. This research introduces a comprehensive intelligent monitoring system for elderly safety, which combines artificial intelligence technology and diverse information fusion techniques. The system incorporates machine learning algorithms, Internet of Things (IoT) devices, and cloud computing applications, focusing on community and home scenarios. Through a series of sensors, it collects daily life data of the elderly in a non-intrusive manner, enabling intelligent alerts for high-risk conditions such as falls, sudden illnesses, abnormal entries/exits, gas leaks, and smoke detection. Innovative research in human posture estimation and behaviour recognition, along with the fusion of information from multiple sensors, can reduce the occurrence of elderly safety accidents and improve the living environment in communities and homes.

Keywords: Elderly Safety Monitoring, AI Recognition, Human Posture Estimation, Behavior Recognition, Comprehensive Safety Caregiving

1. Introduction

As society develops and the ageing population accelerates, the comprehensive safety of the elderly in communities and homes has become an increasingly prominent issue that requires urgent attention. With the surge in ageing in China, elderly care issues have become more severe [1]. In the increasingly serious challenges of elderly care, addressing the contradictions between ageing, changes in family structures, and traditional elderly care models has become a focal point of attention across society. In the future, the elderly in society cannot solely rely on their children for care [2]. Many elderly people living alone may face health and behavioral abnormalities, leading to serious consequences if not detected and addressed promptly [3].

Currently, China's elderly care research includes three models: home-based care, community-based care, and institutional care [4]. Over 99% of the elderly receive home-based and community-based care, with less than 1% receiving institutional care. As individuals age, physical and cognitive declines occur gradually, making elderly individuals more susceptible to falls, sudden illnesses, kitchen accidents, smoke, gas leaks, and safety hazards related to dementia and wandering [5].

Falls are a critical turning point for elderly disability and the leading cause of injury-related deaths, earning the title of "number one killer." The death rate due to falls sharply increases with age [6]. Currently, there are four main types of fall detection technologies for the elderly: wearable devices like wristbands and smartwatches, which are limited due to accuracy issues and elderly resistance to wearing them and frequent charging requirements; far-infrared thermal imaging devices, mainly used in industries due to high costs and expensiveness for elderly care; microwave radar, which protects the privacy of the elderly but has limited application scenarios and can only be used for single-person scenarios, unable to differentiate between humans and animals and susceptible to accuracy issues due to natural environmental disturbances, such as moving curtains due to wind [7]; and camera-based systems, which utilize artificial intelligence technologies like machine learning and deep learning. These camera-based systems are mature, offer high accuracy, have a mature product industry chain, are affordable, and can be flexibly deployed in various elderly care scenarios, including institutions, communities, and homes. However, they may need help deploying in private indoor areas [8].

In summary, the development of our system has the following distinctive features: comprehensive caregiving in all scenarios, covering both home-based and community-based elderly care scenes; non-intrusive caregiving, preserving the elderly's existing living habits; AI-based algorithms for accurate automatic alarms, supporting voice call alerts; privacy protection for the elderly, using stick-figure image representation for home-based scenarios to avoid storing elderly images and reusing existing cameras, local area networks, and computer devices for community-based scenarios, enabling direct import and deployment of the system [9]. The main innovations include creating a high-quality fall dataset specific to the elderly care domain, automatically incorporating false positive and false negative data into the training set to update model files, and introducing seat and ground recognition functions in the fall detection process to enhance algorithm accuracy [10].

2. Design of a Comprehensive Elderly Safety Monitoring System

2.1. Hardware Architecture of Elderly Safety System

By incorporating cutting-edge technologies such as next-generation artificial intelligence, the Internet of Things (IoT), big data, and information fusion, our system can provide various monitoring services for the elderly, including but not limited to body posture, activity trajectory, nighttime sleep records, heart rate, respiration, kitchen air quality, water usage, access control, emergency calls, and outdoor positioning. By running advanced artificial intelligence algorithms, we can identify and predict various potential dangers the elderly might encounter and report them promptly. By analyzing three different basic operators, we can create a matrix X, consisting of [X,], where 1 represents the value of the *j*-th operator of the *i*-th kind. As indicators 1 to 4 in Table 1 are more favorable when larger, while other indicators should be minimized, we need to normalize the indicator matrix.

$$\boldsymbol{X}^* = \left[x_{ij}^*\right]_{3\times 9} = \left[\frac{x_{ij} - \min\limits_i x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}}\right]_{3\times 9} \tag{1}$$

Depending on the situation, the missed detection rate may be more important than the false alarm rate. To better evaluate the importance of each indicator, we need to multiply each column of * in the matrix *X* by the corresponding weight coefficients.

$$x_j^* = x_j^* \alpha_j \tag{2}$$

In this formula, *x* represents the *j*-th column of the matrix *X**and *á* is determined by the weight value of the j-th indicator, which depends on the problem's characteristics. We calculate the real symmetric matrix H.

$$H = X^{*T} X^{*} \tag{3}$$

By solving for the optimal solution of H and mapping the max and related normalized feature vectors Y together, we can obtain more accurate results. Based on the given conditions, we calculate the weight values *wi* for each basic method, which are 1, 2, and 3, respectively. By normalizing w, we can achieve better results. By readjusting the normalized weight w, we can obtain the 0/1 weight o*, where i = 1, 2, 3. If the number of samples in the training set exceeds the preset threshold, we will remove the samples closest to the current time and repeat this process to adjust the weights automatically. We will select the basic method with the highest standard for diagnosis to ensure that its overall performance is better than any other basic method. We can construct three common diagnostic patterns based on the two information fusion techniques proposed earlier. Next, we can focus on constructing an NN-style information fusion pattern and use data from some historical cases to evaluate its accuracy. If the evaluation data meets the requirements, we can make it a complete fusion diagnostic pattern. Otherwise, we can construct an information fusion fault diagnosis pattern with self-adjustment capabilities to evaluate its accuracy better. The NN fusion model performs excellently, and specific evaluation parameters and constraints can vary according to the client's requirements.

2.2. Software Design of Elderly Safety System

According to Figure 1, our software architecture consists of four different layers: the data layer, platform layer, algorithm layer, and application layer. In the data layer, we collect IoT information from various devices, which can be processed in different locations, and the processing results are promptly fed back to our platform. We integrate and store sensor data in the platform layer and perform routing transmission based on task definitions. The algorithm layer includes training and model inference for artificial intelligence models. The application layer extends the algorithm layer and can automatically identify high-risk events, such as falls, sudden illnesses, abnormal entries/exits, gas leaks, etc., and can present various alarm notifications as needed.

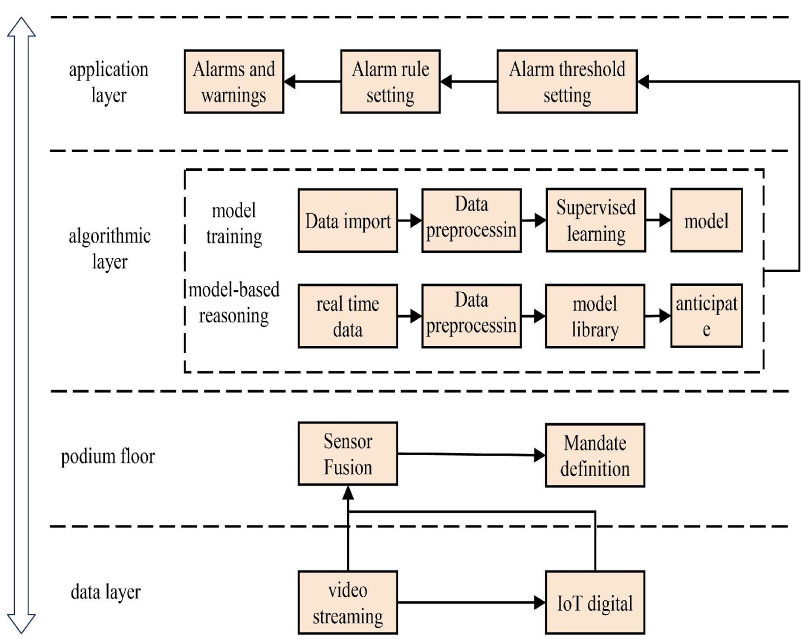

Figure 1. Software architecture of pension safety comprehensive monitoring system scheme

2.3. Technical Solutions for Human Pose Estimation and Behavior Recognition

This solution includes a human posture assessment and behavior recognition system and an IoT monitoring system. This system can help us better understand our physical condition. Through the down-top scheme, we can rapidly recognise human posture, which can help us quickly identify multiple individuals in community elderly care scenarios. This scheme consists of a dataset, model training, model inference, and behavioral action judgment, which can help us achieve this goal. To improve the model's accuracy, we have established a dataset specifically targeting real elderly care scenarios in communities and families. Due to the limited behavioral dataset and small training set for these scenarios, we only need to distinguish between falling and non-falling states. Therefore, we use the traditional machine learning model and use the Federated learning mechanism to build the human posture classification model. This way, we can better understand the real image data of different community and family elderly care scenarios and make the model more accurate. To better protect user data and improve training efficiency, we have adopted an innovative approach by introducing a seat recognition model to effectively avoid false positives caused by some human body joints being obstructed by adjacent seats. This scheme can effectively apply to practical community and home care scenarios, improving recognition efficiency. Advanced ground recognition technology greatly reduces the false alarm rate for falls, thereby greatly improving safety. By comprehensively analyzing the body posture, surrounding environment, and ground information of elderly people, our system can accurately recognize their behavior and issue timely alerts. In addition, we will update images and markers of falls or non-falls in the dataset to improve the algorithm's accuracy further. This system solution does not include images to prevent user privacy breaches and protect information and data security.

2.4. Human Specific Posture Dataset

According to the differences in sampling sources, processing processes, and processing results, the public data for human behavior recognition is divided into four categories: universality, simulation, multidimensional, and complexity. Simulated data comes from camera photos and has simulation properties, while simulated data has higher inter-class differences. Various specific datasets have emerged in recent years to ensure the safety and care of the elderly, children, and other vulnerable groups, such as fall behavior. However, due to the differences in these datasets, there are certain difficulties in using these models to carry out artificial intelligence in practical home community environments. Therefore, the R&D and evaluation methods of different models may also vary, leading to a decrease in the accuracy of the models. Therefore, our system has created a database specifically designed to capture human-specific actions based on the specific circumstances of residential and community settings. The specific posture dataset of the human body is sourced from community elderly care centers, and the action categories of this dataset can be summarized into four situations: (1) standing exercise; (2) Sitting exercise: sitting in a chair, in a wheelchair, leaning against the edge of the bed; (3) Squatting exercise: shallow squatting, deep squatting; (4) Fall movement: lying up on the back, lying up on the side, lying down on the face, leaning up with both hands on the ground, leaning up with the back of the wall, and partially obstructing the fall. Among them, the training, validation, and test sets all have manual validation labels, and JSON documents are used to store label information. Because the dataset comes from different cameras and is accompanied by shading, camera angle, complex temperament, changes in lighting environment, and many other factors, it is very difficult.

3. Experimental Design and Result Analysis

3.1. Recurrent Iterative Model Training

Based on the system's characteristics, we have decided to use a more comprehensive, reliable, and cost-effective Java language to build mobile clients, servers, and backend management. We will divide the functional testing of these languages into three stages: UI user interface functional testing, communication testing, and analysis and processing functional testing, and we will use different black box methods to complete the experiment. After careful design, our experimental platform consists of two components: one designed specifically for software development, and the other for the laboratory. The network platform aims to provide a reliable and reusable experimental framework for the entire project tobetter evaluate the project's performance.

To test the system better, we will use a laboratory testing network platform to create a safe and reliable testing environment, connect different subsystems, and develop simulation testing software to test their capabilities, processes, reliability, and overall operational efficiency. Due to the influence of real images being obstructed, camera angles, complex backgrounds, changes in lighting conditions, and various other factors, there are still some false alarms and omissions in automated monitoring of falls in the elderly. This system automatically and regularly adds false or false alarm images and datasets to pattern training. To solve the problem of false positive and false negative images in falls, this system automatically completes tasks such as outlier image anomaly image collection, labeling, and model automation training.

3.2. System Validation

After confirming the functionality of the relevant modules through testing, a single-item test was conducted on 18 healthy volunteers (aged 50 to 60 years, excluding those with high blood glucose) at a tertiary hospital. The participants ensured sufficient sleep the night before the test and underwent individual examinations around 8:30 in the morning. During the measurements, the participants were required to clean their hands, maintain a still posture, remain calm, and avoid making large movements with their hands. The sensors were inserted into the fingertips using medical finger clips, and the palms of both hands were kept flat.

The system continuously monitored the participants' various characteristic data and blood glucose values. The blood glucose values obtained from the hospital's blood dialysis machine were used as reference values for comparison. The test data curve is shown in Figure 2.

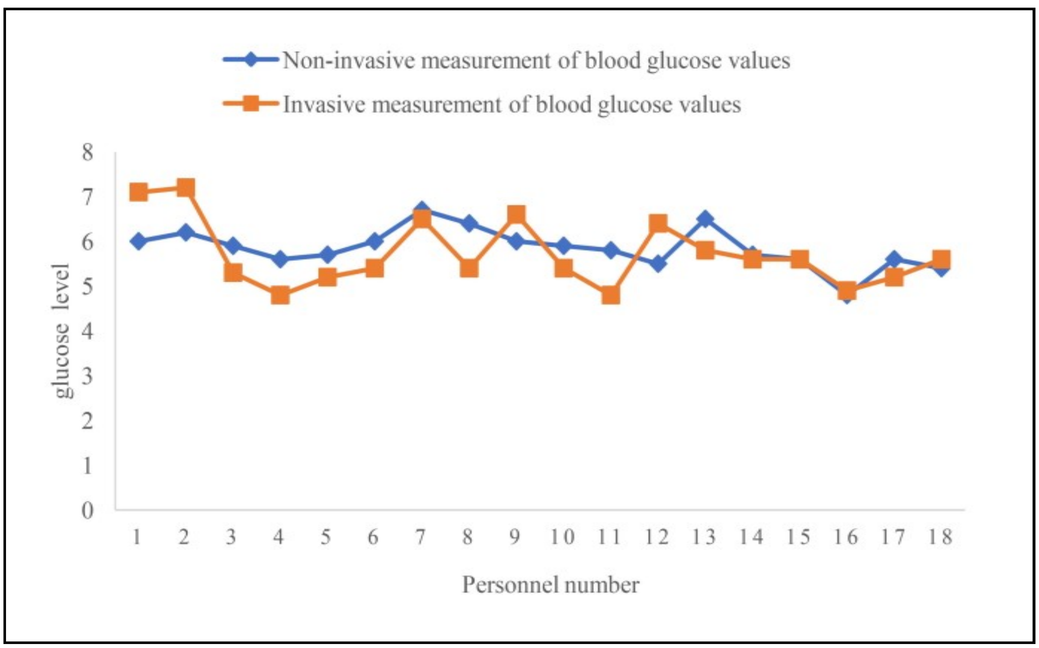

Figure 2. Contrasting Curve of Non-invasive and Invasive Blood Glucose Measurements

The system underwent continuous monitoring, and the alarm rule thresholds were intelligently adjusted using self-learning algorithms. False alarm images were automatically entered for automatic training and improvingthe system's modes. The accuracy of detecting non-falls in the elderly was 98.8%, while the accuracy of detecting falls in the elderly was 95%. Innovative seat recognition and floor recognition models were introduced, significantly reducing system false alarms. As a result, the number of night floor caregivers in the elderly ward decreased from six to two, achieving ideal results in improving quality and efficiency. Compared to the industry's use of another neural network algorithm, such as Yolo, for fall detection, with target detection accuracy generally ranging from 75% to 80%, this system has a greater advantage in fall detection accuracy.

We proposed a new method to extract more information from the existing 100 samples. This method better identifies each node in the Bayesian network and allows for more effective use of this information to improve the network's performance. Additionally, we can create a new, more efficient, and reliable expert system through if-then rules and reasoning to better identify unpredictable issues and use this information more effectively to enhance network performance.

WE CREATED THREE BASIC MODELS through NN fusion and adaptive fusion and applied them to other scenarios. Ultimately, we obtained diagnostic tests for 34 actual historical cases. For more specific details, refer to Figure 3.

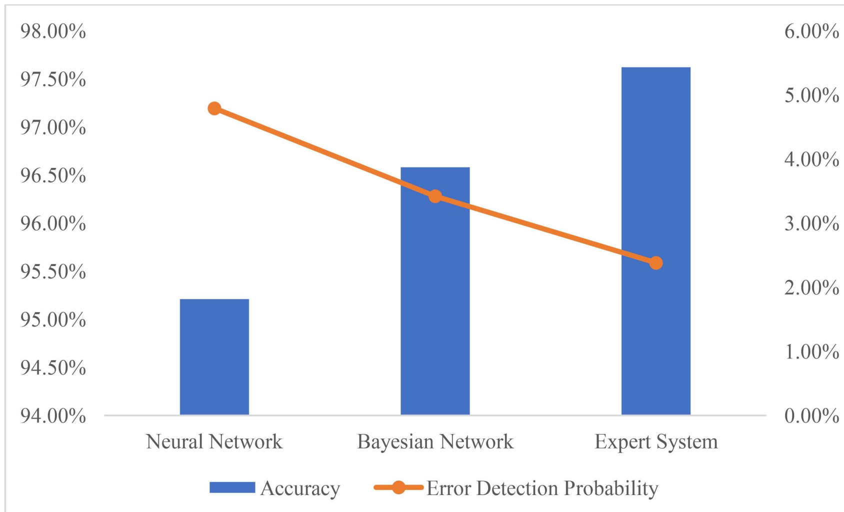

Figure 3. Test results of each method with simulated samples

According to Figure 3, we found that most methods demonstrated excellent diagnostic performance. Most of them had an error detection rate of less than 5% and an accuracy exceeding 95%. Overall, we found that neural networks performed the best among various modes, followed closely by Bayesian networks. However, the expert system had a lower error detection rate, making its performance superior. Through the combination of advanced artificial intelligence technology and IT, the developed comprehensive monitoring system for elderly safety has demonstrated performance surpassing traditional detection methods. Therefore, we recommend that this system be widely used to detect unknown conditions. Our research showed that adaptive fusion diagnostic models can effectively improve prediction accuracy. As a result, we proposed two fusion models—one utilizing adaptive technology to autonomously select better-performing neural network models based on sample performance and the other combining artificial intelligence and information fusion in the comprehensive monitoring system for elderly safety. The latter model had more precise evaluation criteria to obtain more accurate prediction results and better reflect the characteristics of objective factors rather than solely seeking the best basic model. The system can provide accurate diagnostic reports that comprehensively consider multiple factors by analysing the current benchmark models. Extensive research revealed that the comprehensive monitoring system for elderly safety, employing artificial intelligence and information fusion technology, exhibited significantly better diagnostic performance than models based on the best basic models, and this advantage was even more pronounced in numerous practical cases.

4. Conclusions

This study proposes a method for developing and applying a comprehensive monitoring system for elderly safety based on artificial intelligence and information fusion. It involves collecting safety and health data of elderly individuals in communities and homes through multiple sensors, with the main purpose of issuing alarms for various safety and health risks they might encounter. Additionally, through continuous innovative research on human body posture estimation and behavior recognition technology, the accuracy of algorithms in practical applications has been improved. The system automatically guards and manages high-risk events such as falls, sudden illnesses, unusual movements, gas, and smoke, reducing the manpower required for elderly care services. It has promising prospects for application. The design in this paper focuses on the practicality and reliability of safety supervision for elderly people living alone, which has significant practical significance and market value.

References

[1] Qiu, S., Wang, Z., Zou, J., Ma, Z., and Yu, H. (2022). Multi-sensor information fusion based on machine learning for real applications in human activity recognition: State-of-the-art and research challenges. *Information Fusion, 23*(80), 241–265.

[2] Zhang, Y., Zhou, C., Chen, Y., and Liu, X. (2022). Information fusion for edge intelligence: A survey. *Information Fusion, 23*(81), 171–186.

[3] Nweke, H. F., Teh, Y. W., Al-Garadi, M. A., and Alo, U. R. (2019). Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions. *Information Fusion, 20*(46), 147–170.

[4] Ding, W., Wang, G., and Yu, H. (2019). A survey on data fusion in internet of things: Towards secure and privacy-preserving fusion. *Information Fusion, 20*(51), 129–144.

[5] Abdel-Basset, M., Ding, W., and Abdel-Fatah, L. (2020). The fusion of Internet of Intelligent Things (IoIT) in remote diagnosis of obstructive sleep apnea: A survey and a new model. *Information Fusion, 21*(61), 84–100.

[6] Meng, T., Li, Z., and Zhang, Y. (2020). A survey on machine learning for data fusion. *Information Fusion, 21*(57), 115–129.

[7] Muhammad, G., Hossain, M. S., Gumaei, A., and Alamri, A. (2021). A comprehensive survey on multimodal medical signals fusion for smart healthcare systems. *Information Fusion, 22*(76), 355–375.

[8] Ren, X., Wang, Y., Liu, F., and Zhao, Y. (2021). Design of multi-information fusion-based intelligent electrical fire detection system for green buildings. *Sustainability, 13*(6), 3405.

[9] Lv, Z., Zhang, J., and Qiao, S. (2021). Artificial intelligence for securing industrial-based cyber–physical systems. *Future Generation Computer Systems, 38*(117), 291–298.

[10] Nahiduzzaman, M., Tasnim, M., Newaz, N. T., and Rahman, M. M. (2020). Machine learning-based early fall detection for elderly people with neurological disorders using multimodal data fusion. In J. Zhang, Y. Hao, and M. Zhang (Eds.), *International Conference on Brain Informatics* (pp. 204–214). Cham: Springer International Publishing.