

# A Review on AI-Driven Elderly Activity Monitoring System with User-Friendly Interface

Mr. Patel S. J., Mr. Pathan T. G., Prof. Mundhe B. B., Prof. Said S.K.

JCEI's Jaihind College of Engineering, Kuran, Maharashtra, India.

sohelp889@gmail.com and pathantousif777@gmail.com

**Abstract:** *The increasing elderly population poses significant challenges to healthcare systems, particularly due to a shortage of caregivers. Smart aging technologies such as robotic companions and digital home devices have emerged as potential solutions to assist in elderly care by increasing quality of life and reducing caretakers burden. However, existing solutions face limitations concerning data privacy, real-time processing, and reliability. This paper presents an AI-driven system designed to monitor elderly activities in real-time while addressing privacy concerns. Utilizing stereo depth cameras, the system monitors daily activities such as sitting, standing, and transitions between movements. This review paper summarizes the project's current progress, relevant methodologies, and the future scope of this system*

**Keywords:** Elderly care, Smart aging, YOLOv8, Activity monitoring, privacy, Stereo depth cameras, Deep learning

## I. INTRODUCTION

The rapid growth of the elderly population presents challenges for the healthcare system, particularly in providing adequate caregiving services. As more elderly individuals prefer to live independently, smart aging technologies are gaining attention for their potential to assist with daily activities and improve the quality of life. These technologies use AI, machine learning, and the Internet of Things (IoT) to monitor health and activities, offering caregivers real-time information about the elderly. However, privacy concerns and real-time data processing remain significant challenges. Systems that monitor elderly activities must strike a balance between accurate, real-time detection and respecting the privacy of users. This project proposes a solution by leveraging stereo depth cameras and advanced AI techniques, such as YOLOv8 and Motion-CRNN, to achieve real-time monitoring without compromising privacy.

## II. LITERATURE SURVEY

The field of elderly care is rapidly evolving, driven by advancements in artificial intelligence (AI), the Internet of Things (IoT), and smart sensing technologies. These innovations aim to support aging populations by improving their quality of life while reducing the strain on caregivers. Several studies highlight the importance of continuous monitoring systems for elderly individuals, particularly those living independently. This literature review explores relevant research, identifying current gaps and the potential impact of AI-based solutions.

### 1. Human Activity Recognition (HAR) in Elderly Care:

Human Activity Recognition (HAR) has become a critical component of smart aging technologies. HAR systems use sensors and AI models to detect and classify daily activities such as walking, sitting, and standing, as well as abnormal behaviors like falls. Stefania Cristina et al. [2] and S. Juraev et al. [7] provided a comprehensive overview of video-based HAR systems for healthcare, focusing on the advantages of integrating audio and video processing for recognizing activities. Their study emphasized the importance of robust privacy measures, which is a key challenge that limits the adoption of such systems in healthcare applications. Huan-Bang Li et al. [1] and K. Maswadi et al. [8] emphasized the significance of gathering activities of daily living (ADL) data in network-deficient environments. Their work highlights the limitations of current systems that rely heavily on network connectivity. This is a relevant concern for elderly care systems, particularly those deployed in rural or underdeveloped areas where access to continuous

network services may be limited. The proposed use of stereo depth cameras in our project helps mitigate these concerns by processing activity data locally, ensuring privacy and operational reliability in offline scenarios.

## **2. Technological Approaches in Elderly Care:**

Wearable sensors, video cameras, and ambient sensing devices are commonly used in elderly care monitoring systems. However, each method has its own set of challenges. For example, Wei Guo et al. [3] explored human activity recognition using a combination of Wi-Fi and inertial sensors, which provided a non-intrusive method of tracking activities. Their approach demonstrated the potential of combining multiple sensors to improve recognition accuracy. However, wearable devices are often considered intrusive by elderly users, making video-based solutions like stereo depth cameras more appealing in scenarios where user comfort and privacy are prioritized. Lenin Erazo-Garzón et al. [5] introduced a domain-specific language (DSL) for modeling IoT architectures in elderly care systems. This work focused on designing systems that support comprehensive monitoring, including sensors for physical activity, temperature, and environmental conditions. The integration of environmental sensors is a critical feature we plan to include in our system to enhance the overall safety of elderly individuals.

## **3. Privacy Concerns in Elderly Monitoring: -**

Privacy is a major concern when it comes to activity monitoring systems that rely on video or audio data. Systems that capture visual or personal information raise concerns about data misuse, particularly when sensitive information is transmitted over the internet. Laura Romeo et al. [4] addressed this issue by focusing on privacy-conscious video-based mobility monitoring for elderly individuals. By using skeletal data extracted from low-cost cameras, their system ensured that no personally identifiable information was captured while still delivering accurate activity recognition. This approach aligns closely with our proposed system, which uses stereo depth cameras to avoid capturing detailed visual data, thereby maintaining user privacy.

## **4. Advances in AI Models for Activity Recognition: -**

Deep learning models have significantly advanced the field of activity recognition. YOLOv8 (You Only Look Once, version 8), a real-time object detection algorithm, has become an essential tool for systems requiring fast and accurate activity detection. YOLOv8's ability to process video frames in real-time makes it an ideal candidate for elderly care applications, where quick detection of abnormal activities, such as falls, is crucial. Similarly, MotionCRNN, a hybrid model combining Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), has shown effectiveness in capturing both spatial and temporal dynamics of human movement. The combination of YOLOv8 and MotionCRNN in our system allows for accurate real-time monitoring of elderly activities while maintaining computational efficiency.

## **5. Real-World Testing and Data Augmentation**

One of the challenges highlighted in the literature is the difficulty of adapting activity recognition models to new environments. Wei Guo et al. [3] discussed the use of transfer learning and data augmentation to enhance model robustness. By artificially increasing the variability in the training data, such as by applying transformations like rotation and noise injection, systems can better adapt to new scenarios with minimal additional data. Our system will employ similar data augmentation techniques to ensure high accuracy across diverse environments, including care centers and homes

## **III. METHODOLOGY**

The system integrates stereo depth cameras with an AI-driven architecture composed of CNNs and RNNs. Depth cameras provide non-intrusive tracking of movements, capturing critical activities such as sitting, standing, lying down, and transitions between these states. This ensures privacy while maintaining accurate detection. The deep learning architecture combines YOLOv8 for real-time object detection and MotionCRNN to capture and process motion data. YOLOv8 is known for its high-speed performance and accuracy in detecting elderly individuals within video frames,

while MotionCRNN processes temporal data, identifying transitions between actions critical for monitoring balance and mobility.

To further enhance the robustness of the system, data augmentation techniques are employed, including rotation, time warping, and jittering. These methods improve model performance by simulating various environmental conditions and activity speeds.

**1. Proposed System:**

The proposed system focuses on real-time elderly activity monitoring using a combination of stereo depth cameras and AI-based deep learning models. Here's a description of the key components:

**Proposed System Components:**

- Stereo Depth Cameras: These cameras will be used to capture 3D motion data of elderly individuals without recording personally identifiable information, preserving privacy. They track activities like sitting, standing, lying down, and transitions between postures.
- Deep Learning Models: The system integrates Convolutional Neural Networks (CNNs) for image recognition and Recurrent Neural Networks (RNNs) (specifically MotionCRNN) for handling sequential motion data, making it capable of recognizing complex transitions.
- YOLOv8: This object detection model will be used to identify the presence of individuals in real-time video frames, marking them with bounding boxes to track movement.
- GUI (Graphical User Interface): A user-friendly interface will display real-time activity data and enable caregivers to monitor elderly individuals more effectively. The GUI is designed for ease of interaction and accessibility.

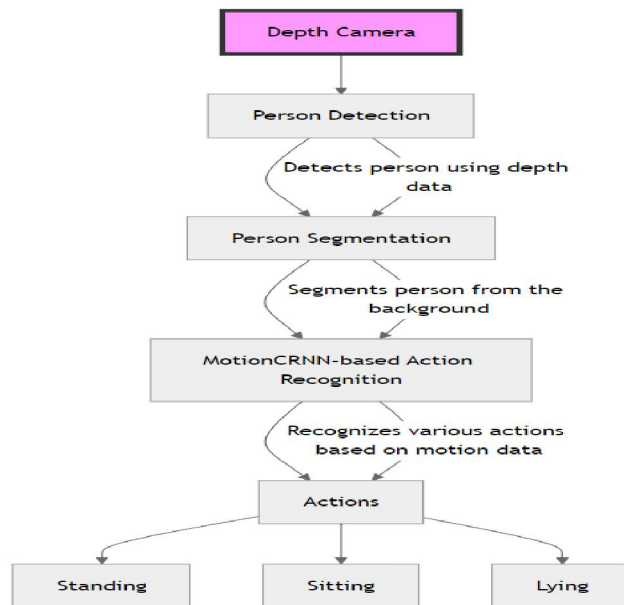


Figure 1: System Overview

**2. Mathematical Model:**

Incorporating mathematical formulations helps explain the deep learning techniques and activity recognition mechanisms used in your system. Here's how you can include this in your methodology:

### 2.1 Convolutional Neural Networks (CNNs):

The convolution operation used in CNNs can be expressed mathematically as:

$$(f * g)(x, y) = \sum_{i=-k}^k \sum_{j=-k}^k f(i, j) \cdot g(x - i, y - j)$$

Where  $f(i, j)$  is the input image, and  $g(i, j)$  is the convolution kernel or filter, CNNs extract features from the depth camera image to recognize movements.

### 2.2 Recurrent Neural Networks (RNNs):

For handling sequential data, the RNN equations are used to compute the hidden state at each time step  $t$ .

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

Where  $h_{t-1}$  is the hidden state at the previous time step, and  $x_t$  is the input at time  $t$ . This model captures the temporal dynamics of elderly movements.

## IV. CURRENT PROGRESS

At this stage, the project is still in its initial phase, focusing on research, system design, and literature review. While no full compilation or testing has been conducted, the system's architecture and implementation strategies have been outlined. The stereo depth camera system and the deep learning models have been selected, and preliminary experiments are planned for the next phase. In addition, a user-friendly Graphical User Interface (GUI) is under design to provide caregivers with real-time insights into the activities of the elderly. This interface will allow caregivers to interact with the system, improving care management and decision-making.

## V. FUTURE WORK

Future work will focus on implementing and testing the system in real-world environments. This will include extensive testing of the stereo depth cameras and deep learning models in various environments, ensuring adaptability and reliability. Additionally, the integration of environmental sensors for monitoring factors like temperature will further enhance the system's functionality.

Further research will also explore optimizing the system's performance in network-deficient environments, similar to the approach described by Li et al. (2024). This will allow the system to operate effectively in rural or remote areas where network connectivity may be limited.

## VI. CONCLUSION

The AI-driven elderly activity monitoring system represents a step forward in the field of smart aging technologies, providing a solution that emphasizes both accuracy and privacy. By leveraging stereo depth cameras and advanced deep learning models, the system offers real-time monitoring while maintaining user privacy. Continued research and development will focus on refining the system, implementing it in real-world scenarios, and addressing any limitations to ensure its effectiveness in supporting elderly care.

## REFERENCES

- [1] H.-B. Li, L. Shan, T. Matsumura, and Y. Fuwa, "Gathering activities of daily living data for elderly care in network deficient environments," *IEEE Access*, vol. 12, pp. 121144–121155, 2024.
- [2] S. Cristina, V. Despotovic, R. P'erez-Rodr'iguez, and S. Aleksic, "Audio- and video-based human activity recognition systems in healthcare," *IEEE Access*, vol. 12, pp. 8230–8245, 2024.
- [3] W. Guo, S. Yamagishi, and L. Jing, "Human activity recognition via wi-fi and inertial sensors with machine learning," *IEEE Access*, vol. 12, pp. 18821–18836, 2024.
- [4] L. Romeo, R. Marani, T. D'Orazio, and G. Cicirelli, "Video based mobility monitoring of elderly people using deep learning models," *IEEE Access*, vol. 11, pp. 2804–2819, 2023.
- [5] L. Erazo-Garzon, P. Cedillo, G. Rossi, and J. Moyano, "A domain-specific language for modeling IoT system architectures that support monitoring," *IEEE Access*, vol. 10, pp. 61639–61665, 2022.

- [6] Z. Zhou, H. Yu, and H. Shi, "Optimization of wireless video surveillance system for smart campus based on internet of things," IEEE Access, vol. 8, pp. 136434–136448, 2020.
- [7] S. Juraev, A. Ghimire, J. Alikhanov, V. Kakani, and H. Kim, "Exploring human pose estimation and the usage of synthetic data for elderly fall detection in real-world surveillance," IEEE Access, vol. 10, pp. 94249–94261, 2022.
- [8] K. Maswadi, N. B. A. Ghani, and S. B. Hamid, "Systematic literature review of smart home monitoring technologies based on iot for the elderly," IEEE Access, vol. 8, pp. 92244–92261, 2020.
- [9] L. Yu, W. M. Chan, Y. Zhao, and K.-L. Tsui, "Personalized health monitoring system of elderly wellness at the community level in hongkong," IEEE Access, vol. 6, pp. 35558–35567, 2018.
- [10] R. Mulero, A. Almeida, G. Azkune, P. Abril-Jiménez, M. T. Arredondo Waldmeyer, M. P´aramoCastrillo, L. Patrono, P. Rametta, and I. Sergi, "An iot-aware approach for elderly-friendly cities," IEEE Access, vol. 6, pp. 7941–7957, 2018.