Enhancing Elderly Safety Through AI-Based Human Activity Recognition for Affordable Community Healthcare

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ABSTRACT

The rapid growth of the ageing population has increased the demand for affordable and effective monitoring solutions that enable older adults to live independently while ensuring their safety. Falls remain a major cause of injury and hospitalization among elderly individuals, highlighting the need for timely detection and intervention. Existing monitoring approaches, such as wearable devices and conventional surveillance systems, may be limited by user compliance, implementation costs, and privacy concerns. This study proposes an artificial intelligence (AI)-based non-contact human activity recognition system for affordable elderly monitoring using a low-cost vision-based approach. The system employs a standard webcam, OpenCV, and MediaPipe-based pose estimation to extract human skeletal landmarks, while an interpretable rule-based classification algorithm is used to recognize four activities: standing, walking, sitting, and falling. Experimental evaluation was conducted using 80 activity samples collected under controlled indoor conditions. The system achieved an overall recognition accuracy of 80%, with class-specific accuracies of 100%, 80%, 75%, and 65% for standing, sitting, walking, and falling, respectively. The findings demonstrate the feasibility of combining AI-based pose estimation with lightweight rule-based classification for real-time activity monitoring using affordable hardware. Local video processing also reduces the need to transmit visual data to external servers, thereby supporting greater data privacy. Although further refinement is required to improve fall detection, the proposed approach provides a practical foundation for accessible elderly monitoring and has the potential to support caregivers, independent ageing, and community-oriented healthcare.

Keywords- Elderly monitoring, Human Activity Recognition, Artificial Intelligence, Computer Vision, Fall Detection, Community Healthcare.

INTRODUCTION

The global ageing population is increasing at an unprecedented rate, creating significant challenges for healthcare systems, caregivers, and society. According to the World Health Organization (WHO), the number of people aged 60 years and above is expected to continue growing over the coming decades, increasing the demand for healthcare services and long-term care support. As more older adults choose to live independently, ensuring their safety and well-being has become a major concern. Among the various health risks faced by elderly individuals, falls remain one of the leading causes of injury, disability, hospitalization, and mortality. Delayed assistance following a fall may result in severe physical complications, reduced quality of life, and increased healthcare costs.

To address these challenges, various elderly monitoring technologies have been developed, including wearable devices, ambient sensors, Internet of Things (IoT)-based systems, and camera-based monitoring approaches [1]–[4]. Wearable devices equipped with accelerometers and gyroscopes have demonstrated promising performance in detecting falls and monitoring daily activities. However, their effectiveness depends heavily on user compliance, as elderly individuals may forget, refuse, or be unable to wear the devices consistently. Ambient sensor systems require additional infrastructure and installation, while conventional camera-based monitoring systems often involve high implementation costs, complex deployment, and privacy concerns arising from continuous video surveillance. Although wearable and sensor-based devices provide continuous monitoring, practical limitations such as user compliance, battery requirements, maintenance, and discomfort may restrict their suitability for long-term elderly monitoring [1]–[3]. Vision-based approaches have therefore emerged as a promising non-contact alternative for monitoring daily activities and detecting falls [4]–[6].

Recent advances in artificial intelligence (AI), computer vision, and human pose estimation have created new opportunities for developing non-contact monitoring systems capable of recognizing human activities in real time [5]–[7]. Instead of relying solely on raw image information, pose-based approaches can represent human movement using skeletal landmarks, body orientation, joint positions, and temporal movement patterns [7], [12]. Such approaches are particularly relevant to elderly monitoring because they enable the identification of activities and potentially hazardous events without requiring body-attached sensors [5], [6]. Human Activity Recognition (HAR) has emerged as an important research area that enables computers to interpret body posture and movement from visual information. Combined with lightweight pose estimation frameworks such as MediaPipe and image processing libraries such as OpenCV, vision-based HAR systems can detect activities without requiring wearable sensors while performing local processing to better preserve user privacy. These technologies offer affordable and scalable solutions that can support independent ageing and reduce the burden on caregivers.

Despite these advances, reliable fall detection remains challenging because falls are dynamic events involving rapid changes in body orientation and may exhibit transitional postures similar to sitting, bending, or lying down [4], [8]–[10]. Recent studies have employed temporal decision fusion, Transformer architectures, pose estimation, and deep learning to improve the recognition of complex fall movements [8]–[12]. However, these approaches may increase computational complexity, particularly when deployed on resource-constrained or low-cost platforms [11], [12].

This study proposes an AI-based non-contact human activity recognition system for affordable elderly monitoring and community healthcare. The proposed system utilizes a standard webcam, OpenCV, and MediaPipe pose estimation to recognize four essential activities which are standing, walking, sitting, and falling, through the analysis of human skeletal landmarks using a rule-based classification algorithm. By performing all computations locally, the system eliminates the need for wearable devices and cloud-based data transmission, thereby enhancing user privacy while reducing implementation costs.

The objectives of this study are to develop a functional prototype for real-time human activity recognition and to evaluate its performance in detecting standing, walking, sitting, and falling under controlled indoor conditions. The findings provide insights into the feasibility of employing affordable AI-based vision technologies for elderly monitoring and demonstrate their potential to enhance elderly safety, support independent living, and contribute to more accessible and community-oriented healthcare services.

This paper is organized as follows. Section II reviews related studies on elderly monitoring and human activity recognition. Section III describes the methodology and development of the proposed system. Section IV presents the experimental results and discussion, followed by the conclusion in Section V.

LITERATURE REVIEW

This section reviews existing research and technological approaches related to elderly monitoring and HAR. The review focuses on wearable, ambient sensor-based, and vision-based monitoring approaches, with particular attention to the application of artificial intelligence and computer vision in elderly care. Existing approaches are examined in terms of their suitability for real-time monitoring, affordability, user convenience, privacy, and ability to recognize daily activities and fall events. The review also identifies current limitations and research gaps that motivate the development of a low-cost, non-contact monitoring approach for elderly and community healthcare applications.

Elderly Monitoring Systems

The global increase in the ageing population has accelerated research into technologies that support independent living while ensuring the safety of older adults. Falls are among the most common causes of injury, hospitalization, and reduced quality of life for elderly individuals, particularly those living alone. Consequently, continuous monitoring systems have become an essential component of modern elderly healthcare. An effective monitoring system should enable timely detection of emergencies while allowing elderly individuals to perform their daily activities comfortably and independently.

Existing elderly monitoring systems can generally be categorized into wearable sensor-based, ambient sensor-based, IoT-based, and vision-based systems [1]–[4]. Each approach presents different trade-offs in terms of detection performance, implementation cost, computational requirements, user convenience, privacy, and suitability for continuous monitoring [1], [3], [4]. Recent research has increasingly investigated unobtrusive monitoring approaches that enable elderly individuals to perform their normal daily activities without continuous interaction with wearable devices [5], [6]. Such systems have considerable potential for supporting independent living and assisting caregivers in monitoring elderly individuals remotely.

Human Activity Recognition (HAR) for Elderly Care

HAR enables the automated identification of human behaviours from sensor or visual information and has become increasingly relevant in assisted living and elderly healthcare applications [5], [6], [14], [15]. In elderly monitoring, HAR can be used to recognize activities of daily living while also identifying potentially hazardous events, particularly falls. Traditional HAR approaches commonly relied on handcrafted features extracted from wearable sensor data or video sequences. However, recent advances in computer vision and machine learning have enabled more effective analysis of human posture and movement, providing greater potential for non-contact activity monitoring.

Among these developments, human pose estimation has emerged as a useful approach for vision-based HAR. Rather than analysing the entire image, pose estimation represents the human body through skeletal keypoints corresponding to major body joints. Information such as joint angles, body orientation, relative landmark positions, and temporal movement can then be used to distinguish between different activities [7], [12], [14]. This representation provides a more focused description of body posture and movement while reducing dependence on visual characteristics such as clothing and background appearance.

Furthermore, pose-derived features provide a compact representation of body configuration compared with raw image-based approaches, potentially reducing the amount of visual information required for activity classification [7], [12]. This makes pose-based HAR particularly suitable for lightweight elderly monitoring applications where real-time operation, computational efficiency, and affordability are important considerations. Such characteristics provide the basis for employing pose estimation in the proposed system to recognize standing, walking, sitting, and falling activities.

Vision-Based Human Activity Recognition

Vision-based has received considerable attention as a non-contact monitoring approach because cameras can capture human posture and movement without requiring users to wear sensing devices [4]–[7]. This characteristic is particularly beneficial for elderly monitoring, where wearable devices may be inconvenient or may not be used consistently. With recent advances in computer vision, vision-based systems have incorporated techniques such as pose estimation, deep learning, object detection, semantic segmentation, and temporal modelling to recognize daily activities and detect fall events [7]–[12], [16], [17].

Among these approaches, pose estimation provides a practical means of representing human posture through skeletal landmarks corresponding to key body joints. These landmarks can be analysed to determine joint configurations, body inclination, and movement patterns associated with different activities. Compared with approaches that analyse entire image frames, pose-based representations provide more focused information about body configuration and movement. Lightweight frameworks such as MediaPipe have further enabled pose estimation to be implemented in real time using standard cameras and relatively affordable computing devices, making the approach suitable for home and community-based elderly monitoring applications [11].

Although deep learning approaches have demonstrated promising performance in activity recognition and fall detection, their computational requirements can present challenges for implementation on resource-constrained platforms. Lightweight pose-based approaches therefore offer a practical alternative when affordability, computational efficiency, interpretability, and real-time operation are important considerations [11]. In such applications, skeletal landmarks can be combined with predefined decision rules to classify activities without requiring computationally intensive model training. Nevertheless, vision-based HAR remains affected by environmental and activity-related factors. Variations in lighting, camera position, occlusion, background conditions, and visibility of body landmarks can influence pose estimation and subsequent classification. Dynamic activities such as falling are particularly challenging because the rapid transition in body posture may temporarily resemble normal movements such as sitting or bending [4], [8]–[10]. These challenges highlight the need to balance recognition performance with computational simplicity when developing an affordable real-time monitoring system for elderly care.

Artificial Intelligence (AI) in Community Healthcare

AI has emerged as an enabling technology for improving healthcare accessibility, efficiency, and quality of care. In community healthcare, AI applications include disease diagnosis, remote patient monitoring, predictive healthcare analytics, and intelligent assistive technologies. AI-based monitoring systems allow continuous observation without requiring constant human supervision, reducing the workload of caregivers while supporting independent living among elderly populations. The integration of AI into elderly and community healthcare provides opportunities for continuous monitoring, automated activity recognition, and early identification of potentially hazardous events [6], [10], [13], [20]. However, camera-based monitoring introduces privacy concerns because continuous visual information may contain sensitive personal information. Recent studies have investigated privacy-preserving approaches based on edge AI, local processing, anonymization, and alternative visual representations [13], [20].Local processing is particularly relevant because visual information can be analysed without continuously transmitting raw video to external servers. This approach can reduce network dependency while limiting the exposure of sensitive visual information [13]. Therefore, combining local processing with lightweight AI techniques provides a promising direction for affordable and privacy-conscious elderly monitoring

Research Gap

Although recent studies have demonstrated substantial advances in vision-based activity recognition and fall detection using deep learning, pose estimation, object detection, and Transformer-based architectures [7]–[12], [16], [17], several challenges remain for practical elderly monitoring applications. Many advanced approaches require large datasets, extensive model training, and relatively high computational resources, which may limit their suitability for affordable and resource-constrained monitoring systems. In addition, privacy, system complexity, and the ability to perform real-time processing remain important considerations for practical deployment in home and community healthcare environments [13], [20].

Accurate recognition of dynamic activities, particularly falls, also remains challenging because rapid changes in body posture may resemble normal transitional movements such as sitting or bending. This increases the difficulty of distinguishing actual falls from routine daily activities, particularly when the system relies on limited visual or pose information. Therefore, there is a need for lightweight and interpretable approaches that balance recognition performance with affordability, computational efficiency, privacy, and real-time operation. To address these considerations, this study investigates an AI-based non-contact human activity recognition system using readily available hardware and lightweight processing techniques. The proposed system integrates a standard webcam with OpenCV, MediaPipe pose estimation, and a rule-based classification algorithm to recognize four activities: standing, walking, sitting, and falling. Rather than relying on computationally intensive model architectures, the proposed approach emphasizes affordability, local processing, simplicity, and real-time operation, providing a practical foundation for elderly monitoring applications that support independent living and community healthcare.

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METHODOLOGY

This section describes the methodology employed to develop and evaluate the proposed non-contact human activity recognition system. The methodology follows a systematic process covering system development, activity data acquisition, pose estimation and feature extraction, rule-based activity classification, and performance evaluation. The overall approach was designed to enable real-time recognition of standing, walking, sitting, and falling using a standard webcam and locally executed computer vision techniques.

Research Design

This study adopted a prototype development and experimental evaluation approach to develop and assess an AI-based non-contact human activity recognition system for elderly monitoring. The proposed system was designed to recognize four fundamental human activities, namely standing, walking, sitting, and falling, using a vision-based approach without requiring wearable sensors. The overall methodology consisted of system development, data acquisition, pose estimation, feature extraction, activity classification, and performance evaluation. The system was evaluated through controlled real-time experiments to determine its suitability for affordable elderly monitoring applications.

System Architecture

The proposed system consists of four main components which are video acquisition, pose estimation, activity classification, and output visualization, as illustrated in Figure 1. A Logitech C920 HD webcam continuously captures video frames, which are processed locally on a standard laptop using OpenCV. Human skeletal landmarks are extracted using the MediaPipe Pose framework, which detects 33 body landmarks representing the spatial positions of major body joints. These landmarks are subsequently analysed using a rule-based algorithm to classify four predefined activities which are standing, walking, sitting, and falling. The recognized activity is then displayed in real time without transmitting any data to external servers, thereby preserving user privacy.

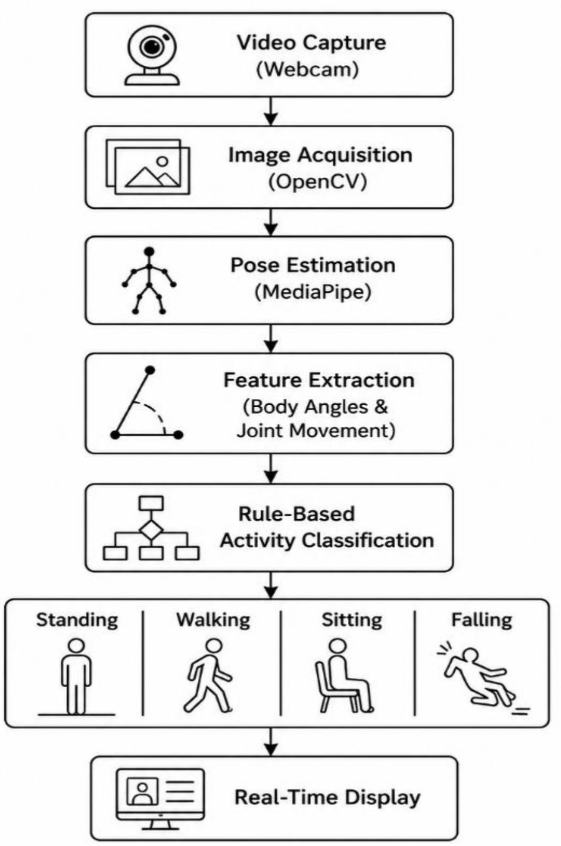

Figure 1: Overall architecture of the proposed elderly monitoring system.

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Hardware and Software Configuration

The proposed system was implemented using widely available hardware and open-source software to ensure affordability and ease of deployment. The hardware configuration consisted of a Logitech C920 HD webcam operating at a resolution of 1920 × 1080 pixels and 30 frames per second, connected to a standard laptop serving as the processing unit via Universal Serial Bus (USB) cable. The webcam was mounted on a 2.5m height pole for better viewing. Figure 2 depicts the hardware configuration for the experiment.

The software environment was developed using Python, with OpenCV employed for video acquisition and image preprocessing, while MediaPipe was used for real-time pose estimation. Figure 3 displays the software configuration for the work. All processing tasks, including landmark extraction, feature computation, activity classification, and visualization, were executed locally on the laptop, eliminating the need for cloud-based processing and preserving user privacy.

Activity classification thresholds configured as Table I. The activity classification algorithm applies a sequential set of threshold-based rules derived from body posture and ankle movement. Fall detection is evaluated first, followed by sitting detection, while walking and standing are distinguished using inter-frame ankle displacement and a cumulative movement counter.

Figure 2: Hardware configuration for the experiment.

Figure 3: Software configuration using Python with OpenCV.

Table I: Activity Classification Threshold

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Activity	Condition	Threshold/ Decision Rule	Description
Standing	Default condition after fall and sitting checks	Body angle ≥ 45°, knee angle ≥ 120°, and walk_counter ≤ 5	If the person is neither falling nor sitting and sustained ankle movement is insufficient, the activity is classified as standing.
Walking	Accumulated walk_counter to confirm walking activities. Absolute horizontal displacement of the left ankle between consecutive frames.	walk_counter > 5, and Movement > 0.01	The activity is classified as walking only after sufficient consecutive movement has accumulated. Each frame satisfying this condition increases the walk_counter by 1.
Sitting	Knee angle calculated from left hip–left knee–left ankle.	Knee angle < 120°	If no fall is detected and the knee angle is below 120°, the activity is classified as sitting.
Falling	Body angle calculated from left shoulder–left hip–left knee.	Body angle < 45°	A sufficiently low body angle is classified as a fall.

Data Acquisition

The experimental dataset was collected under controlled indoor conditions using a Logitech C920 HD webcam mounted at a fixed position to ensure a consistent field of view. Four activities relevant to elderly monitoring were selected which are standing, walking, sitting, and falling. Each activity was performed naturally by the participant while remaining fully visible within the camera frame.

A total of 80 activity samples were collected, comprising 20 samples for each activity category. During data collection, video streams were processed directly on the local computer without permanent storage or cloud transmission, thereby enhancing data privacy and minimizing security concerns.

Pose Estimation and Feature Extraction

Human pose estimation was performed to obtain skeletal landmarks representing key anatomical points of the body. Pose-derived features have been increasingly employed in activity and fall recognition because skeletal keypoints provide a compact representation of human posture and movement [7], [12]. Similar approaches have demonstrated the usefulness of pose information for analysing body orientation, joint configuration, and temporal movement characteristics in fall detection applications [11], [19]. In the proposed system, the AI component is primarily associated with MediaPipe-based human pose estimation, which automatically detects and tracks human skeletal landmarks. The subsequent activity recognition is performed using an interpretable rule-based decision algorithm applied to the extracted landmarks and derived posture and movement features. To characterize human posture, body joint angles were calculated using three selected landmarks. The angle between adjacent body segments was computed using trigonometric functions based on the Cartesian coordinates of the detected joints. These body angles served as discriminative features for distinguishing between different human activities.

In addition to joint angles, the displacement of ankle landmarks across consecutive video frames was

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calculated to capture movement information. The combination of body posture and motion features enabled the system to differentiate between static and dynamic activities.

Activity Classification

A lightweight rule-based classification algorithm was implemented to recognize human activities in real time. Unlike computationally intensive deep learning models, the proposed approach applies predefined decision rules based on body posture and movement characteristics, allowing efficient execution on standard computing hardware. Fall detection is performed by analysing the body inclination angle, where an angle below a predefined threshold indicates a potential fall. If no fall is detected, the system evaluates the knee joint angles to identify a sitting posture, with angles below the specified threshold classified as sitting. For walking detection, the system analyses the continuous displacement of the ankle landmarks between successive frames. When the detected displacement exceeds the movement threshold, the activity is classified as walking; otherwise, the individual is classified as standing. The use of a rule-based decision structure was selected to maintain low computational complexity and enable real-time implementation without requiring model training. Although recent studies increasingly employ deep learning and Transformer-based classifiers [8], [9], [12], lightweight pose-based approaches remain relevant where computational simplicity and low-cost deployment are primary considerations [11], [19]. The classification process follows sequential decision stages as depicted in Figure 4.

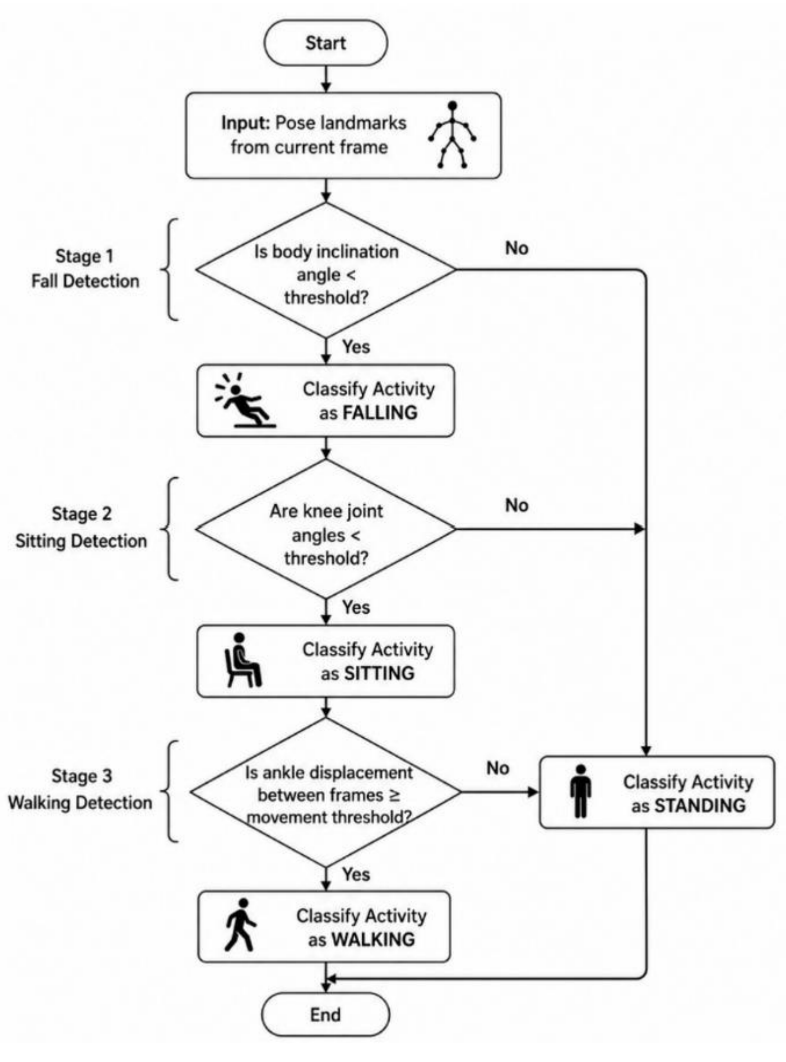

Figure 4: Sequential decision stages for activities classification.

This hierarchical decision-making process enables real-time activity recognition while maintaining low computational requirements suitable for affordable elderly monitoring systems.

Performance Evaluation

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The performance of the proposed system was evaluated through controlled real-time experiments. Recognition performance was assessed by comparing the predicted activity labels with the corresponding ground truth labels for each activity category. Classification accuracy was calculated using Equation (1):

$$\text{Accuracy}(\%) = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Samples}} \times 100 \quad \text{(Equ. 1)}$$

The evaluation considered four activity classes which are standing, walking, sitting, and falling. A total of 20 test samples were collected for each activity, resulting in 80 observations for performance assessment. The obtained accuracies were analysed to determine the capability of the proposed system for real-time elderly monitoring and to identify activities requiring further improvement.

RESULT AND ANALYSIS

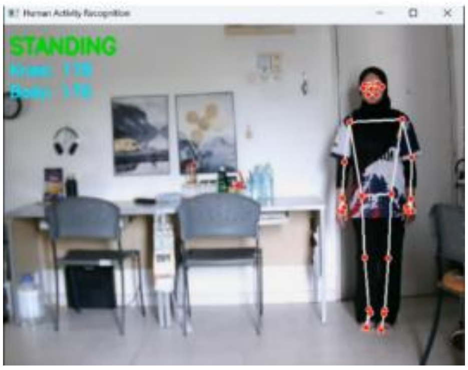
This section presents the experimental results and analysis of the proposed human activity recognition system. The system was evaluated based on its ability to correctly recognize four activities which are standing, walking, sitting, and falling. The recognition performance for each activity was analysed to assess the effectiveness of the proposed approach and to identify limitations in distinguishing between static and dynamic human movements.

Validation of the Functionality of the Developed System

The functionality of the developed system was validated by performing the four predefined activities under controlled indoor conditions. Figure 5 presents examples of successful real-time activity detection for (a) standing, (b) walking, (c) sitting, and (d) falling. For each activity, the system successfully detected the human body and generated skeletal landmarks corresponding to key body joints. These landmarks were subsequently used to determine body posture and movement for activity classification.

As shown in Figure 5(a), an upright body posture with minimal movement was correctly identified as standing. Figure 5(b) demonstrates the detection of walking, where changes in ankle position and body movement between consecutive frames were used to distinguish walking from a stationary posture. In Figure 5(c), the sitting activity was identified based primarily on the changes in knee joint angles associated with a seated posture. Figure 5(d) demonstrates fall detection, where the change in body orientation and inclination was recognized as a falling posture.

Overall, the observations in Figure 5 confirm that the developed system is functionally capable of acquiring video input, detecting body landmarks, extracting relevant posture and movement information, and producing the corresponding activity classification in real time. These functional validation results establish that the complete processing pipeline operates as intended before its recognition accuracy is quantitatively evaluated in the subsequent section.



(a)

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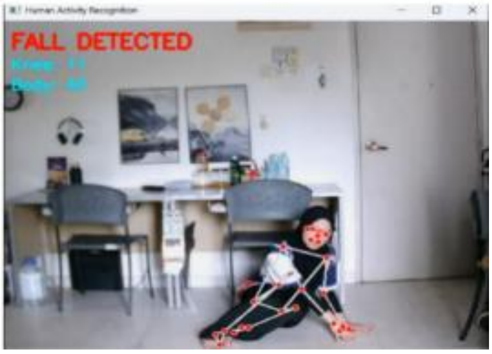
(b)

(c)



(d)

Figure 5: Correct activity detection (a) standing, (b) walking, (c) sitting, and (d) falling.

In addition, the scenario of incorrect detection was also identified. Figure 6 presents an example of incorrect activity detection during the functional validation of the developed system. Although the participant was in a sitting position, the system classified the activity as standing. This misclassification may occur when the detected knee and body angles do not sufficiently satisfy the predefined threshold for sitting. In this case, the body was partly visible.

Variations in body posture, camera viewing angles, landmark position, and partial visibility of the lower limbs may also influence the calculated joint angles and consequently affect the classification decision. This observation demonstrates that, although the system is capable of real-time pose detection and activity recognition, the rule-based classification approach remains sensitive to variations in posture and landmark estimation. The incorrect detection observed in Figure 6 highlights the need for further refinement of the classification thresholds and decision rules to improve the robustness of the system.

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Figure 6: Example of incorrect activity detection

Evaluation of the Accuracy Performance

The performance of the proposed AI-based human activity recognition system was evaluated through controlled real-time experiments involving standing, walking, sitting, and falling activities presented in Table II. A total of 80 activity samples were collected, with 20 samples representing each activity category. System performance was assessed by comparing the predicted activity labels with the corresponding ground truth labels, and classification accuracy was calculated for each activity.

Table II: Activity Recognition Performance

Activity	**Number of Samples**	**Correct Predictions**	**Accuracy (%)**
Standing	20	20	100%
Walking	20	15	75%
Sitting	20	16	80%
Falling	20	13	65%

The results demonstrate that the proposed system achieved the highest recognition accuracy for standing (100%), followed by sitting (80%), walking (75%), and falling (65%). The overall findings indicate that the system effectively recognizes static human postures, while dynamic movements remain more challenging to classify accurately. This produced overall system performance of 80%, which calculated as follows:

$$\frac{\text{Correct prediction}}{\text{Total sample}} = \frac{20 + 15 + 16 + 13}{80} \times 100\% = 80\%$$

Table III presents the actual and predicted activity labels for the 20 trials conducted for each activity category.

Table III: Actual Over Predicted Activities Evaluation

Predicted Activities	**Sample No.**	**Actual Activities**			
		Standing	**Walking**	**Sitting**	**Falling**
	1	Standing	Walking	Standing	Sitting

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	2	Standing	Walking	Sitting	Sitting
	3	Standing	Standing	Sitting	Sitting
	4	Standing	Standing	Standing	Falling
	5	Standing	Walking	Sitting	Falling
	6	Standing	Standing	Sitting	Falling
	7	Standing	Standing	Sitting	Falling
	8	Standing	Standing	Standing	Falling
	9	Standing	Walking	Sitting	Falling
	10	Standing	Walking	Sitting	Falling
	11	Standing	Walking	Standing	Falling
	12	Standing	Walking	Sitting	Walking
	13	Standing	Walking	Sitting	Falling
	14	Standing	Walking	Sitting	Walking
	15	Standing	Walking	Sitting	Falling
	16	Standing	Walking	Sitting	Walking
	17	Standing	Walking	Sitting	Falling
	18	Standing	Walking	Sitting	Falling
	19	Standing	Walking	Sitting	Sitting
	20	Standing	Walking	Sitting	Falling

Table II presents a comparison between the actual and predicted activities across 20 samples for each activity category. The results show that standing was consistently classified correctly, while several misclassifications occurred for walking, sitting, and falling. Walking was occasionally predicted as standing, while sitting was also misclassified as standing in several samples. For falling, some samples were incorrectly identified as sitting or walking, indicating greater difficulty in recognizing dynamic fall movements. Overall, the results demonstrate that the system performs more reliably for static and clearly defined postures, while activities involving greater movement and posture transitions are more susceptible to misclassification

The perfect recognition accuracy obtained for standing indicates that the extracted skeletal landmarks and body-angle features provide a stable representation of static upright postures. Since standing involves minimal body movement and relatively consistent joint angles, the rule-based classifier was able to identify this activity reliably across all test samples.

Sitting also demonstrated satisfactory performance with an accuracy of 80%. Most sitting activities were correctly recognized based on knee and hip joint angles extracted from the pose estimation model. However, several sitting samples were incorrectly classified because transitional movements between standing and sitting temporarily produced body configurations that resembled other activities. These posture variations occasionally caused the predefined decision thresholds to classify the activity incorrectly.

Walking achieved an accuracy of 75%, reflecting the greater complexity associated with continuous body motion. Unlike static postures, walking requires the system to analyse movement trajectories over consecutive video frames. Variations in walking speed, stride length, and temporary pauses influenced the measured ankle displacement, causing several walking samples to be classified as standing. Similar findings have been reported in previous human activity recognition studies, where dynamic activities generally exhibit lower recognition accuracy than static postures due to temporal variations in movement patterns.

Fall detection produced the lowest accuracy (65%) among all evaluated activities. Falls are characterized by rapid body transitions that often share similar intermediate postures with sitting, bending, or crouching. As the proposed system relies primarily on body inclination angles and skeletal landmarks, some fall events were incorrectly identified as sitting before the complete falling posture was observed. Furthermore, the limited number of fall samples restricted the diversity of falling scenarios available for evaluation, reducing the classifier's ability to generalize across different fall patterns.

From a community healthcare perspective, the findings demonstrate the potential of low-cost vision-based monitoring as a supportive technology for elderly individuals living independently. The use of readily available camera hardware and local processing may reduce dependence on specialized wearable devices and cloud-based infrastructure, potentially improving accessibility for households and community care settings with limited resources. Beyond activity recognition performance, the proposed approach therefore highlights how affordable AI technologies could complement caregiver supervision and support safer independent ageing. However, its practical adoption requires further evaluation involving elderly users, caregivers, and real-world home environments to assess usability, acceptance, privacy concerns, and long-term effectiveness.

Limitations

The present study has several limitations. First, the evaluation involved only 80 activity samples collected under controlled indoor conditions, limiting the generalizability of the findings. Second, the experimental evaluation did not involve a representative elderly population and should therefore be regarded as a proof-of-concept assessment. Third, the rule-based classifier relies on predefined thresholds that may be sensitive to variations in body posture, camera position, lighting, occlusion, and individual movement patterns. Finally, the relatively low fall recognition accuracy indicates that further algorithmic refinement and evaluation using more diverse fall scenarios are required before practical deployment

CONCLUSION

This study presented an AI-based non-contact human activity recognition system designed to enhance elderly safety through affordable and privacy-preserving monitoring. By integrating computer vision techniques with MediaPipe pose estimation and a lightweight rule-based classification algorithm, the proposed system successfully recognized four essential human activities namely, standing, walking, sitting, and falling, using only a standard webcam and local processing. Experimental evaluation demonstrated promising recognition performance, achieving accuracy of 100% for standing, 80% for sitting, 75% for walking, and 65% for falling, indicating the feasibility of employing low-cost vision-based technologies for real-time elderly monitoring. Although the system demonstrates proof-of-concept feasibility, the 65% fall recognition accuracy is not yet sufficient for safety-critical deployment. Further refinement and validation are therefore required before the system can be considered for practical elderly monitoring applications.

The proposed approach addresses several limitations associated with conventional elderly monitoring systems by eliminating the need for wearable devices and cloud-based data processing, thereby improving user convenience while preserving privacy. Although fall detection remains challenging due to the dynamic nature of human movement and similarities between fall and sitting postures, the results demonstrate potential to support independent living and assist caregivers through continuous non-contact monitoring through continuous, non-intrusive monitoring.

Future research should focus on expanding the dataset to include a larger and more diverse population, particularly elderly participants, and evaluating the system in real-world environments. Testing should also be conducted under varied conditions, including changes in lighting, partial occlusion, different camera angles, and the presence of multiple users, to assess the system's robustness and generalisability. Further optimisation of the classification thresholds and decision rules is required to improve the recognition of dynamic activities, particularly walking and falling, which are more susceptible to misclassification. Hybrid approaches that combine rule-based thresholds with lightweight machine learning, deep learning, or temporal models should also be investigated to better distinguish between similar postures and movement sequences while maintaining low computational requirements. To support secure and practical deployment, future work should explore privacy-preserving techniques, such as skeletal-only representations, on-device processing, and edge-AI-based anonymisation. The integration of automatic emergency notifications, mobile applications, and IoT healthcare platforms could further improve caregiver responsiveness. Finally, longitudinal studies involving elderly users and caregivers are recommended to evaluate usability, user acceptance, compliance, reliability, and long-term effectiveness in community healthcare settings.

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REFERENCES

1. N. T. Newaz and E. Hanada, "The methods of fall detection: A literature review," Sensors, vol. 23, no. 11, Art. no. 5212, 2023, doi: 10.3390/s23115212.
2. K. Vasuthavan and M. N. Ismail, "IoT based falling detection system," Evolution in Electrical and Electronic Engineering, vol. 4, no. 1, pp. 501–508, 2023.
3. J. Strohmayer and M. Kampel, "Blind modalities for human activity recognition," Studies in Health Technology and Informatics, 2023, doi: 10.3233/SHTI230601.
4. A. Benkaci, L. Sliman, and H. N. Dellys, "Vision-based human fall detection systems: A review," Procedia Computer Science, vol. 241, pp. 203–211, 2024, doi: 10.1016/j.procs.2024.08.028.
5. S. Gaikwad, S. Bhatlawande, S. Shilakar, and A. Solanke, "A computer vision-approach for activity recognition and residential monitoring of elderly people," Medicine in Novel Technology and Devices, vol. 20, Art. no. 100272, 2023, doi: 10.1016/j.medntd.2023.100272.
6. R. Ullah, I. Asghar, S. Akbar, G. Evans, J. Vermaak, A. Alblwi, and A. Bamaqa, "Vision-based activity recognition for unobtrusive monitoring of the elderly in care settings," Technologies, vol. 13, no. 5, Art. no. 184, 2025, doi: 10.3390/technologies13050184.
7. M. Gao, J. Li, D. Zhou, Y. Zhi, M. Zhang, and B. Li, "Fall detection based on OpenPose and MobileNetV2 network," IET Image Processing, vol. 17, no. 3, pp. 722–732, 2023, doi: 10.1049/ipr2.12667.
8. J. Kim, B. Kim, and H. Lee, "Fall recognition based on time-level decision fusion classification," Applied Sciences, vol. 14, no. 2, Art. no. 709, 2024, doi: 10.3390/app14020709.
9. D. Kibet, M. S. So, H. Kang, Y. Han, and J.-H. Shin, "Sudden fall detection of human body using Transformer model," Sensors, vol. 24, no. 24, Art. no. 8051, 2024, doi: 10.3390/s24248051.
10. Y. Wang and T. Deng, "Enhancing elderly care: Efficient and reliable real-time fall detection algorithm," Digital Health, vol. 10, 2024, doi: 10.1177/20552076241233690.
11. M. Ryu and J. Shim, "A practical approach to fall detection: Lightweight AI for low-cost implementation," Journal of The Korea Society of Computer and Information, vol. 30, no. 1, pp. 53–63, 2025, doi: 10.9708/jksci.2025.30.01.053.
12. A. Raza et al., "Human fall detection using pose estimation: From traditional machine learning to vision transformers," Engineering Applications of Artificial Intelligence, vol. 143, Art. no. 109809, 2025, doi: 10.1016/j.engappai.2024.109809.
13. S. Kim, J. Park, Y. Jeong, and S. E. Lee, "Intelligent monitoring system with privacy preservation based on edge AI," Micromachines, vol. 14, no. 9, Art. no. 1749, 2023, doi: 10.3390/mi14091749.
14. A. N. Zereen et al., "Video analytic system for activity profiling, fall detection, and unstable motion detection," Multimedia Tools and Applications, vol. 82, no. 27, pp. 42395–42415, 2023, doi:

10.1007/s11042-023-14993-y.
15. P. Rajesh and R. Kavitha, "An imperceptible method to monitor human activity by using sensor data with CNN and bi-directional LSTM," International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, 2023, doi: 10.17762/ijritcc.v11i2s.6033.
16. S. Mobsite, N. Alaoui, M. Boulmalf, and M. Ghogho, "Semantic segmentation-based system for fall detection and post-fall posture classification," Engineering Applications of Artificial Intelligence, vol. 117, Art. no. 105616, 2023, doi: 10.1016/j.engappai.2022.105616.
17. H. Khan et al., "Visionary vigilance: Optimized YOLOV8 for fallen person detection with large-scale benchmark dataset," Image and Vision Computing, vol. 149, Art. no. 105195, 2024, doi: 10.1016/j.imavis.2024.105195.
18. P. Saenkaew, C. Pumthurean, J. Boonsob, N. Varisthanist, T. Tardtong, and K. Srijiranon, "Standing posture monitoring system for the elderly," Journal of Information Science and Technology, 2024.
19. V. P. Kothari and P. S. Chakurkar, "Towards safer environments: A YOLO and MediaPipe-based human fall detection system with alert automation," MethodsX, vol. 15, Art. no. 103623, 2025, doi: 10.1016/j.mex.2025.103623.
20. C.-Y. Wang and F.-S. Lin, "AI-driven privacy in elderly care: Developing a comprehensive solution for camera-based monitoring of older adults," Applied Sciences, vol. 14, no. 10, Art. no. 4150, 2024, doi: 10.3390/app14104