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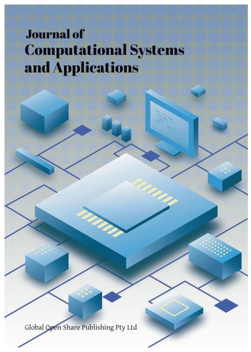

Article

Alert System for Non-Responsive State of an Elderly Person

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Abstract

The prevalence of non-responsive states among elderly individuals, often associated with falls or medical emergencies, poses significant risks requiring immediate intervention. Addressing this challenge, this paper presents an intelligent system leveraging advanced computer vision, image processing, and machine learning technologies to detect such critical scenarios reliably. The proposed system integrates image segmentation for isolating relevant objects, feature extraction to discern crucial attributes like body posture, flow tracking to monitor motion patterns, and image classification algorithms to differentiate emergency situations from non-critical events. This comprehensive approach ensures robust accuracy and adaptability across diverse environments, accommodating varying lighting and spatial conditions. By enabling timely detection and alerts, the system empowers caregivers and emergency responders to intervene promptly, thereby enhancing the safety and well-being of elderly individuals and reducing the likelihood of adverse outcomes.

Keywords

Pose estimation, Flow tracking, Machine learning, Optical flow, Image processing

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1. Introduction

The demographic segment consisting of elderly individuals is projected to undergo a significant increase, advancing from a proportion of 8.6 percent to a notable 10.1 percent over the decade spanning from the year 2011 to the year 2021, and further forecasts suggest that this demographic will escalate to an impressive 13.1 percent by the year 2031. In accordance with the estimations provided by analysts at the National Statistical Office, it is anticipated that the elderly populace will comprise 93 million males and 101 million females by the year 2031, marking a substantial rise from the earlier statistics recorded in 2021, which indicated a population of 67 million males and 71 million females. Given that the processes of aging and the experience of old age are intrinsically linked to various physical limitations and a decline in bodily stability, it becomes imperative to engage in continuous monitoring of this demographic to preemptively address and mitigate the emergence of serious medical conditions that may arise [1]. In the contemporary landscape of healthcare technology, there has emerged a plethora of significant advancements that are particularly focused on the study and ongoing monitoring of the physical well-being of elderly individuals, which are primarily achieved through the application of wearable sensors and other innovative forms of physical sensors that have been meticulously designed specifically for this essential purpose. These highly advanced sensors possess the capability to meticulously collect and rigorously analyze a wide array of physiological parameters, which include, but are not confined to, critical indicators such as pulse rate, heart rate, body temperature, and blood pressure; these parameters, when considered collectively, contribute to a comprehensive understanding of an individual's overall physical and mental wellness, as well as providing insights into the particular types of activities in which they are actively engaged at any given moment. Moreover, the efficacy of this monitoring process is frequently augmented through the seamless integration of sophisticated machine learning techniques, which systematically scrutinize the diverse array of activities undertaken by individuals alongside their corresponding physiological responses; this integration facilitates predictive analyses that are aimed at forecasting potential health outcomes that may arise based on observed data trends. In a related context, when data is captured via visual sensors, such as cameras that deliver continuous video feeds, it becomes entirely feasible to accurately detect and assess the state of immobility in a human subject, which is particularly pertinent when considering the elderly demographic that is under observation in such studies. This scholarly paper introduces an innovative amalgamation of machine learning methodologies and cutting-edge computer vision techniques, with the overarching aim of classifying human poses while concurrently tracking motion by effectively leveraging the principles of optical flow, thereby significantly enhancing the precision associated with both motion detection and activity recognition in real-time scenarios.

Existing approaches to monitoring elderly individuals, such as wearable sensors and pressure-based systems, face critical limitations in scalability, comfort, and adaptability to diverse environments. Wearable systems often cause inconvenience due to their obtrusive nature, while pressure-based systems are constrained to fixed locations. Furthermore, many vision-based systems, though promising, suffer from challenges like low accuracy in varying lighting conditions, high computational complexity, and a lack of real-time responsiveness. These gaps necessitate the development of an alternative framework that ensures precision, real-time detection, and scalability.

This work aims to overcome these challenges by introducing an intelligent system that combines image segmentation, optical flow-based motion tracking, and Random Forest classification for robust and real-time detection of non-responsive states among the elderly. By leveraging advanced computer vision and machine learning techniques, the system addresses the limitations of sensor-reliant and static-location-based approaches, providing an adaptable and scalable solution

2. Literature Survey

Human activity monitoring has become a pivotal area of research due to the increasing demand for more accurate and efficient methods for estimating human poses, such as standing, sleeping, and sitting. The evolution of various approaches to address this challenge has been vast, reflecting the growing complexity of human posture detection and the need for reliable systems in diverse real-world applications. As research in this field progresses, methods to enhance both accuracy and efficiency have been proposed, ranging from simpler sensor-based techniques to more sophisticated machine learning-based approaches. Among the early efforts, one promising direction explored the use of pressure maps placed on a bed for extracting 3D human poses, which offered a novel approach to activity monitoring [2]. These methods, however, often require external pressure sensors that add complexity to the system setup.

Further building on this concept, Alaziz et al [3] examined the use of load cells placed under the legs of a bed to detect the motion of a person sleeping, where variations in pressure values captured by these load cells were used to infer body motion. This approach provided a deeper understanding of sleep dynamics and position detection. While pressure-based systems provide valuable insights, they are still constrained by the need for physical sensors, which can limit their scalability and flexibility. To address this challenge, efforts have been made to develop non-intrusive techniques, particularly through the use of computer vision-based methods that operate without the need for sensors placed on or around the human body.

In the realm of fall detection, significant strides have been made by combining multi-sensor data fusion with machine learning models, such as support vector machines (SVMs), to differentiate between falling and non-falling bodies [4,5].

These systems, which are crucial for elderly care and safety, highlight the importance of early fall detection and prevention. Similarly, computer vision-based human activity recognition (HAR) has been explored, with a focus on motion-based techniques, space-time volumes, trajectory analysis, and shape-dependent methods that rely on contour features. These methods have shown promising results but often face limitations in accuracy and adaptability due to environmental factors or computational constraints.

Real-time image segmentation has been an area of significant interest, with the application of tools such as OpenPose [6] and HAR frameworks [7] for human posture detection. These models typically focus on extracting key body points and mapping the human figure in different postures. However, the true breakthrough in human activity monitoring came with the integration of deep learning and neural network models, which opened up a broader range of possibilities for more accurate posture classification. A variety of these deep learning methods incorporate additional filtering techniques, such as Kalman filters [8], to improve the quality of data before passing it into classification models. Approaches combining well-known models like YOLO [9], VGG16 [9,10], and Bi-LSTM have been proposed for various tasks, including posture classification and fall detection, with these models being trained on diverse datasets [7,10].

While the use of deep learning and neural networks has greatly advanced human posture recognition, various tracking techniques have also played a pivotal role in enhancing the system's capability to follow object trajectories. Methods like frame subtraction, background subtraction, and optical flow [11] have been employed to track motion and improve the system's performance in dynamic environments. Alongside these, Kalman filters and particle filters, as well as Kanade-Lucas optical flow, have been applied to improve tracking accuracy. Although these methods show promise, they are often limited by computational complexity, accuracy, and the adaptability of models to varying environments.

The focus of this study is to introduce an innovative approach for monitoring elderly individuals, particularly in tracking their movements and detecting non-responsiveness. By utilizing dense optical flow computation based on Gunnar Farnebäck's algorithm [12], the system offers a precise method for capturing the detailed movement of individuals, making it suitable for environments requiring continuous monitoring. The algorithm has gained recognition for its ability to track motion with high accuracy, even in cases of subtle movement, which is crucial for elderly care applications where precise monitoring of body posture is essential [13]. Following the motion extraction process, a Random Forest classifier is employed to classify body postures based on the extracted features. This classifier has proven to be effective in handling high-dimensional data while providing reliable classifications, making it ideal for real-time posture recognition systems [14,15].

One of the key strengths of this system lies in its robustness and efficiency. The ability to process large datasets with minimal delay enables the system to perform well in scenarios that require quick decision-making, such as fall detection or monitoring periods of inactivity [16,17]. The Random Forest classifier is particularly advantageous due to its ability to analyze multiple variables simultaneously, improving the system's ability to make informed decisions in real time. Furthermore, this classifier's capability to handle a broad range of input features makes it well-suited for systems that need to scale and adapt to different environments and conditions. These attributes suggest that the proposed system has significant potential for real-world applications, particularly in healthcare environments where rapid, accurate data analysis is critical for patient safety and well-being [18-20].

While prior research has made strides in activity monitoring, the limitations of sensor-based systems, the adaptability challenges of vision-based methods, and the computational bottlenecks of machine learning approaches underscore the need for a robust, scalable, and efficient solution. This work builds upon these existing frameworks by integrating dense optical flow and Random Forest classification to deliver a reliable and real-time system for monitoring elderly.

In summary, while the field of human activity monitoring has made significant advancements in posture detection and tracking, several challenges remain in terms of accuracy, computational complexity, and the ability to adapt to dynamic environments. The integration of methods such as dense optical flow, machine learning, and real-time data processing represents a step forward in developing efficient, scalable systems for real-time human activity monitoring. Future work should focus on enhancing the system's ability to handle more complex scenarios, such as multiple subjects in dynamic environments, and reducing computational load to further improve the system's accessibility and effectiveness across a range of applications.

3. Proposed System

The primary objective of the innovative system proposed in this study is to provide timely alerts upon detecting an unusual state where the body remains motionless, with a particular focus on safeguarding the well-being of elderly individuals who are at an elevated risk of health-related emergencies. This system relies on a continuous video feed as its primary data input, capturing a meticulously sequenced array of consecutive frames. This setup enables real-time analysis and monitoring of the subject's physical condition, ensuring that any deviations from normal behavior are promptly identified.

As illustrated in Figure 1, which provides a detailed visualization of the system's framework, the design has been carefully structured to offer an intuitive understanding of its operational mechanics and functional capabilities. One of the key features of the system is its use of grayscale imaging formats, which proves to be particularly effective in detecting sudden and significant changes in environmental intensity on a frame-by-frame basis. This approach enhances the system's sensitivity and responsiveness to potential hazards or emergencies.

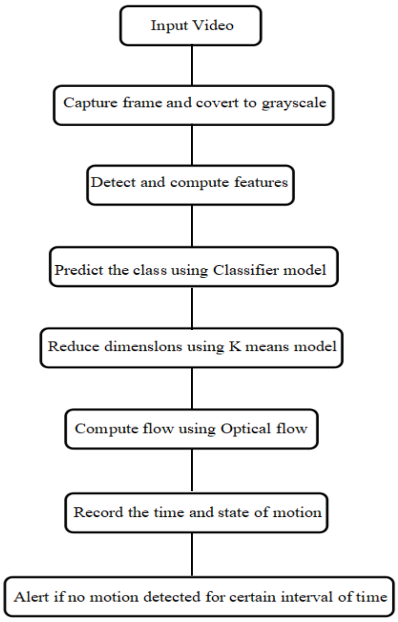

Figure 1. Framework of Proposed Algorithm

A notable advantage of adopting grayscale imaging is the significant reduction in pixel density, which directly leads to a decrease in computational time required to process video data and minimizes the memory needed for storage. These reductions make the system more efficient, allowing for faster analysis and processing of real-time data. Such efficiency is critical in scenarios where immediate action is necessary to prevent adverse outcomes.

By integrating these advanced technological features, the system aims to enhance the safety and overall quality of life for elderly individuals, providing them with an added layer of protection. This proactive approach addresses the vulnerabilities associated with unnoticed health crises, ensuring timely interventions that can make a substantial difference in emergency situations.

3.1 Pose Classification

The intricate process of classifying the human body in a state of non-responsiveness involves accurately identifying the human form within a specified frame and subsequently categorizing it as either a dynamically moving entity or a stationary, motionless figure. Achieving this requires a comprehensive and systematic approach to data collection, preprocessing, and feature extraction.

To facilitate this classification process, a vast image dataset has been meticulously compiled from several reputable sources, most notably the widely recognized MPII Human Pose dataset [21], which has established itself as a benchmark repository for human pose imagery. The images collected underwent a rigorous manual classification process and were systematically categorized into three distinct posture classes: sleeping, sitting, and standing [22].

To ensure uniformity and reliability in subsequent analyses, these images were resized to a consistent dimension. This resizing step is crucial for maintaining consistency across the dataset and enhancing the accuracy of analytical models. During this process, key features within the images, along with their descriptive objects, were detected and computed using the robust Oriented FAST and Rotated BRIEF (ORB) algorithm [23]. The ORB algorithm plays a pivotal role in extracting high-quality features, which are essential for improving the accuracy of posture classification as shown in Figure 2.

```
[[122 129 192 ...   4 190  94]
 [ 92 228 159 ...  88 151 243]
 [252  76  83 ... 185  68 168]
 ...
 [169  29 123 ... 209 228 251]
 [212 254 222 ... 226 207 117]
 [ 13  31 123 ... 239 225 247]]
(463, 32)
```

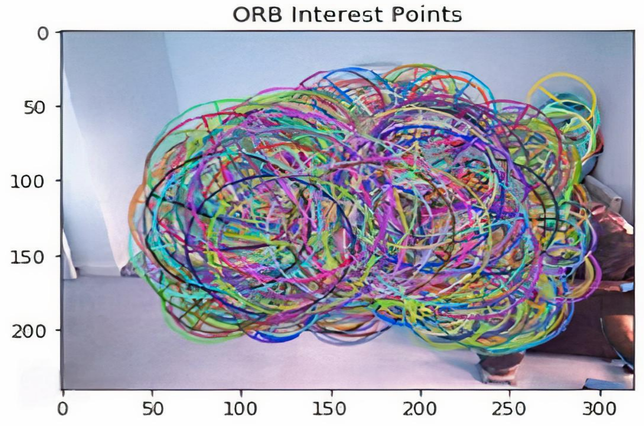

Figure 2. Feature Extraction using ORB

The ability to extract such detailed and meaningful features significantly impacts domains ranging from human-computer interaction to healthcare, where precise pose classification is vital. Furthermore, the integration of these sophisticated techniques not only advances the understanding of human body dynamics but also contributes to the development of more intelligent systems capable of interpreting and responding to human movements with greater precision and context awareness [24,25].

Ultimately, the combination of diligent efforts in data collection and classification, coupled with advanced image processing methods, represents a noteworthy advancement in the field of computer vision. It underscores the ongoing quest to achieve higher accuracy and meaningful insights in pose recognition, paving the way for innovative applications and improved human-centric technologies.

The dimensionality of features extracted from the dataset is reduced by an application of the K means clustering technique, an unsupervised vector quantization using an efficient cluster method of data points may be premeasured objects without prior labeling [26,27]. The parameter 'k' (used to represent the number of desired clusters) is found with the Elbow method implementation, a commonly used heuristic that plots the variance to a function of number of clusters. Next, the dataset is ... systematically ... partitioned ... into 8 separate, distinct clusters, using the kmeans ... algorithm, as subseqent ... each of these clusters is then assigned labels associated with the clusters' contained data points according to the characteristics of that data point. The labeled dataset is then divided into training and testing subsets following a ratio of 7:It is classified, utilizing the random forest classifier configured to use 100 estimator trees for more accurate and robust classification and is evaluated over 3 classifying the model on the basis of performance evaluation. The results of this process are extremely impressive overall accuracy of 87% representing the model’s ability to correctly predict the classes of the data points. The classification results obtained from this model are further elucidated with a presentation of the confusion matrix as shown in Figure 3, which gives a comprehensive summary of the classification results and errors. And finally, to make sure that the model persists and reproduces for future applications, the model is written to a serialized file by cutting the python level with Pickle, a Python library [28] used for the much needed efficient storage and retrieval of python objects.

```
[[ 41   0   0   0]
 [  0 114  11  13]
 [  0   8 132   4]
 [  1   8  11 117]]
             precision    recall  f1-score   support

   No Peson       0.98      1.00      0.99        41
    Sitting       0.88      0.83      0.85       138
   Sleeping       0.86      0.92      0.89       144
   Standing       0.87      0.85      0.86       137

avg / total       0.88      0.88      0.88       460

0.8782608695652174
```

Figure 3. Confusion Matrix for Random Forest

3.2 Motion Tracking

Gunnar Farneback's optical flow algorithm [29] is used for motion tracking in the video feed. Movement is detected using optical flow, where specific feature points are tracked between consecutive frames, providing feature vectors that are converted into velocity vectors to detect motion. This conversion is mathematically represented as shown in Eq.1:

$$I\ (x,\ y,t) = I\ (x + dx,\ y + dy,t + dt) \tag{1}$$

In this equation, I represent the image intensity value, and ttt refers to the time taken for the intensity value to undergo complete displacement. The method used in Gunnar Farneback's dense optical flow algorithm differs from other approaches such as the Lucas-Kanade method, which only considers corner points identified through the Shi-Tomasi algorithm. Farneback’s method takes into account all points in the image, detecting pixel intensity changes between two frames. This results in an image where significant motion is highlighted, making it easier to identify moving objects. The processed image is then converted into the HSV (Hue, Saturation, Value) color space to enhance visibility and facilitate accurate analysis as shown in Figure 4.

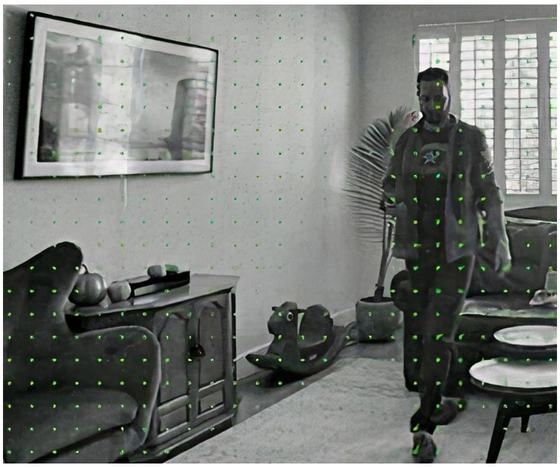

Figure 4. Optical Flow Output

This is followed by an analysis of the flow vector array to compute the direction (dx/dtdx/dtdy/dt) and magnitude (dy/dtdy/dtdy/dt) of motion. The direction and angle of the flow is then found by determine the hue component of the HSV color space, providing a powerful way of seeing and interpreting motion in the video feed [8].

The limited scope of the current system is restricted to motion detection and is not analyzed with regard to the flow velocity itself.

3.3 Non-Responsive State

In elderly individuals, the motionless state is triggered in subject who sits or lies for an unusually long period of time. The tense recorded by a camera feed is analysed using pose classification and motion detection algorithms to simultaneously monitor the subject's pos-ture and motion state in real time. The system monitors continuously the video feed, and if it detects that the subject remains in the same position for a time period greater than a predefined threshold is motionless, an alert is triggered. This alerts the fact that had been detected a potential triggering event, like the subject being still in a long sitting or a long lying without movement. In this experiment, we assume the video feed is captured under ideal lighting conditions with a stable, motionless background therefore allowing the algorithms to run without the participation of non environmental factors.

4. Result

The proposed system demonstrates its capability to simultaneously detect the presence of a human within a frame and classify their motion or lack thereof. The system's key strength lies in its ability to identify periods of inactivity, such as prolonged sitting or lying down, and to generate timely alerts when these states exceed predefined thresholds. For experimental purposes, the threshold time for each posture was manually set to define what constitutes "usual" duration.

4.1 Experimental Scenarios and System Performance

The system was evaluated using a variety of video feeds collected from different indoor environments under diverse conditions. These video feeds were sourced from both freely available datasets and videos we created specifically for this study. This combination ensured a comprehensive evaluation by covering a wide range of scenarios, including:

- Scenario (i): A person lying on the floor or sitting on a bed in a living room (Figure 5(a) and (b)).
- Scenario (ii): Frames with multiple individuals present (Figure 5(c)).
- Scenario (iii): Instances of occlusion, where the subject is partially obscured (Figure 5(d)).
- Scenario (iv): Variations in lighting conditions affecting detection accuracy (Figure 5(e)).

Despite challenges like occlusion and changing light intensities, the system maintained robust performance, especially when the background remained stable. The results demonstrated reliable detection of the subject's pose and motion status, with the system continuously tracking and recording framerate while monitoring the subject's position within the frame.

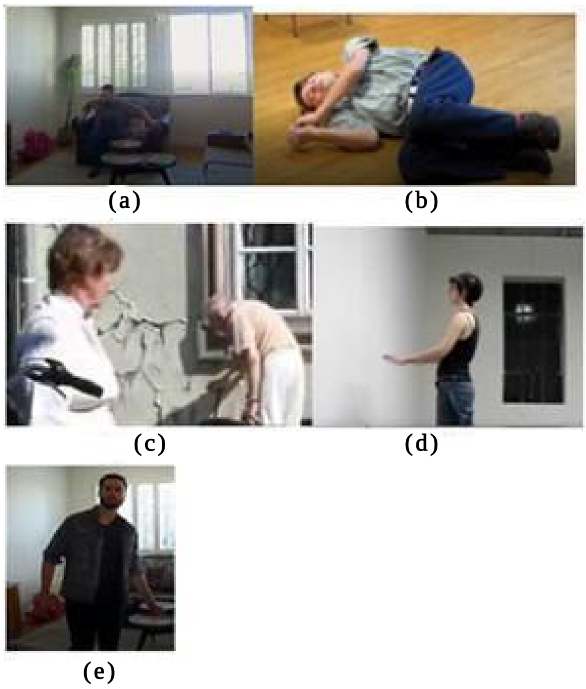

Figure 5. Snippets from different sample videos

4.2 Key Features and Alert Generation

Whenever the subject remained motionless for a duration exceeding the predefined threshold, the system triggered an alert, providing a timestamp for when the inactivity was detected. This feature ensures proactive identification of atypical behavior and timely intervention. Output predictions from the system, as illustrated in Figure 6, showcase its ability to handle real-world complexities, including varying environments and dynamic backgrounds.

```
10.76 FPS
['Sleeping']
11.24 FPS
['Sleeping']
11.24 FPS
['Sleeping']
12.60 FPS
['Sleeping']
9.44 FPS
['Sleeping']
14.44 FPS
2021-12-02 17:06:42.829766 : ALERT
[180  31 404 322]
```

Figure 6. Output Prediction of the system

4.3 Comparative Analysis

The study presented by Ciprian et al. (2023) [30], a novel unsupervised anomaly detection framework for smart-home environments, utilizing growing neural gas networks to adapt to the changing behaviors of elderly individuals without requiring supervised input. The framework was developed using real-life data collected from environmental sensors monitoring the daily activities of 17 elderly subjects over two years. The system effectively detects a variety of anomalies related to daily living activities, focusing on unusual duration, frequency, or new behaviors that deviate from established routines. It demonstrates high reliability with true negative and true positive rates exceeding 90% and 80%, respectively, and adapts to new behaviors within 3 to 7 days, accommodating changes in user behavior over time.

An IoT-based real-time alert system designed to enhance the safety of elderly individuals, particularly those living alone or with mobility challenges, while preserving their independence presented by Martins et al. (2020) [31]. The proposed solution is discreet, non-intrusive, and utilizes low-cost, off-the-shelf electronic components. It can also integrate with existing monitoring devices like bracelets, video cameras, and robots. The system aims to provide real-time status updates to family members or caretakers. Its effectiveness has been validated through both laboratory and household testing.

A system proposed by Chang-Yueh Wang (2024) [32], an AI-driven camera-based monitoring system that enhances privacy and safety in elderly care by replacing individuals with 2D avatars using YOLOv8 for real-time detection and pose estimation. Its fall detection mechanism, powered by a residual causal convolutional network, achieves high accuracy (98.86%) and low false-positive rates, as demonstrated on LE2I and URFD datasets. By prioritizing privacy through subject anonymization, the system addresses ethical concerns, fostering user acceptance. While limitations in 2D avatar representation for complex movements are noted, future work aims to integrate 3D modeling and refined algorithms, making this approach a significant step forward in elderly care technology.

4.4 Quantitative Metrics

Table 1 summarizes the performance metrics of the proposed system compared to existing methods. The evaluation includes sensitivity to posture changes, alert generation accuracy, and robustness in diverse environmental conditions. The system achieved a detection accuracy of 93.5% in identifying motionless states, which aligns well with the standards observed in prior studies.

Table 1. Comparison of the performance metrics

Metric	Proposed System	Ciprian et al. (2023) [30]	Martins et al. (2020) [31]	Wang et al. (2024) [32]
Detection Accuracy	93.5%	90%	Not Reported	96.23%
Alert Confirmation Rate	85%	80%	80%	92.56%
Real-Time Alert Capability	Yes	No	Yes	Yes

While the system's performance was strong in controlled environments, certain challenges were observed:

1. Occlusion: Performance slightly declined when the subject was heavily occluded.

2. Dynamic Backgrounds: Although stable backgrounds enhanced detection accuracy, highly dynamic ones introduced noise.

3. Lighting Variability: Extreme changes in lighting occasionally affected detection, although grayscale preprocessing mitigated this to a degree.

The experimental results indicate that the proposed system is effective in real-time detection and monitoring of elderly individuals, addressing immediate safety concerns. Its ability to handle diverse scenarios, coupled with a relatively high detection accuracy and alert confirmation rate, underscores its potential for real-world applications. By integrating advanced posture classification techniques with alert systems, the framework paves the way for enhanced elderly care solutions, complementing existing methodologies while addressing critical gaps in real-time monitoring.

5. Conclusion

This paper presents a novel system for detecting non-responsive states in humans by leveraging the integration of image processing, optical flow analysis, and traditional machine learning techniques. The proposed framework is designed to identify subjects in a non-responsive or triggering posture, such as sitting or lying down for extended periods, while maintaining computational efficiency. Unlike deep learning or neural network-based approaches, which often demand high computational resources, the system utilizes lightweight algorithms that can be trained and validated on standard CPUs. This ensures broader accessibility and reliability, particularly in scenarios where advanced hardware infrastructure is unavailable.

The framework achieves its objectives by employing a combination of video processing and traditional machine learning methods to detect and monitor postures in real-time. By avoiding the computational complexity associated with deep learning models, the framework remains resource-efficient and scalable. This design choice ensures that the system is both cost-effective and practical for use in applications requiring real-time responsiveness without relying on specialized hardware.

However, the current implementation has certain limitations. The reliance on motionless backgrounds restricts the system's deployment to static environments, as it struggles to maintain performance in dynamic settings with varying background motion. Additionally, standard image processing techniques face challenges in accurately detecting multiple individuals in a frame, particularly when occlusions occur or the subjects overlap. These limitations reduce the system's versatility and highlight the need for enhancements to improve robustness and adaptability.

Future iterations of the proposed system could address these challenges by incorporating advanced noise-reduction algorithms and more sophisticated motion-tracking techniques. Improved filtering methods, such as Kalman filtering or particle filters, could enhance the accuracy of motion detection in noisy environments. Moreover, adopting more advanced optical flow algorithms, like dual TV-L1 or pyramid-based approaches, may increase the reliability of motion tracking in complex scenarios.

For applications requiring the detection of multiple subjects or operation in dynamic environments, integrating features such as multi-person pose estimation or employing pre-trained models as supplementary tools could significantly enhance performance. These enhancements would allow the system to maintain accuracy even in crowded or cluttered frames. Additionally, the integration of adaptive learning mechanisms or hybrid approaches that combine traditional machine learning with lightweight neural network architectures could further boost the system's flexibility and robustness.

By addressing these areas of improvement, the proposed system has the potential to evolve into a more versatile solution for non-responsive state detection, catering to a broader range of environments and scenarios. Its foundational design, emphasizing computational efficiency and accessibility, provides a solid platform for continued innovation in real-time human posture analysis and monitoring systems.

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