A Vision-Based System for Monitoring Elderly People at Home

Objective:

The study introduces a computer vision-based system to monitor elderly individuals, aiming to enhance their independence and safety at home. The system avoids intrusive sensors, instead relying on RGB cameras and advanced action recognition models to detect daily activities and alert caregivers about potentially hazardous situations.

Key Contributions:

1. **Action Recognition Dataset: ALMOND**
    - Developed the *Assisted Living Monitoring Dataset (ALMOND)* by aggregating and curating samples from existing datasets like IXMAS, NTU, UWA3D, MSR Daily Activity 3D, and N-UCLA.
    - Defined three groups of actions tailored for elderly care:
        - **Status Actions**: Poses like sitting, standing, lying, walking.
        - **Alerting Situations**: Potentially hazardous actions such as falling, vomiting, sneezing, or waving for help.
        - **Daily-Life Actions**: Common household activities like eating, reading, or using a phone.
    - Addressed dataset limitations such as imbalanced data by balancing training sets and ensuring diverse environmental conditions.
2. **Proposed Monitoring Approach:**
    - **Subject Localization**:
        - Used Faster R-CNN, fine-tuned to detect subjects even in lying or unconventional positions by augmenting training data with rotated images.
        - Achieved improved accuracy for detecting subjects in various poses and orientations.
    - **Action Recognition**:
        - Evaluated two architectures: I3D (3D convolutional neural network) and DeepHAR (pose-based model).
        - Designed a multi-branch network for independent classification of Status, Alerting, and Daily-Life actions.
        - I3D outperformed DeepHAR, achieving 97% accuracy for Status actions, 83% for Alerting situations, and 71% for Daily-Life actions.
3. **Experimental Validation:**
    - Conducted extensive testing on ALMOND.
    - Results highlighted challenges in distinguishing similar actions (e.g., drinking vs. eating) and suggested improvements for action generalization.

    - Demonstrated the importance of subject size (in pixels) in video frames for reliable classification, offering guidelines for camera placement (e.g., maximum distance of 6m for optimal recognition).
4. **Client-Server System Design:**
    - Developed a practical application for caregivers to monitor activities:
        - Video and action data are processed on the server.
        - A web interface provides multiple views:
            - **Timeline View**: Enables browsing specific periods and events.
            - **Storyboard View**: Summarizes actions visually.
            - **Statistics View**: Aggregates data for broader insights.
        - Customizable alerts notify caregivers of emergencies in real-time.

Highlights and Results:

- The system is non-intrusive and suitable for real-world application, avoiding wearable devices.
- Fine-tuned models for elderly-specific scenarios achieved robust performance.
- Recognized the need for better handling of overlapping or ambiguous actions in datasets.
- Demonstrated the effectiveness of real-time monitoring with minimal false positives.

Future Directions:

- Integration of multi-camera systems for comprehensive coverage and subject re-identification.
- Ensuring privacy compliance through anonymization techniques.
- Expanding the ALMOND dataset with more diverse samples, including elderly-specific movements.
- Exploring lightweight models for edge-device deployment.

Conclusion:

The proposed vision-based system effectively balances autonomy and safety for elderly individuals. It offers caregivers real-time insights and alerts while being unobtrusive and easy to implement. The study sets a foundation for future advancements in assisted living technologies.

A Machine Learning Based System for Fall Detection and Elderly Care

Objective:

The study proposes a dual-approach fall detection system combining **Inertial Measurement Units (IMU)** and **computer vision (CV)** methods, integrating these approaches through an ensemble model. It aims to enhance the accuracy, sensitivity, and robustness of fall detection systems, addressing a significant need for elderly safety and well-being.

Key Contributions:

1. **Dual-Approach Fall Detection**:
    - **IMU-based System**: Utilizes accelerometer data to detect sudden changes in motion indicative of falls.
    - **Computer Vision System**: Employs visual analysis of body movements using Histogram of Oriented Gradients (HOG) features and Random Forest classification.
    - **Ensemble Model**: Combines predictions from both approaches through a soft voting classifier, leveraging their complementary strengths.
2. **Real-World Dataset Creation**:
    - **IMU Dataset**: Collected acceleration data from wearable devices during normal activities and simulated falls, resulting in 240,000 data points.
    - **CV Dataset**: Generated 20,000 images from video footage of participants performing various activities, including falls, recorded at different angles and distances.
3. **Implementation for Real-Time Use**:
    - System deployed on a Jetson Nano computing board for real-time fall detection and alerts.
    - Alerts include audio notifications and text messages sent to caregivers.

Methodology:

1. **IMU-Based Approach**:
    - Uses the MPU-6050 sensor to measure acceleration along three axes (X, Y, Z) and an ESP8266 microcontroller for processing.
    - Features extracted from acceleration data (e.g., mean values) are classified using a Random Forest algorithm.
    - Designed as a wearable wrist device, the casing was tested for durability and comfort using SOLIDWORKS simulations.
2. **Computer Vision-Based Approach**:

    - Video recordings of participants performing normal and abnormal activities were analyzed.
    - HOG features were extracted to represent edge and gradient information from frames.
    - A Random Forest classifier was trained to distinguish between activities such as standing, walking, and falling.
3. **Ensemble Model**:
    - Fuses predictions from the IMU and CV models using a soft voting mechanism, improving overall accuracy and robustness.
    - The ensemble approach balances sensitivity (recall) and precision, minimizing false alarms.

Results and Performance Analysis:

1. **IMU-Based System**:
    - Achieved an average accuracy of **96.8%**, with fall detection accuracy at **98%**.
    - Decision-making time: **400 milliseconds**.
2. **Computer Vision-Based System**:
    - Achieved an average accuracy of **95.6%**, with fall detection accuracy at **96%**.
    - Decision-making time: **1.2 seconds**.
3. **Ensemble Model**:
    - Outperformed individual systems with an accuracy of **97%**.
    - Precision and recall were balanced at **96%**, with an F1 score of **97%**.
    - Decision-making time: **1.5 seconds**.
4. **Real-World Testing**:
    - Conducted on five elderly participants in controlled environments using three cameras and wearable devices.
    - Systems were tested on 200 scenarios, including 150 normal activities and 50 falls, demonstrating high reliability and minimal false positives.

Significance:

- The system provides **real-time fall detection**, ensuring prompt alerts for caregivers.
- By integrating IMU and CV approaches, it achieves a high degree of accuracy and reduces the likelihood of false alarms.
- The study highlights the potential for scalable, cost-effective solutions in elderly care, enhancing their independence and safety.

Limitations and Future Work:

1. **Dataset Diversity**:
    - The study involved a limited sample size of five participants. Future research should expand datasets to include diverse populations and real-world scenarios.
2. **Environmental Constraints**:
    - The CV system depends on controlled lighting and camera angles, which might limit its effectiveness in unstructured environments.
3. **Privacy Concerns**:
    - The CV system requires video recording, raising potential privacy issues. Incorporating anonymization techniques could address this.

Conclusion:

This innovative fall detection system effectively integrates IMU and CV methods, achieving high accuracy (97%) and sensitivity. Its real-time deployment capability and robust performance make it a valuable tool for enhancing elderly care. The study paves the way for further advancements in healthcare technologies for vulnerable populations.