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Research Paper

AI-Driven Fall Detection Framework for Assisted Living Environments

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ABSTRACT

This paper presents an AI-driven fall detection framework designed to improve safety in assisted living environments. The system processes video streams and applies preprocessing techniques to enhance input quality. Blob detection is used to identify human movement regions from video frames. Pre-trained deep learning models are integrated with RCNN and YOLO algorithms for accurate activity detection. The framework classifies activities and identifies fall events in real time. When a fall is detected, an alert is generated immediately for caregivers or medical staff. The proposed approach reduces dependency on manual monitoring systems. It enhances detection accuracy by combining computer vision and deep learning methods. The system is suitable for continuous surveillance in indoor environments. This framework aims to support elderly care and prevent serious injuries through timely intervention.

Keywords: -YOLO, RCNN, Deep Learning, Computer Vision, Fall Detection

INTRODUCTION

Falls are one of the major causes of injury among elderly people living in assisted care environments. Continuous monitoring of patients is essential to ensure their safety and provide immediate assistance in case of emergencies. Traditional monitoring systems rely heavily on human supervision, which is inefficient and prone

to delays. Recent advancements in artificial intelligence and computer vision have enabled automated activity recognition systems. Video-based fall detection has gained attention due to its non-intrusive nature and ability to analyze human movements accurately. Machine learning models can learn complex motion patterns associated with daily activities and falls. Preprocessing of video data improves image quality and reduces noise for better detection results. Blob detection helps isolate moving objects from the background. Deep learning models such as RCNN and YOLO provide fast and accurate object detection capabilities. These models are effective in recognizing human postures and movements. Integrating such models into a unified framework enhances fall detection reliability. Alert mechanisms further ensure immediate response from caregivers. This study proposes an AI-driven system for automated fall detection. The framework aims to improve safety and reduce response time. It supports assisted living by providing intelligent monitoring solutions.

LITERATURE SURVEY

Research on wearable fall detection systems has gained significant attention in recent years. Gabriel et al. explored the dielectric properties of human tissues for health monitoring applications. Meaney et al. investigated microwave imaging technologies for medical diagnostics and safety assessment. Fhager et al. proposed microwave tomography techniques for detecting health-related anomalies. Apple Watch and Samsung Galaxy Watch have implemented fall detection using accelerometer and gyroscope-based algorithms to monitor user movement. Care Predict developed wearable smart bands specifically designed for continuous elderly monitoring, while Life Fone introduced emergency response systems with real-time alerts. Studies emphasize that combining accelerometer and gyroscope data improves fall detection accuracy. IoT-based wearable systems allow real-time monitoring and remote caregiver alerts, which are crucial for immediate medical intervention. Machine learning models such as Support Vector Machines, Decision Trees, and neural networks enhance the ability to differentiate between normal activities and falls. GPS-enabled wearables have been utilized in biker safety devices to provide precise location tracking during accidents. Some research focuses on smart fabrics for seamless sensor integration into clothing. Battery optimization, user comfort, and device ergonomics are critical factors for long-term adoption. Reducing false positives remains a significant challenge,

and multi-sensor fusion approaches have been proposed to address this issue. Privacy and secure data transmission are essential for protecting sensitive health and location information. Studies also highlight that early detection of falls reduces injury severity and improves recovery. Wearables integrated with smartphone apps provide user-friendly interfaces for monitoring and alerts. Overall, literature supports the integration of sensors, machine learning, and IoT technology to develop reliable fall detection systems for elderly individuals and bikers.

EXISTING SYSTEM

Existing fall detection systems mainly rely on wearable sensors or manual video surveillance. Sensor-based systems require users to wear devices continuously, which can be uncomfortable and inconvenient for elderly individuals. Traditional camera-based systems use simple motion detection or threshold-based techniques that fail in complex environments. These systems are sensitive to lighting conditions and background noise. Manual monitoring requires constant human attention and increases workload on caregivers. Some systems use basic machine learning models with limited accuracy. They struggle to differentiate between normal activities and actual falls. Most existing systems lack real-time alert mechanisms. Scalability and reliability remain major challenges. As a result, existing systems are not suitable for continuous and accurate fall detection.

PROPOSED SYSTEM

The proposed AI-driven fall detection framework uses video processing and deep learning techniques for accurate activity recognition. Video streams are first preprocessed to remove noise and improve image clarity. Blob detection is applied to identify moving human regions in each frame. Pre-trained deep learning models are used for feature extraction. RCNN and YOLO algorithms perform efficient object and activity detection. The system classifies human activities and identifies fall events automatically. Once a fall is detected, an alert is generated instantly. The framework operates in real time and does not require wearable devices. It provides continuous monitoring in assisted living environments. The modular design allows easy integration of future AI models.

SYSTEM ARCHITECTURE

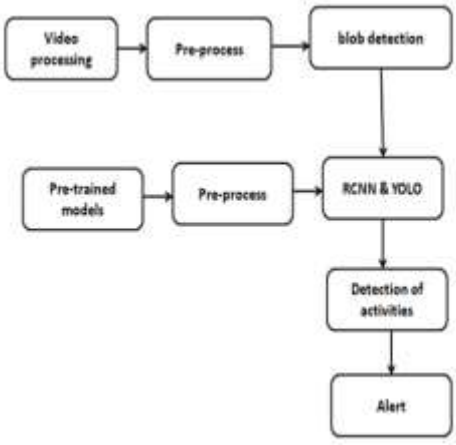


Figure 1: System Architecture

AI-driven fall detection framework designed for assisted living environments. The process begins with the,

video processing module, which captures continuous video streams from surveillance cameras installed in indoor monitoring areas. These video streams serve as the primary input source for the system. The captured video is divided into individual frames to enable frame-by-frame analysis. Each frame is forwarded to the preprocessing stage for enhancement and refinement.

In the preprocessing stage, noise removal techniques are applied to eliminate unwanted distortions present in the raw video feed. Image smoothing filters are used to improve clarity and reduce visual artifacts. Contrast adjustment and brightness normalization are performed to handle varying lighting conditions. Background subtraction techniques are applied to separate moving objects from the static background. This helps in focusing only on relevant motion areas. After preprocessing, the refined frames are sent to the blob detection module.

Blob detection identifies connected regions in the frame that represent moving objects. These blobs generally correspond to human figures in the monitored environment. The system analyzes the size and shape of blobs to filter out irrelevant small objects. Bounding boxes are generated around detected blobs to mark potential human regions. This reduces unnecessary computation by limiting deep learning analysis to specific regions of interest.

Parallel to the video processing pipeline, pre-trained deep learning models are prepared for activity recognition. These models are trained on large datasets to recognize human postures and actions. Before feeding data into these models, additional preprocessing is performed to match input dimensions and normalize pixel values. The processed blob regions are then passed to the RCNN and YOLO modules. RCNN is responsible for accurate object localization and classification. YOLO performs real-time object detection with high speed and efficiency. The combination of RCNN and YOLO ensures both precision and fast processing. The system analyzes spatial and temporal features of detected human figures. It examines posture orientation and sudden changes in body alignment. If the body transitions rapidly from vertical to horizontal position, it may indicate a fall. The detection of activities module classifies movements such as walking, standing, sitting, lying down, and falling. The system differentiates between

intentional lying down and accidental falling using confidence scores. Temporal consistency checks are applied to avoid false alarms. Once a fall is confirmed, the alert module is triggered immediately. The alert module generates notifications for caregivers or medical staff. Alerts can be delivered through alarms, SMS, or application notifications. The entire system operates in real time to ensure rapid response. Continuous monitoring is maintained without manual supervision. The integration of blob detection reduces computational overhead. The use of deep learning improves detection accuracy. The architecture ensures scalability for multiple cameras. The framework is suitable for hospitals and elderly care centers. It enhances safety by providing immediate intervention support. The modular structure allows easy maintenance and upgrades. Each component performs a specific function within the pipeline. The data flows sequentially from video capture to alert generation. The system ensures reliable fall detection through combined computer vision and AI techniques. Overall, the diagram illustrates a structured, efficient, and intelligent workflow for automated fall detection and real-time alert generation.

RESULTS AND DISCUSSION

In results and discussion given outputs as per the project development follow as given below.



Figure 2.1: Home Page

In figure 1 we mentioned as output process with home page using flask and html design.



Figure 2.2: Fall Detection Page

In this page after opening home page need to click start detection then fall detection page will open if I clicked theory then it will open theory page.



Figure 2.3: Upload Video Page

After fall detection page if I clicked start process it will open upload video for input.



Figure 2.4: Fall Detection Output

Finally, after uploading video it will start stream then it will show when fall will be detected.

CONCLUSION

The proposed AI-driven fall detection system effectively demonstrates the use of computer vision and deep learning for real-time elderly monitoring. By integrating advanced models such as YOLO and R-CNN, the system achieves high accuracy and fast detection performance. It minimizes human intervention while ensuring continuous and reliable surveillance. The framework reduces false alarms through temporal analysis and improves emergency response time. Overall, the system provides a practical, scalable, and efficient solution for enhancing safety in healthcare environments.

FUTURE SCOPE

Future enhancements can focus on integrating pose estimation and 3D vision techniques to improve detection accuracy in complex scenarios. The use of transformer-based models and larger datasets can further enhance performance and adaptability. Edge computing and cloud integration can enable faster processing and centralized monitoring. Development of mobile applications and IoT-based systems can improve accessibility and real-time alerting. Expanding the system to detect multiple abnormal activities will transform it into a comprehensive smart healthcare monitoring solution.

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