Intelligent Video-Based Fall Surveillance System for Elderly Safety

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ABSTRACT

Elderly people and those who need constant attention are more vulnerable to falls. A real-time vision-based fall detection system utilizing deep learning and human position estimate methods is presented in this study. The suggested method combines MediaPipe Pose for skeletal landmark extraction from video frames with the YOLOv8 model for precise human detection. Using a rule-based decision procedure with time-based validation to minimize false alarms, fall events are detected by examining posture changes and body orientation. The device immediately produces audible and visual alarms when a fall is confirmed. A non-intrusive and effective solution for healthcare monitoring, the system is developed as a Flask-based web application that supports both live video streaming and recorded video analysis.

Keywords: Fall Detection, Computer Vision, Deep Learning, YOLOv8, Human Pose Estimation, MediaPipe, Real-Time Monitoring, Healthcare Applications, Vision-Based System, Non-Intrusive Monitoring.

INTRODUCTION

Falls are a serious safety risk, especially for patients and the elderly who need constant supervision. In order to lower the risk of serious injuries and guarantee prompt medical attention, falls must be detected as soon as possible. Conventional fall detection techniques frequently depend on manual supervision or wearable sensors, which can be uncomfortable, invasive, or unreliable. Because they are non-intrusive, vision-based fall detection systems have attracted a lot of attention as a solution to these problems. This research detects falls in real time using deep learning and computer vision technology. The YOLOv8 deep learning model is used to quickly and accurately identify people in video frames. Important human body landmarks are extracted for posture analysis using MediaPipe Pose. The system can successfully differentiate fall incidents from typical activities by examining body posture and movement patterns. The Flask framework is used to develop the solution as a web-based application that allows for real-time monitoring via submitted video analysis and live video streaming.

LITERATURE REVIEW

In order to increase accuracy and real-time performance, recent research in vision-based fall detection has concentrated on utilizing position estimation and deep learning algorithms. A non-intrusive method appropriate for real-time monitoring applications in healthcare settings is provided by Adithya et al.'s "Human Fall Detection Algorithm for the Elderly Based on Posture Estimation," which uses YOLO for object detection and posture analysis from video frames to distinguish between normal activities and falls. Similar to this, Khawam, Al-Hashimi, and Abdulateef created a "Real-Time Fall Detection for the Elderly in Home Settings Using a Vision-Based YOLOv8-Pose Model," which combines skeletal keypoint extraction and human detection to detect falls with high accuracy and low false positives, proving efficacy in home-like settings with a useful automatic alert mechanism. By comparing various YOLO versions and integrating pose estimation, Ye's work on "Elderly Fall Detection Based on YOLO and Pose Estimation" achieved dependable real-time fall identification by tracking motion patterns, highlighting the significance of effective keypoint tracking for differentiating falls from other activities. Furthermore, hybrid techniques like Liu et al.'s modified YOLOv8s and AlphaPose method improve multi-person fall detection by enhancing skeletal analysis and small object recognition, pointing to areas for further improvements in speed and robustness. Together, these research show that vision-based deep learning systems that incorporate pose estimation and object detection offer potential solutions for precise and scalable fall detection in practical healthcare applications.

RELATED WORK

Vision-based fall detection systems have emerged as effective non-intrusive solutions for healthcare monitoring. Adithya *et al.* proposed a posture-based fall detection system using the YOLO object detection model, demonstrating improved accuracy over traditional sensor-based approaches. Khawam *et al.* introduced a real-time fall detection framework integrating YOLOv8 with pose estimation to detect humans and extract skeletal keypoints simultaneously. Their results showed reduced false alarms and reliable performance in home environments. Ye presented a YOLO and pose-based fall detection system that analyzed body orientation to distinguish falls from daily activities. Liu *et al.* further enhanced fall detection accuracy by combining a modified YOLOv8s model with AlphaPose for robust skeletal analysis in multi-person scenarios. These studies confirm that integrating deep learning-based object detection with human pose estimation provides accurate and efficient fall detection

EXISTING METHOD

Existing fall detection methods mainly use computer vision techniques combined with posture estimation to identify fall events. In the work by Adithya *et al.*, YOLO-based human detection is used along with posture analysis to detect falls. Although this approach is non-intrusive, it relies on fixed posture thresholds, which may not adapt well to different body types and camera perspectives. The system shows reduced accuracy under poor lighting conditions and partial occlusions. It also has limitations in handling multiple people within the same frame. Rapid movements such as sitting or bending may be incorrectly classified as falls. Additionally, the absence of strong temporal validation can increase false positives.

PROPOSED METHOD

The proposed method enhances existing fall detection approaches by integrating advanced deep learning and pose estimation techniques. The YOLOv8 model is used for accurate and real-time human detection in video frames. MediaPipe Pose extracts detailed skeletal landmarks to analyze body posture and orientation. A time-based validation mechanism is applied to reduce false detections caused by temporary movements. The system supports both live video streaming and recorded video analysis. It is implemented as a Flask-based web application for easy access and monitoring.

SYSTEM ARCHITECTURE

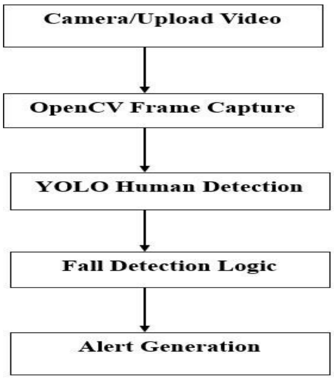

Fig 1: Block Diagram

METHDOLOGY DESCRIPTION

The suggested fall detection system uses a non-intrusive, vision-based approach to track human activity in real time. The system first records input from either a pre-recorded video or a live camera stream. The YOLOv8 deep learning model is used to process each video frame in order to precisely identify and locate human subjects. MediaPipe Pose is used to extract important skeletal markers after a person has been identified, allowing for accurate posture and orientation analysis. Throughout successive frames, the system continuously tracks variations in posture angles, movement patterns, and body alignment. In order to reduce false positives, a time-based validation method is integrated to differentiate real fall occurrences from transient behaviors like bending or sitting. The technology initiates a notification system and creates visual alerts when a fall is verified. A Flask-based web application is used to implement the complete workflow, offering user interaction, system control, and real-time visualization in an effective and scalable way.

RESULTS AND DISCUSSION

Fig 2 : Home Page

The home page loads successfully and allows smooth navigation to other modules of the system.

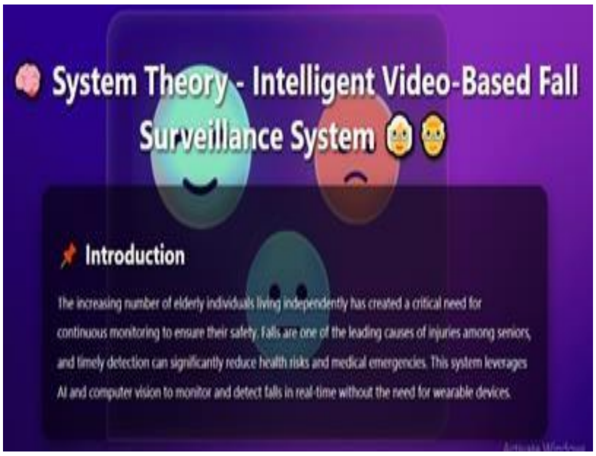

Fig 3: System Overview Page

The overview page clearly communicates the purpose and functionality of the system, helping users understand the detection process before execution.

Fig 4: Fall Detection Page

The page provides clear options and enables smooth selection of detection modes.

Fig 5: Video Upload Page

When a person is standing or walking, the system displays a green bounding box with the label “**Normal**”. When a fall occurs, the system displays a red bounding box with the label **“Fall Detected”**. The system correctly differentiates between normal posture and fall posture.

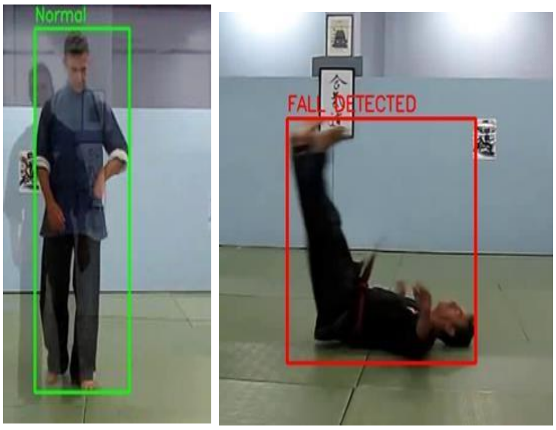

Fig 6: Normal Activity and Fall Detected Activities

The system accurately detects fall events from uploaded videos and visually distinguishes them from normal activities

Fig 7: Live Stream Fall Detection with Multi Person

The system demonstrates stable performance and accurate detection during continuous live monitoring

CONCLUSION AND FUTURE ENHANCEMENT

The proposed vision-based fall detection system successfully demonstrates a non-intrusive and real-time approach for monitoring human activities using deep learning techniques. By integrating YOLOv8 for human detection and MediaPipe Pose for posture analysis, the system achieves accurate fall identification with reduced false alarms. The time-based validation mechanism further enhances reliability by differentiating falls from normal movements. The web-based implementation ensures ease of use and real-time visualization. In the future, the system can be enhanced by incorporating

multi-camera support for wider coverage. Integration with mobile applications and cloud-based alert services can improve accessibility. Advanced temporal models such as LSTM can be used for better activity prediction. The system can also be extended for elderly care and smart healthcare environments.

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