ISSN 2319-5991 www.ijerst.com
© 2026 IJERST. All Rights Reserved
Peer Reviewed, Referred & Indexed Journal

Research Paper

Ai-Driven Fall Detection Framework for Assisted Living Environments

[1]Yadavalli Koteswara Rao, [2]Dr. M. Lakshmana Rao
[1]M. Tech Student, Department of CSE, Prakasam Engineering College (Autonomous), Kandukur, India
[2]Professor, Department of CSE, Prakasam Engineering College (Autonomous), Kandukur, India

ABSTRACT- ***The project presents an AI-Driven Fall Detection Framework for Assisted Living Environments to improve the safety of elderly people. Falls are a major cause of injuries and hospitalization among older adults, making continuous monitoring important. The proposed system uses artificial intelligence and video-based monitoring to detect falls without requiring wearable devices. Initially, video frames are preprocessed using noise removal, contrast adjustment and background subtraction. Blob detection, RCNN and YOLO algorithms are used to identify people and classify activities such as walking, sitting, standing, lying down and falling. Temporal analysis helps distinguish accidental falls from normal activities and reduces false alarms. Immediate alerts notify caregivers or medical staff when a fall occurs.***

KEYWORDS: - Fall Detection, Artificial Intelligence, Deep Learning, Computer Vision, YOLO.

INTRODUCTION

Falls are a major health concern among elderly people and can cause serious injuries and disability. Continuous monitoring is important in hospitals and nursing homes, but manual monitoring is difficult for caregivers. Traditional systems use wearable devices, which may cause discomfort and require regular charging. To overcome these limitations, the proposed system uses Artificial Intelligence and computer vision to detect falls through video surveillance. Video preprocessing and blob detection identify moving human regions, while RCNN and YOLO algorithms recognize activities such as walking, sitting, standing and falling. Temporal analysis helps reduce false alarms. When a fall is detected, an immediate alert is sent to caregivers for quick assistance, improving elderly safety.

RELATED WORK

Previous fall detection systems mainly used wearable sensors such as accelerometers and gyroscopes, but they faced discomfort and battery limitations. Later, computer vision techniques like background subtraction and

motion detection were introduced. Machine learning algorithms such as SVM, Decision Trees and Random Forest improved activity classification but required manual feature extraction. Deep learning techniques such as CNN improved activity recognition, while RCNN provided accurate object localization and YOLO enabled real-time detection. Recent approaches use LSTM, pose estimation and multi-camera systems to improve accuracy. However, challenges like poor lighting, occlusion and false alarms still exist.

LITERATURE SURVEY

Previous studies explored wearable sensors and computer vision techniques for fall detection. Machine learning algorithms like SVM and Decision Trees improved activity classification. Recent deep learning models such as CNN, RCNN and YOLO provide better human detection and real-time recognition. However, poor lighting, occlusion and false alarms remain major challenges. The proposed system combines preprocessing, blob detection, RCNN and YOLO to improve fall detection and generate immediate alerts.

EXISTING METHOD

The existing fall detection methodology mainly uses wearable sensors, CCTV cameras and traditional machine learning techniques to identify accidental falls. Wearable devices such as accelerometers and gyroscopes detect sudden changes in body movement and orientation. Manual CCTV monitoring allows caregivers to observe elderly people through video recordings. Some systems use background subtraction, motion detection and handcrafted features to recognize human activities. Machine learning algorithms such as Support Vector Machine (SVM) and Decision Trees are also used for activity classification. However, these methods have limitations, including user discomfort, battery problems, false alarms, poor lighting conditions and delayed responses. Therefore, an improved AI-based fall detection system is needed to provide accurate and real-time monitoring without depending on wearable devices.

PROPOSED METHOD

The proposed system is an AI-based fall detection framework designed to monitor elderly people in indoor environments without using wearable devices. It uses surveillance cameras to capture video continuously and applies computer vision techniques to identify human activities. Initially, the captured video is divided into frames and preprocessed through noise removal, image smoothing, contrast adjustment and background subtraction to improve image quality. Blob detection is then applied to identify moving human regions and separate them from the background. Pre-trained deep learning

models, along with RCNN and YOLO algorithms, are used to detect people and recognize activities such as walking, standing, sitting, lying down and falling. Temporal analysis examines movements across consecutive frames, while confidence scores help distinguish actual falls from normal activities and reduce false alarms. Whenever a fall is detected and confirmed, the system automatically sends an alert to caregivers or medical staff, helping them provide timely assistance. This approach provides continuous, non-intrusive and efficient monitoring in hospitals, nursing homes and assisted living environments.

SYSTEM ARCHITECTURE

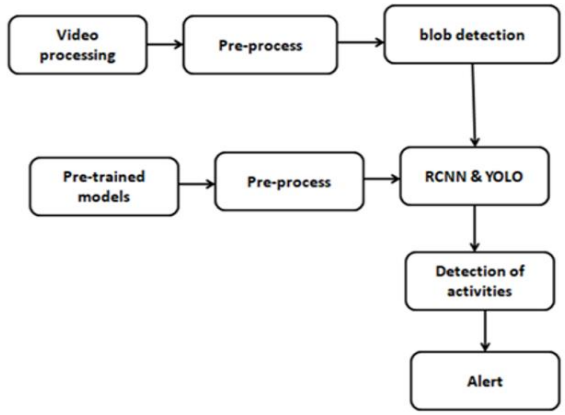

Fig. 1. Overall system architecture of the AI-driven fall detection framework using RCNN and YOLO.

METHODOLOGY DESCRIPTION

Data Collection: Data collection is the initial stage of the proposed fall detection system. Video sequences are collected from indoor surveillance cameras, public datasets and custom recordings. The collected videos contain different human activities, such as walking, sitting, standing, lying down and falling. The dataset includes variations in lighting conditions, camera angles, human movements and different environments. Frame-level labels are used to identify activities, while bounding boxes mark human regions. These collected video samples are used for training, validation and testing the proposed fall detection model to improve its accuracy and reliability.

Data Pre-processing Module: The data preprocessing module improves the quality of collected video frames before applying fall detection algorithms. Initially, video frames are extracted from the input video and processed to remove unwanted noise. Image smoothing techniques are applied to reduce noise and improve frame clarity. Contrast and brightness adjustments are performed to handle different lighting conditions. Background subtraction is used to separate moving objects from the background. These processed frames help blob detection identify human movement regions more effectively and improve the accuracy of the fall detection system.

Data Splitting Module: The data splitting module divides the collected and preprocessed dataset into three parts: training data, validation data and testing data. Training data is used to train the deep learning models, while validation data helps monitor model performance and adjust parameters. Testing data is used to evaluate

the model's performance on unseen video samples. The dataset is divided with balanced fall and non-fall activities to improve classification performance and reduce overfitting. This process helps ensure reliable and accurate fall detection.

Training Data: Training data is used to teach the deep learning models to identify and recognize different human activities. The collected video frames are provided as input to the models, including RCNN and YOLO. The training data contains activities such as walking, sitting, standing, lying down and falling. Bounding boxes are used to identify human regions, and data augmentation techniques such as rotation, scaling and flipping are applied to improve model learning. This process helps the system recognize fall patterns and distinguish normal activities from accidental falls with better accuracy.

Model Building Module: The model building module develops the fall detection system using pre-trained deep learning models. RCNN and YOLO algorithms are integrated to detect human objects and recognize different activities. RCNN provides accurate human localization, while YOLO enables fast and real-time detection. The models are prepared using resized and normalized video frames.

They learn different activity patterns and identify abnormal movements. This module helps improve fall detection accuracy and supports quick identification of accidental falls.

Testing Module: The testing module evaluates the performance and accuracy of the trained fall detection model using unseen video data. The test videos are provided as input to identify different human activities, such as walking, sitting, standing, lying down and falling. The model's predictions are compared with the actual labels to measure its performance. Evaluation metrics such as accuracy, precision, recall and F1-score are used to analyze the results. This module helps identify errors, reduce false alarms and ensure reliable fall detection in real-time environments.

Predictions Module: The prediction module identifies human activities from the processed video frames using trained RCNN and YOLO models. It predicts activities such as walking, sitting, standing, lying down and falling. The system analyzes the detected movements using confidence scores and temporal analysis to identify possible falls.

If a fall is confirmed, an immediate alert is generated and sent to caregivers or medical staff. This module helps provide quick assistance and improves the safety of elderly people in assisted living environments.

RESULTS AND DISCUSSION

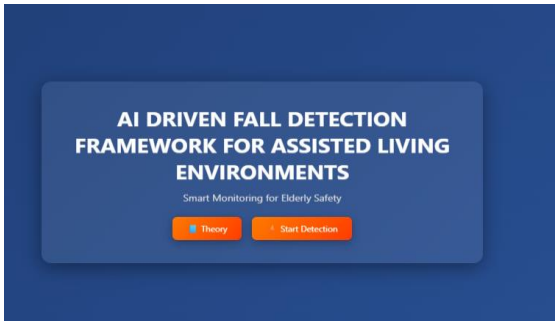

Fig. 2: Home Page of the AI-Driven Fall Detection Framework

The home page is the main entry point of the system. It shows the project title and gives access to the *Theory* and *Start Detection* modules.

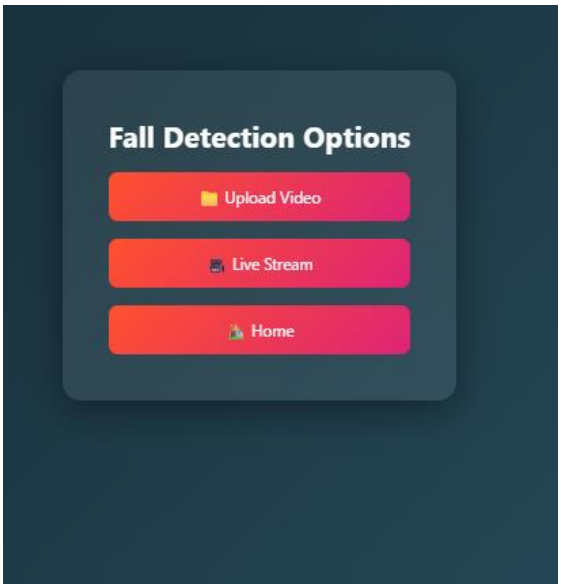

Fig. 3: Fall Detection Options Page

This page lets the user choose the input source for detection: *Upload Video* for recorded footage or *Live Stream* for real-time monitoring. A *Home* button returns to the main page.

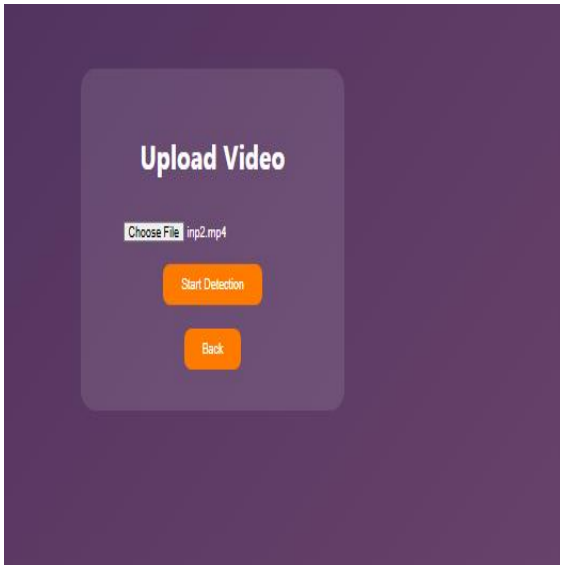

Fig. 4: Video Upload Page

This page lets the user select a recorded video file (e.g., *inp2.mp4*) and click *Start Detection* to analyze it for fall events. A *Back* button returns to the options page.

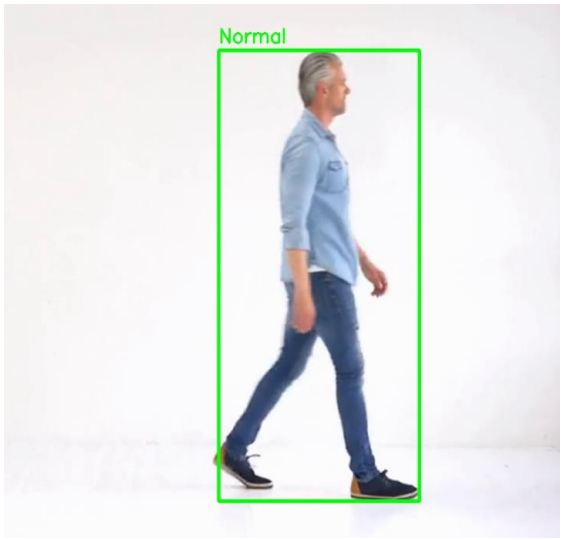

Fig. 5: Normal Activity Detection Output

The system detects the person walking and marks them with a green bounding box labeled *"Normal"*, which means no fall event is detected.



Fig. 6: Fall Detection Output

The system detects the sudden change in body posture and marks the person with a red bounding box labeled *"FALL DETECTED"*, which indicates that a fall event has occurred.

CONCLUSION

The proposed AI-driven fall detection framework provides an intelligent and non-intrusive solution for monitoring elderly people. It combines video preprocessing, blob detection, RCNN and YOLO algorithms to identify human activities and detect accidental falls. Temporal analysis helps reduce false alarms and improve detection reliability. The system generates instant alerts to caregivers or medical staff when a fall occurs. It reduces dependency on wearable devices and continuous manual monitoring. This framework can be useful in hospitals, nursing homes and assisted living facilities to improve elderly safety and provide timely assistance.

FUTURE SCOPE

The proposed system can be improved in the future by integrating advanced deep learning models and pose estimation techniques for better fall detection accuracy. 3D and depth cameras can be used to reduce occlusion problems and improve human movement tracking. Edge computing can help achieve faster processing and reduce detection delays. Cloud-based dashboards can support monitoring across multiple healthcare facilities. A mobile application can be developed to send instant notifications to caregivers. The system can also be extended to detect wandering, prolonged inactivity and predict fall risks, providing better safety and care for elderly people.

REFERENCES

1. N. Noury et al., "Fall Detection – Principles and Methods," *IEEE Engineering in Medicine and Biology Society*, pp. 1663–1666, 2007.

2. M. Mubashir, L. Shao, and L. Seed, "A Survey on Fall Detection: Principles and Approaches," *Neurocomputing*, vol. 100, pp. 144–152, 2013.

3. R. Girshick et al., "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014.

4. R. Girshick, "Fast R-CNN," *IEEE International Conference on Computer Vision (ICCV)*, 2015.

5. S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object

Detection with Region Proposal Networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, 2017.

6. J. Redmon et al., "You Only Look Once: Unified, Real-Time Object Detection," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

7. World Health Organization, "WHO Global Report on Falls Prevention in Older Age."

8. X. Wang, J. Ellul, and G. Azzopardi, "Elderly Fall Detection Systems: A Literature Survey," *Frontiers in Robotics and AI*, vol. 7, p. 71, 2020.

9. S. S. Khan and J. Hoey, "Review of Fall Detection Techniques: A Data Availability Perspective," *Medical Engineering & Physics*, vol. 39, pp. 12–22, 2017.

10. I. Charfi et al., "Optimised Spatio-Temporal Descriptors for Real-Time Fall Detection: Comparison of SVM and AdaBoost-Based Classification," *Journal of Electronic Imaging*, vol. 22, no. 4, 2013.

11. M. A. Habib et al., "Smartphone-Based Solutions for Fall Detection and Prevention: Challenges and Open Issues," *Sensors*, vol. 14, pp. 7181–7208, 2014.

12. A. Alam et al., "Vision-Based Human Fall Detection Systems Using Deep Learning: A Review," *Computers in Biology and Medicine*, vol. 146, 105626, 2022.

13. X. Gaya-Morey, C. Manresa-Yee, and J. M. Buades-Rubio, "Deep Learning for Computer Vision Based Activity Recognition and Fall Detection of the Elderly: A Systematic Review," *Applied Intelligence*, vol. 54, pp. 8982–9007, 2024.

14. N. T. Newaz and E. Hanada, "The Methods of Fall Detection: A Literature Review," *Sensors*, vol. 23, no. 11, 5212, 2023.

15. "Comprehensive Review of Vision-Based Fall Detection Systems," *Sensors*, vol. 21, no. 3, p. 947, 2021.