Available online at www.qu.edu.iq/journalcm
JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS
ISSN:2521-3504(online) ISSN:2074-0204(print)

Real-Time Fall Detection for the Elderly in Home Settings Using a Vision-Based YOLOv8-Pose Model

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A R T I C L E I N F O

Article history:
Received: 29/06/2025
Rrevised form: 23 /07/2025
Accepted : 05 /08/2025
Available online: 30/09/2025

Keywords:

Fall detection,

computer vision,

YOLO,

Deep learning,

Real-time detection,

Pose estimations.

A B S T R A C T

Fall constitute a significant source of death and morbidity among the elderly, particularly in domestic settings when quick assistance is unavailable. Accurate and timely detection of falls is crucial to prevent associated health repercussions. The study proposes a deep learning-based fall detection model YOLOv8-pose that features simultaneous fall detection and pose estimation. A new dataset was created, including 186 high-resolution videos (1080p, 30 fps) captured by a smartphone camera in the home-like environment simulating falling and everyday activity. The video frames were marked and organized according to the COCO format to attain effective training. We used transfer learning to train the state-of-the-art YOLOv8-Pose model in order to detect falls. The system also analyses human skeletal keypoints in real time to accurately differentiate between fall events and non-fall activities, resulting in strong detection performance and a low false positive rate. An automatic alarm system was implemented to deliver immediate fall alerts to providers using the Telegram messaging bot. The proposed approach is an economical, non-invasive, and highly effective alternative for continuous monitoring of the elderly in a household environment, potentially enhancing safety and reaction time during emergencies. The experimental findings revealed that all of the models did a good job of detecting falls and estimating poses. Larger models, such YOLOv8m-pose, got a 99% accurate mAP@50 and the confusion matrix showed that the model was able to classify falls well, with a very low error rate in classifying other cases, reflecting its high effectiveness in distinguishing between falls, normal falls, and bending. This study found that YOLOv8-Pose is a good model for finding falls in older people since it is fast and accurate. In the future, we want to make the model better at imaging under difficult situations and broadening the model to incorporate more activities.

https://doi.org/10.29304/jqcsm.2025.17.32425

1. Introduction

The speedy advancement of science and technology has resulted in an overall enhancement of healthcare and living standards. Consequently, individuals are experiencing increased longevity in their living environments. Consequently, the ageing of the global population is a universal tendency. The World Health Organization

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(WHO) projects that the worldwide population of those aged 60 and over will reach 2 billion by 2050. The rise in the overall population of older individuals will pose problems to global public health and medical systems [1].

According to WHO statistics data, around 684,000 individuals globally succumb to falls annually, with adults over 60 years of age being the predominant population of deaths from falls. Consequently, the health and safety of the elderly has emerged as a significant priority [2]. Numerous electronic goods pertaining to geriatric health monitoring have been pushed, including smart wristbands and intelligent monitoring systems [3]. There is an urgent necessity to expedite the detection of human falls using advanced technology to prevent the elderly from being left unattended and in need of quick assistance following such incidents [4]. Consequently, preventative measures in the residential environment are of considerable importance [5]. A fall may lead to significant injuries or health issues and hence need prompt action. To address this issue, many strategies and methods have been devised to detect falls promptly and offer immediate aid [6] [7].

Currently, real-time fall detection is primarily categorized into three types: wearable fall detection, environmental fall detection, and computer vision fall detection. The primary issue with the first technique is that older individuals may neglect to wear the device in their daily routines, while the principal drawback of the second way is the exorbitant expense associated with the installation of environmental equipment, along with a usually elevated incorrect estimation rate for both methods.

Fall detection via computer vision is characterized by ease of use, a low rate of incorrect estimation, excellent real-time performance, and several relevant scenarios. Feature extraction methods may be primarily categorized into three types: threshold analysis, machine learning-based detection algorithms, and deep learning-based detection algorithms [8] . This approach is widely favored in fall detection research because of its attributes, including a stationary camera, real-time monitoring by a constant power supply, the absence of wearable devices to prevent external interference, and excellent detection accuracy [9]. This study presents a deep learning-based technique utilizing the YOLO-pose framework for object recognition and location estimation to identify falls among the elderly in domestic settings. Real-life images of falls and natural activities were recorded to ascertain the causes of falls. The dataset was employed to train the YOLO model, and its performance was evaluated using advanced computer vision techniques. This study aims to enhance the precision of real-time fall detection and develop scalable solutions.

One of the most notable contributions of this study is the creation of a custom dataset containing diverse scenes, including falls, bending, and natural motion. A system based on the YOLOv8-Pose model was also developed to accurately detect and track human body motion points, enabling it to record falls in real time. This model was designed to be simple and easy to use, adapting to the home environment and the needs of the elderly.

This study examines initiatives to safeguard older adults at home through the early identification of fall accidents utilizing the YOLOv8-Pose approach. This approach is characterized by its amalgamation of accurate object detection and pose estimation, allowing the identification of an individual's presence and a comprehensive study of body postures to precisely and efficiently identify fall incidents. The research examines the efficacy of this method in fall detection, emphasizing high accuracy and the reduction of mistakes and environmental impacts. An overview of prior experiments and findings concerning fall detection utilizing contemporary deep learning models is presented.

This paper is structured as follows: Section 2 reviews related literature; Section 3 introduces the YOLOv8 pose perspective; Section 4 outlines the methodology; Section 5 details experimental results and discussions; and Section 6 concludes with prospective research directions.

2. Related Work

The issue of fall detection is receiving considerable attention from the scientific community, During the years of study, several methodologies were developed, datasets acquired, and use cases studied. Therefore, the issue of fall detection may be regarded from many viewpoints, depending on the objective application, the hardware employed, and the mathematical approaches applied [10]. In recent years, deep learning has been extensively utilized for posture and human behavior identification [11]. In comparison to conventional manual and sensor-based identification, deep learning provides a more precise and dependable method for addressing challenges such as occlusion and congested environments.

Currently, deep learning-based object identification algorithms may be categorized into one-stage and two-stage frameworks. The two-stage methods encompass R-CNN [12], Fast R-CNN [13], Faster R-CNN [14], and R-FCN [15]; nonetheless, their processing is comparatively intricate, resulting in a sluggish detection speed. The SSD [16] method and the YOLO [17], [18] [19] [20] series exemplify one-stage algorithms, characterized by rapid detection speed, excellent real-time performance, and high accuracy. For example, Kan et al. [21] developed CGNS YOLO for fall detection by modifying the neck network of YOLOv5 by the incorporation of the GSConv module and GDCN module, they employed a normalization-based attention module (NAM) to enhance the method's accuracy. Chen et al. [22] improved the YOLOv5 structure by integrating an expanded Efficient Channel Attention (ECA) network. They used average pooling layers into a Spatial Pyramid Pooling (SPP) network to enhance multi-scale feature extraction. Khan et al. [23] included a focus module into the backbone to enhance feature extraction and strategically integrated Convolutional Block Attention Modules (CBAMs) into an enhanced YOLOV8S model. Furthermore, Qin et al. [24] enhanced the YOLOv8 model by substituting C2f with C2Dv3 modules in the backbone and including a DyHead block in the neck layer to unify various attention operations. Despite significant advancements in deep learning models such as YOLOv8-pose, their real-world application is constrained by substantial computational requirements and the necessity for high-quality data. Their efficacy is heavily dependent on the availability of well-annotated information and optimal operational conditions. YOLOv8-pose has exhibited remarkable accuracy and real-time performance in elderly fall detection, surpassing existing methodologies in both detection speed and reliability. However, practical challenges persist, including variations in lighting, body shapes, and privacy concerns within domestic settings. This research aims to develop an intelligent, cost-effective, and efficient YOLOv8-pose-based fall detection system to facilitate real-time and precise fall detection, thereby enhancing safety for older individuals in home environments and ensuring prompt response.

3. Overview of the YOLOv8-pose model

YOLOv8-pose is a high-performance, real-time model for human posture estimation introduced in 2023 by Ultralytics, part of the YOLOv8 (You Only Look Once) technology family. This model is built on the basic design of a regular YOLOv8 object detection system and improves it by identifying key points on the human body, which is very helpful for tasks that need accurate posture analysis, like detecting falls. [25] [26]. The model pre-processes the images and produces bounding boxes and a pre-specified number of keypoints (usually 17 or 33), their (x, y) coordinates, and a confidence level. The network described in this structure can come up in real-time in relation to inferences of a human skeletal pose in different settings, such as lighting conditions and occlusion cases [27]. YOLOv8-Pose architecture has three components [28]:

1.Backbone We use CSP Darknet to carry out the hierarchical feature extraction, providing a reasonable trade-off between speed and accuracy.

2.The neck combines different sizes of features to help with locating objects more accurately.

3. Head: A decoupled head design simultaneously produces bounding boxes and keypoint predictions and serves the dual roles of optimizing detection and pose estimation tasks.

YOLOv8-Pose contains several enhancements, including anchor-free detection, dynamic input scaling, and better loss functions, all contributing to improved performance in mean Average Precision (mAP) and inference time. These improvements render the model efficient and lightweight for deployment on edge devices [29]. YOLOv8-pose comes in many variations (YOLOv8n-pose, YOLOv8s-pose, YOLOv8m-pose, YOLOv8L-pose, and YOLOv8x-pose,) to meet different computational and accuracy requirements.

YOLOv8-Pose has been stable in different lighting and positions of the body, hence making it a good tool for vision-based human monitoring. Its ability to monitor real-time changes in posture makes it especially beneficial in the detection of non-invasive fall systems among the elderly population [6].

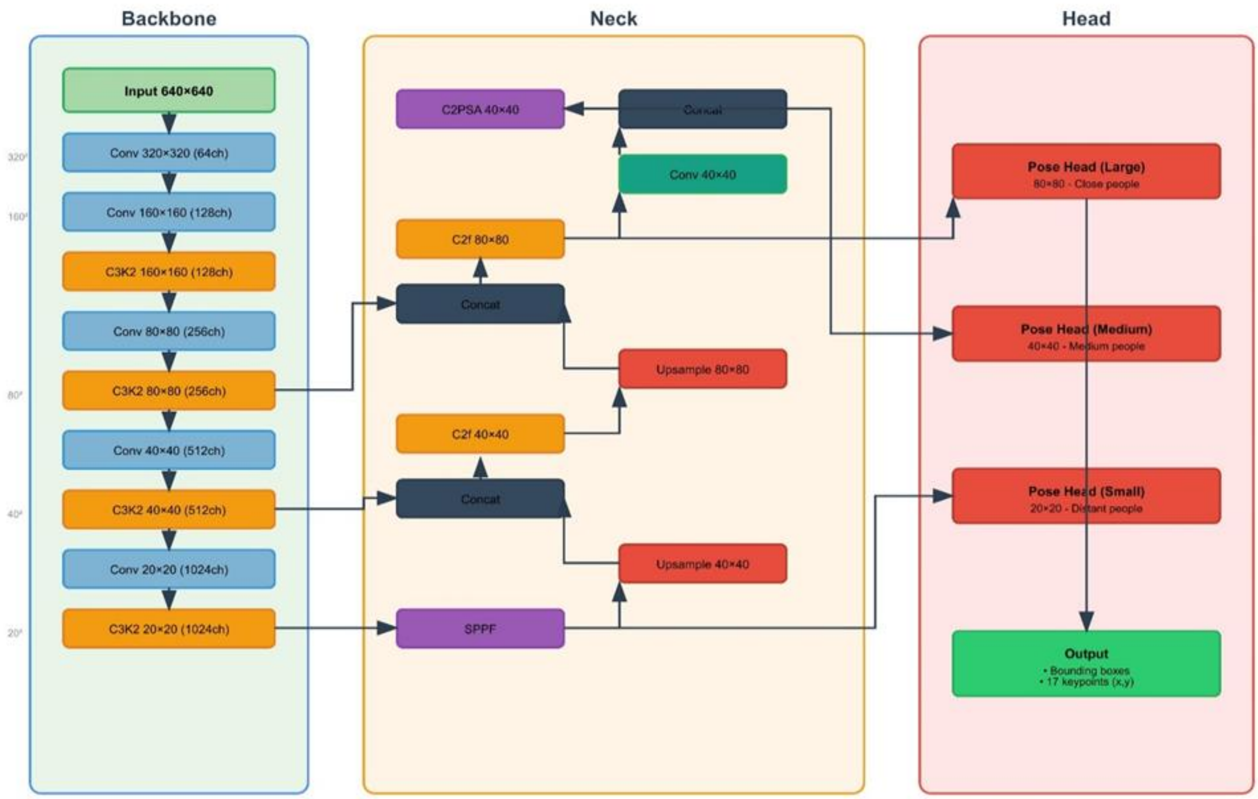


Fig 1. The architecture of YOLOv8- pose model.

4. Methodology

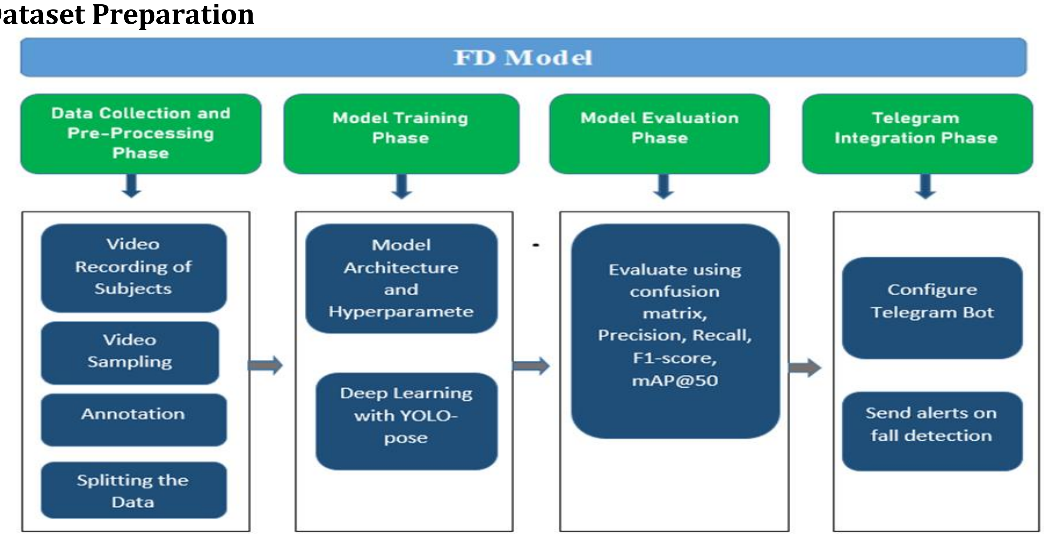
This section shows the methodology for the proposed fall detection and posture analysis for the elderly with the YOLOv8-pose model. The technique encompasses collecting data, pre-processing, model training, validation, and assessment of model performance. Figure 2 illustrates the sequence of these processes, showcasing the study's conceptual framework that ensures the selection of the optimal model for accurate fall detection.

Fig 2. study's conceptual structure.

4.1 Dataset collection

It was conducted to record videos using a smartphone camera at 30 frames per second and 1080p resolution to gather information needed to train and test a fall detection model utilizing computer vision-based approaches. We selected the resolution to ensure visual quality and distinguish minute details across various jobs. The data included a wide range of natural activity and fall scenarios. The videos included individuals aged 21 to 29. This age group was deliberately selected due to the reduced incidence of falls in comparison to older individuals, hence enhancing safety during data collection. Additionally, the choice of such an age group provides a diverse range of body compositions and motor proficiencies and allows preserving the safety of the research participants. Different lighting conditions and angles have been taken into consideration when making the recording. In order to make the data as rich as possible and to cover all the possible challenges the model would have to handle in the real-world scenarios, movies were made in a few indoor locations and under a few lighting conditions, such as bright and low light. Different camera angles, such as above, lateral, frontal, etc., were used to make sure that the model was able to fit falls occurring at any angle. The dataset was split into three major groups based on the type of activity in the video: falling, bending, and normal. The constructed dataset contained 77 falling movies, 60 bending movies, and 49 movies with normal activities.

4.2 Dataset Preparation



The falls dataset, which includes such characteristics as normal activity, bending, and falling, was prepared in a specific way to train the YOLO-Pose model. Videos have been made with the controlled indoor environment with different perspectives and with the uniform lighting conditions. Manual extraction of images was done at the rate of 24 frames in one second and saved as individual JPEG files. The pictures were re-aligned and resized to 640 640 pixels. The data was split into train, validation and test in the ratio of 70:20:10. After augmentation, the training set consisted of 3784 photos, the validation set had 1022 and the test set had 745, giving a total of 5551 photos. Data augmentation techniques were employed to enhance data quality and diversity, thereby improving model performance, augmenting its generalization ability, and mitigating risks associated with class imbalance. An automated script was employed to label photographs and categorize them according to their source folder. The data were converted to the COCO format, which facilitates the retention of keypoints and annotations necessary for training a human posture recognition model.

4.3 Model Training

We chose to train the YOLOv8-pose model because it is better at estimating posture in real time, which makes it a good fit for fall identification systems. All of the photos that were sent in were reduced to 640 × 640 pixels. The model was trained for 100 epochs, with a batch size of 8 and a learning rate of 0.001. We used Stochastic Gradient Descent (SGD) as an optimizer with a momentum of 0.937 and a weight decay of 0.0005 to speed up convergence and lower the risk of overfitting. To make the model more robust, data augmentation techniques such as random flipping, scaling, and rotation were used. The training approach used supervised learning, which used labelled keypoints to make posture predictions more accurate in different falling situations. These hyper parameters, listed in Table 1, were carefully selected to create a standardized training environment, allowing for fair comparison between various models.

Table 1. Model Hyperparameters

Training parameters	**Values**
Number of epochs	100
batch size	8
optimizer	(SGD)
momentum of	0.937
Initial learning rate	0.001
weight decay	0.0005
Image size	640 × 640

4.4 Evaluation Metrics

To assess the efficacy of the suggested study, various metrics must be employed that concentrate on the classifier's capacity to accurately identify classes. The primary metrics employed in previous research have been deemed essential for assessing the efficacy of the planned task [30]. Currently, the four most frequent measures used to evaluate performance are precision, recall, F1-score, and mAP [31].

- **Precision:** Precision is defined as the ratio of accurately categorized positive cases to the total number of instances labeled as positive.

$$\text{Precision} = TP/(TP+FP) \qquad (1)$$

- **Recall:** The recall can be defined as the true positive rate, which is the ratio of properly identified positive occurrences to the total number of positive instances.

$$\text{Recall} = TP/(TP+FN) \qquad (2)$$

- **F1-score:** The F1 score aims to measure accuracy by averaging Recall and Precision.

F1-score = (2*precision * recall) / (precision + recall) (3)

- **Mean Average Precision (mAP):** Calculates the average AP across all classes.

5. Results and Discussion

Data preparation and pre-processing were conducted using the Windows 11 operating system, whereas the specific training and testing of the YOLOv8-Pose model were executed on the Google Colab cloud platform, which provided sufficient computing resources. The model consistently converged during the 100-epoch training period, continually decreasing loss and enhancing accuracy in keypoint localization.

5.1 Result of the Evaluation Metrics Performance

As Figure.3 shows the fall detection results, YOLOv8m-pose achieved the best F1-score of 97.66%, following by YOLOv8s-pose at 97.4%, and YOLOv8n-pose at 97.26%. Considering accuracy, YOLOv8m achieved 97.80%, followed close by YOLOv8s-pose at 97.2% and YOLOv8n-pose at 97.13%. The mAP values for the models were 99%, 98.81%, and 98.7%, confirms a better and more effective generalization in this experiment is the YOLOv8m-pose model.

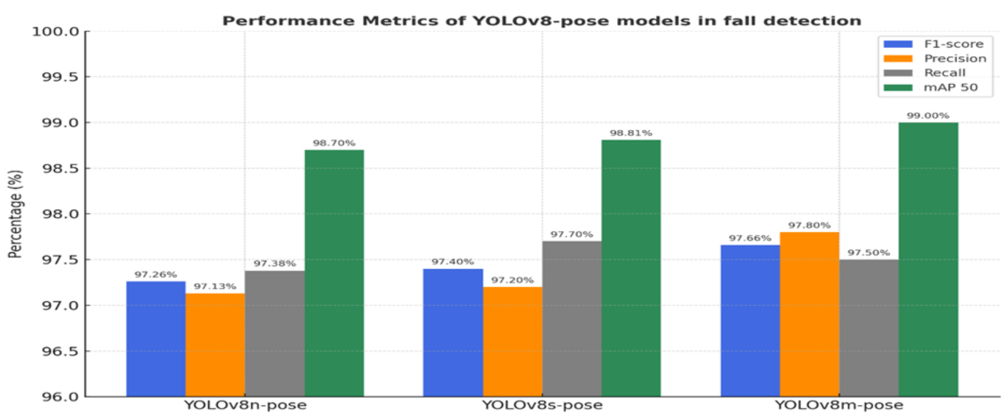
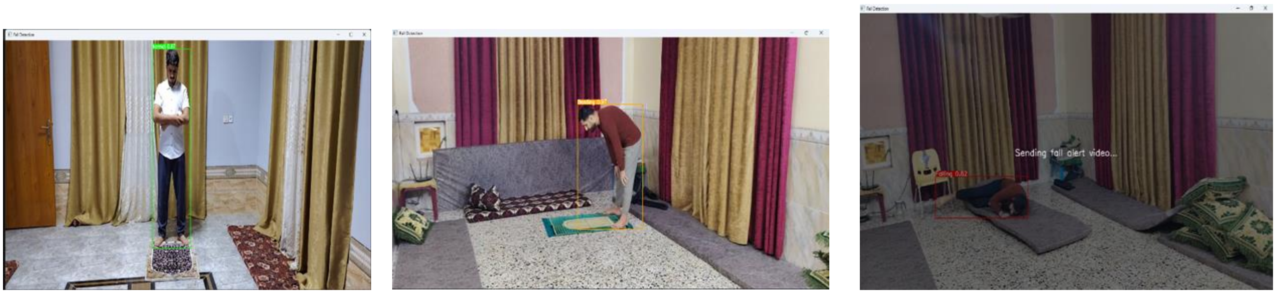


Fig 4: Confusion Matrix

In Fig .4, A confusion matrix was used to graphically depict how effectively the YOLOv8m-Pose model functioned in recognizing the presence of the falling event in comparison to the other activities done. The confusion matrix is a quantitative element that highlights the accuracy of the predominance of different activity categories such as Normal, Bending, Falling, and Background. The conclusion drawn from the confusion matrix and the graphical representations, particularly figure 4, is that the YOLO-based model demonstrates accuracy and efficacy in detecting falls among the elderly in typical home environments, illustrating the practical applicability of this concept in real-world scenarios.

5.2 Test the Model Fall Detection

Figure 5, presents the evaluation outcomes of the YOLOv8-pose model for identifying falls among older individuals inside their residences. The model employs computer vision methods to identify human body postures in real time by analyzing visual input using pose estimation algorithms. It has increased sensitivity for detecting fall-related patterns by documenting motion sequences and identifying anomalous movement behaviors. The assessment incorporates a multi-tiered confidence rating system, enabling the model to differentiate between actual falls and similar motions such as sitting or bending. The findings indicate that the model exhibits strong performance across several fall scenarios while being resilient to changes in ambient conditions like as lighting and furniture density.



(a) (b) (c)

Figure 5. Experimental Results.: (a) A person performing a normal activity; (b) identification of a person bending over; (c) identification of falling.

One of the most notable contributions of this study is the creation of a custom dataset containing diverse scenes, including falls, bending, and natural motion. A system based on the YOLOv8-Pose model was also developed to accurately detect and track human body motion points, enabling it to record falls in real time. This model was designed to be simple and easy to use, adapting to the home environment and the needs of the elderly.

5.2.1 The Alert System

The alarm system is designed to promptly notify family members or caregivers in the event of an suspected fall. This strategy ensures prompt assistance for the fallen individual, which may be vital in preventing further injury or complications. An alert system based on the Telegram Bot API is integrated into our system. The system alerts a designated chat ID when detecting a fall (Figure 6).

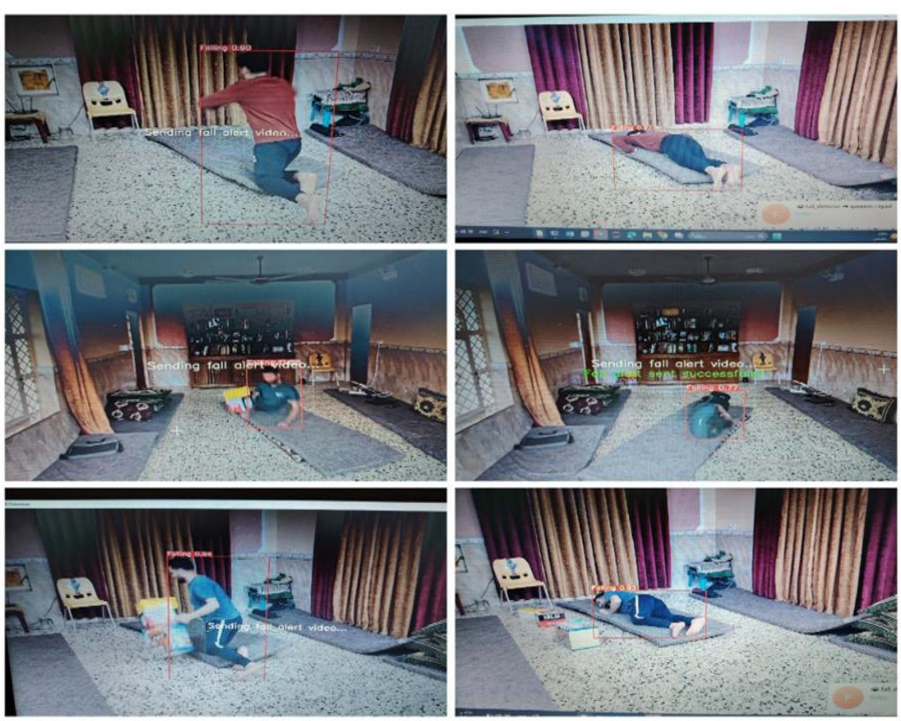


Fig 6. Real-time fall detection.

5.3 Comparative analysis with the related detection models

A multitude of studies has been undertaken to improve the accuracy, robustness, and real-time applicability of fall detection. Tirziu et al. [32] introduced the YOLOv7-W6-Pose model for real-time detection of falls among the elderly, attaining great accuracy using joint detection and GPU-based acceleration. Nonetheless, their solution continued to depend on high-performance computing infrastructure, constraining adoption in resource-limited settings. Zhao et al. [33] presented YOLOv7-Fall, incorporating architectural enhancements such SDI attention and GSConv modules, which improve feature extraction and decrease computational complexity. Nonetheless, despite advancements in model size and inference speed, issues persisted in generalising to varied real-world contexts characterised by occlusions and differing activities. Gutiérrez et al. [34] examined fall detection in low-light environments utilising far-infrared (FIR) images alongside pose estimation, providing dependable detection during nocturnal settings. Nonetheless, their methodology is constrained by the specific FIR hardware prerequisites, which impede scaling in typical domestic environments. Conversely, Yang et al. [35] introduced a streamlined 3D pose-based fall detection model emphasising computing economy. Their technology lowered processing costs but compromised detection accuracy and necessitated specialised 3D camera configurations, hence restricting its use in typical household settings.

In contrast, the suggested study is based on a YOLOv8-Pose architecture trained on a diverse dataset collected via smartphone cameras, covering numerous fall and daily activity scenarios. The model achieved a higher mAP@50 of 99%, which was superior in terms of accuracy and generalisability to other techniques. Furthermore, the approach was able to reduce false alarms using enhanced pose-based post-processing and an optimised thresholding approach. In contrast to earlier models, the method strikes a compromise between good detection capabilities and efficient computation requirements, allowing the operation to be completed in real time with medium hardware while maintaining performance. The diversity of the entire dataset improved model robustness under diverse lighting situations, body postures, and environmental settings, addressing several problems identified in previous studies.

Table 2. A comparison of our proposed method with other studies.

Study	Model Used	Precision %	Recall%	F1-score%	mAP@50%
Gutiérrez et al.[34]	ViTPose + CoGNet	**---**	**94.4%**	**---**	**95.9%**
Tîrziu et al. [32]	YOLOv7 W6-Pose	**97%**	**97.98%**	**97.48%**	**96.15%**
Zhao et al. [33]	YOLO- fall	**88.2%**	**89.8%**	**---**	**---**
Yang et al. [35]	SFDM(3D Lightweight Open Pose)	**92%**	**93%**	**92.5%**	**92.5%**
Proposed model	YOLOv8-Pose	**97.8%**	**97.50%**	**97.66%**	**99%**

6. Conclusion and Future Work

The results of this study demonstrated that the YOLOv8m-based model has promising potential for accurately and efficiently detecting falls in indoor environments. The model was optimized to accurately estimate body joint points, enabling the system to analyze motion postures and detect falls in real-time. The system demonstrated its ability to effectively detect falls and other activities, achieving an accuracy of 94.8% on the Mean Accuracy (mAP) criterion, demonstrating its technical proficiency in real-world settings. The system also features real-time notifications of falls via Telegram, enhancing its integration into elderly care settings. One of the major challenges this study faced was using young participants to collect data and record falls. The reason for choosing this age group at this stage of the research was due to safety and ethical considerations, as realistically simulating falls requires a degree of physical fitness to avoid exposing participants to any physical danger during the simulation. Future studies will aim to expand the dataset by incorporating additional patient groups and clinical situations, integrating temporal motion analysis to predict falls as soon as possible, and broadening the model to incorporate more activities.

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