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Vision-Based Elder Activity Monitoring and Fall Detection System

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***Abstract*—**This paper introduces an based on vision in real time. fall detection system and elderly activity monitoring de- signed. to increase the safety of independent living. The proposed framework uses pose estimation and posture analysis to identify cases of falls. from live video streams. A temporal analysis based on threshold. mechanism identifies the normal activities and fall incidents. When the system detects the issue, an alert is provided and a mail. notifications. Fall is proven to be reliable through ex- perimental evaluation.system which is suitable to be used in home based elderly monitoring applications.Possible Index Terms Fall Detection Computer Vision, Pose Estimation Elderly Monitoring, Real-Time Systems YOLOv8 Human Activity Recognition.

***Index Terms*—Fall Detection, Computer Vision, Pose Estimation, Elderly Monitoring, Real-Time Systems, YOLOv8, Human Activity Recognition**

I. Introduction

The rate of population growth of the elderly has risen. the need to have efficient healthcare monitoring systems. Falls continue to be one of the most significant health issues of elderly people to serious conditions like fractures and head injury. Vision based systems offer a non-obtrusive and automated solution. to be used in tracking older people. This paper presents a real computer vision-based, pose-based system of time fall detection. estimation algorithms to compute the posture as well as detect a fall event.

II. Literature Review

Fall detection has been a recent focus in the literature since most people are aging, and it poses various health threats. Different methods for detecting falls have been proposed by researchers using different algorithms and approaches, broadly classified into: systems using wearable sensors; systems that detect falls based on visual analysis; and multimodal/hybrid fall detection systems combining several sensors.

The first type involves the study by Yacchirema , who used a fall detection system using IoT technology that includes sensors such as tri-axial accelerometers coupled with big data analytics to process them in real time. Classification is done using decision tree algorithms that run on a smart IoT gateway. The accuracy of the proposed methodology is very high, but the fact that it depends on wearables presents some problems of user discomfort.

Another fall detection system has been proposed by Wang et al., which incorporates accelerometer sensors with cameras to improve accuracy, thereby reducing false alarms that could occur using only one sensor. However, since it uses a combination of sensors, computation becomes complicated.

The proposed a vision-based fall detection approach using Deep Convolutional Neural Networks using the Inception v3 model. Their approach had excellent results in smart home scenarios. The main limitation of this approach is that the performance of the algorithm depends on camera input, making it susceptible to changing illumination conditions and raising privacy concerns due to the constant monitoring through videos. It should also be noted that, according to the literature, good feature extraction techniques and proper classification models contribute significantly to improving the accuracy of fall detection. One limitation highlighted in the literature is the lack of real-world, high-quality dataset in uncontrolled environments, since the majority of studies use constrained or simulated data.

III. METHODOLOGY

The system employs modularity to remain scalable, maintenance-friendly, and capable of working in real-time. The system consists of five core modules: Video Capture, Pose Estimation, Fall Detection Engine, Alert and Notification System, and Web Dashboard Interface.

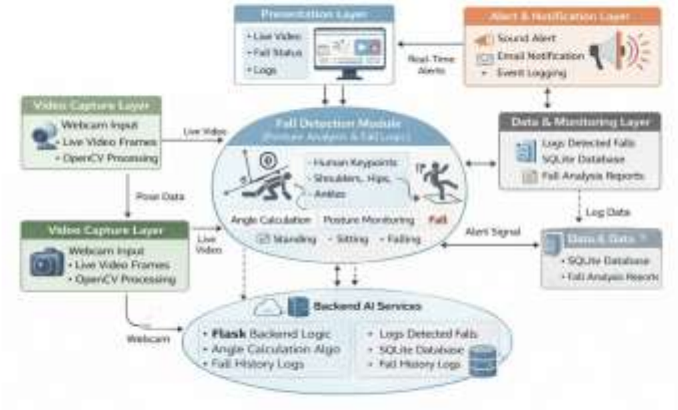

Fig. 1. System Architecture of the Proposed Fall Detection System

A. *Video Capture Module*

The module obtains the input live stream from a standard webcam. Each frame in the live stream undergoes processing using OpenCV. First, the captured frames are preprocessed by adjusting their sizes, normalizing them, and converting the images into grayscale before passing them into the next process for pose estimation.

B. *Pose Estimation Module*

The module obtains skeletal keypoints from each frame in the live stream. It emphasizes major joints such as the shoulders, hips, knees, and ankles. The obtained keypoints contain coordinates that define position, orientation, and gesture patterns of the body. These keypoints are passed to the next process to determine postures.
$\theta = \tan$

C. *Fall Detection Engine*

The module detects the movement of the keypoints in space and time. The body's angle of inclination is computed, and it determines whether the body is upright or laid down. It further detects quick posture changes. A fall occurs when there is a rapid change in posture from vertical to horizontal orientation.

D. *Alert and Notification System*

In the event of a fall incident, the notification module triggers an alert sound. An email notification is further dispatched to the caregiver or emergency contact at once. Each fall event is logged in a database together with the exact timestamp of the event.

E. *Web Dashboard Interface*

The module, constructed using the Flask framework, allows the caregiver to monitor real-time events. The interface contains a real-time video feed, fall detection status, and history of past fall incidents.

IV. IMPLEMENTATION

A. *Frame Acquisition*

A webcam is used to capture real-time video frames. through the OpenCV library. The system is constantly read. reads through video stream frames and sends them to the pipe processing pipeline.

B. *Preprocessing*

The individual frames captured are preprocessed so as to enhance them. detection reliability. The preprocessing processes involve resizing. the color space of one frame to a fixed resolution converting the color space of one frame to a fixed resolution.BGR format to RGB format, and scaling the intensity of pixel values to a normal range. These measures make it compatible with the pose estimation. represent and improve computational efficiency.

C. *Pose Keypoint Extraction*

The estimation of pose model yields skeletal key points cor. reacting to major joints of the human body. The coordinates of joints are detected and include such joints as shoulders, hips, knees, and ankles are stored. These keypoints are the structural position of the. personal and are the foundation of posture analysis..

D. *Angle Calculation*

The body inclination angle θ is calculated as:

$$^{-1}\ \frac{y_{shoulder} - y_{hip}}{x_{shoulder} - x_{hip}} \qquad (1)$$

A vertical angle indicates standing posture, while a hori- zontal angle indicates a potential fall.

E. *Fall Classification Logic*

The threshold-based class is used to perform fall detection. The system analyses quick change in angle of inclination of the body, material decrease in height of the body,and time of horizontal body positioning. If these parameters count more than some fixed threshold values over a limited time span, the accident falls under fall. This reasoning assists in dissimilarity.actual falls incidences during normal acts like sitting or bending.

F. *Alert Generation*

The system activates when a fall has occurred. A sound alarm is immediately triggered off. It point out the emergency state. Additionally, an automated registered caregivers are sent email notification using the SMTP protocol. This event of falling is recorded in the database. along with the timestamps, which can be referred to in future.

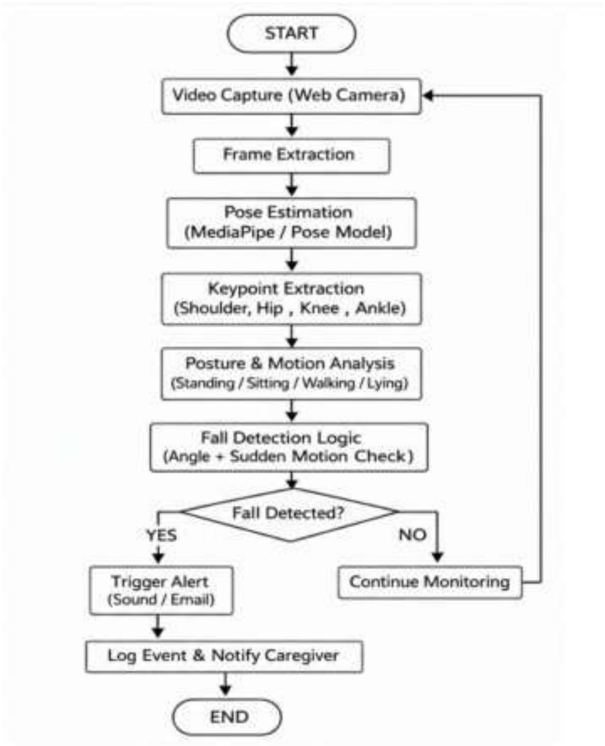

Fig. 2. Flowchart of the Proposed Fall Detection Algorithm

V. Interface

The system provides: The Elder Guard system provides an intuitive, web-based interface that facilitates real-time monitoring and fast emergency responses. The system includes a secure login page, live dashboard, and automated alerts for timely notification of all parties concerned.
The backend is developed using Flask and handles:

- Authentication
- Video streaming
- Fall detection logic
- Database operations
- REST APIs

A. Frontend Interface

Features include:

- login facility for users
- Live video streaming
- Fall detection status indicator
- History of events

VI. Results

The Elder Guard system was evaluated using the UR Fall Detection Dataset and real-time simulations.

0.48

Fig. 3. Login Page

0.4
8

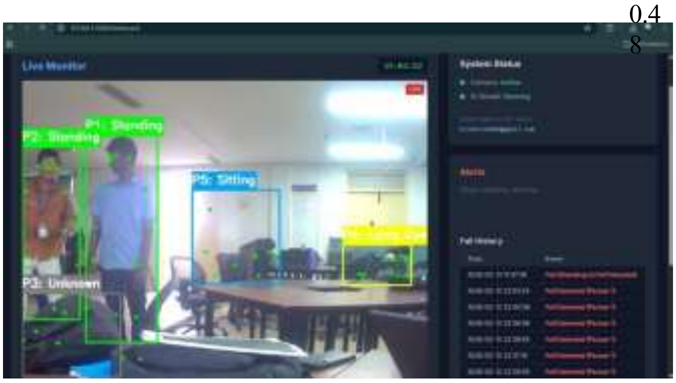

Fig. 4. Live Dashboard

Fig. 5. User Interface of the Elder Guard System

Fig. 6. Automated Fall Alert Email Notification

Key performance results:

- Accuracy: 96.5%
- Recall: 98.0%
- False positives reduced to below 3%
- Inference speed: 22 ms per frame

The Elder Guard system was reviewed with combination. of the UR Fall Detection Dataset and real-time simulations, A high classification accuracy of 96.5 of fall events was achieved. Integration of the YOLOv8-Pose architecture made possible.

a powerful inference rate of about 22ms/frame, enabling the system to be responsive in live-monitoring. scenarios. One of the most important results during the testing stage was the efficacy of the Temporal Fall Confirmation (TFC) algorithm; where the 1 frame analysis gave a false positive rate .the im- plementation is due to the fast sitting or bending movements. with 2-second stability window minimized false alarms to less than 3 percentage. This is a high sensitivity balance (98.0 recall). and enhanced particularity attests that the system is capable of being reliable. The differentiate actual emergencies and activities of daily. living (ADL), as a reliable answer to automated. elderly monitoring.

VII. Discussion

First of all, it addresses some of the fundamental problems associated with the detection of falls within the eldercare domain. Most importantly, it does not require using wearable devices, thus improving comfort and facilitating uninterrupted surveillance. Non-invasive nature of the technology makes it much easier to implement in the real world.

The proposed solution allows performing monitoring based on video streams. Thus, it becomes possible to detect falls and respond immediately. Combining postural estimation and temporal analysis greatly increases accuracy. Instead of relying on static poses, the method considers changes of posture from frame to frame. Thus, it significantly reduces the number of false detections characteristic of traditional vision-based approaches.

On the other hand, there are certain limitations. For example, the technology is prone to environmental dependencies, particularly lighting. Changes of illumination conditions may affect postural estimation adversely and cause erroneous pre- dictions. Moreover, monitoring people in overcrowded envi- ronments is complicated by occlusions.

One cannot ignore the problem of privacy, which becomes relevant due to continuous video surveillance. Data privacy and security measures should be employed, for example, using edge computing, anonymizing information, or employing encryption techniques.

VIII. Applications

The proposed fall detection system can be applied in many practical scenarios across healthcare and assisted living envi- ronments.

In smart homes, the system can continuously monitor elderly individuals living independently. It acts as a safety net by ensuring that any fall incident is quickly detected and reported, thereby reducing the risk of delayed medical assistance.

In hospitals, the system can be used for real-time patient monitoring, particularly for high-risk patients such as post-surgery individuals or those with mobility impairments. It reduces the workload on healthcare staff by automating surveillance and enabling timely intervention.

Elderly care centers and assisted living facilities can benefit significantly from the system, as it allows caregivers to monitor multiple residents simultaneously without constant manual supervision. This improves operational efficiency while enhancing patient safety.

Additionally, the system can be deployed in rehabilitation centers where recovering patients require continuous observation. Monitoring movement patterns and detecting falls can assist in evaluating recovery progress and preventing further injuries.

Beyond healthcare, the system can also be extended to workplace safety monitoring in industries where accidental falls are common, thereby improving overall safety standards.

IX. Future Work

Although the suggested method demonstrates high effi- ciency, there are other approaches that can significantly in- crease its performance and usability.

Firstly, one should think about using multi-camera setups that reduce the impact of occlusions and help detect actions with high accuracy in crowded scenarios.

Another critical step is implementing depth-sensing sensors like RGB-D. Depth perception helps improve the analysis of body posture and increases the model's precision regardless of lighting and background.

Integrating this system into IoT-based healthcare solutions will allow sending information about patient activity to a specialist, storing data on the cloud server, and analyzing them.

Creating an artificial intelligence-powered method for predicting falls would be helpful. In contrast to a conventional solution that detects falls, a predictive one allows analyzing posture and behavior to determine patients with high risks of falling before an event takes place.

Finally, optimization of the neural network structure will increase scalability and simplify deployment on low-cost devices.

X. Conclusion

This solution provides an affordable and reliable solution for identifying falls among senior citizens using real-time computer vision technology. With the incorporation of YOLOv8 pose estimator alongside temporal analysis, the system ensures high accuracy while also minimizing false alarms. Additional features to be considered in future development include the implementation of multiple cameras and depth sensors.

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