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# FALL DETECTION USING AI IN SURVEILLANCE SYSTEMS

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***Abstract:***

*Falls are the leading cause of fatal and non-fatal injuries among older adults, with over 36 million falls reported annually in the U.S., according to the CDC. AI-based fall detection systems offer an advanced solution by enhancing response times and safety through real-time, device-free monitoring using machine learning and computer vision. These systems provide continuous surveillance, accurately detecting falls and reducing the severity of injuries. Healthcare facilities, nursing homes, and private residences benefit from improved patient care and faster response times. By eliminating the need for wearable devices, these AI systems are more convenient and accessible for elderly users, ensuring wider coverage and increased reliability. As the elderly population grows, AI-driven fall detection will play a vital role in promoting independent living, timely interventions, and reducing healthcare costs associated with fall-related injuries.*

***Index Terms:*** *Fall detection, computer vision, elderly safety, non-wearable devices, real-time monitoring*

## Introduction:

Elderly individuals are particularly vulnerable to falls, often resulting in severe injuries and a decline in overall health. Traditional methods, like wearable sensors, face challenges such as limited detection zones and user non-compliance. This project addresses these limitations by utilizing surveillance video technology and advanced computer vision techniques for passive, device-free monitoring. Through machine learning algorithms, our system continuously analyzes video footage, accurately detecting falls and sending immediate alerts to caretakers. This approach eliminates the need for wearables and extends monitoring coverage, ultimately enhancing safety and timely assistance for elderly individuals prone to falls.

**Related Works:**

In recent years, various algorithms for fall detection have gained attention, particularly those employing deep learning techniques. For instance, Wang and Jia (2020) proposed a fall detection algorithm based on YOLOv3, which demonstrated promising results in accurately identifying falls in real-time scenarios Wang and Jia, 2020. Similarly, lightweight solutions have been explored, such as the bidirectional recurrent neural network developed by Kim et al. (2020), which emphasizes efficiency while maintaining accuracy in fall detection Kim et al., 2020.

Kang et al. (2021) conducted a comprehensive study on fall detection, contributing valuable insights into the different methodologies employed in this field, including both vision-based and sensor-based approaches Kang et al., 2021. Furthermore, the integration of depth images has shown potential in enhancing the detection capabilities, as discussed by Bundele et al. (2020), who proposed a system tailored for elderly individuals Bundele et al., 2020. The use of motion vector modeling has also been explored by Vishnu et al. (2021), providing a novel method for detecting falls within surveillance videos Vishnu et al., 2021. In mobile robotics, Chen and Duan (2021) presented a vision-based fall detection algorithm that could be implemented on robotic platforms, highlighting the versatility of such systems in practical applications Chen and Duan, 2021.

Moreover, a hybrid approach combining deep learning and multi-sensor fusion has been introduced by Lv et al. (2020), demonstrating the effectiveness of utilizing multiple data sources for real-time fall detection Lv et al., 2020. Gupta et al. (2020) focused on IoT-based solutions, proposing a monitoring and alarm system designed specifically for elderly individuals, showcasing the importance of proactive measures in fall prevention Gupta et al., 2020.

Lastly, mobile devices have been harnessed for fall detection, as shown by Abdullah et al. (2020), who utilized built-in smartphone accelerometers for detecting falls Abdullah et al., 2020. Liu and Lockhart (2014) further contributed to this field by developing a prior-to-impact fall event detection algorithm, laying the groundwork for subsequent advancements in this area Liu and Lockhart, 2014.

**Issues We Have Worked On:**

For our fall detection system, we addressed several critical issues that are prevalent in existing systems but resolved in ours, enhancing reliability and accuracy:

**Accurate Pose Estimation Despite Loose Clothing:**

Unlike many systems that struggle to detect key body points when individuals wear loose clothing, our system is designed to handle this effectively. Through careful tuning of the pose estimation model and optimized detection parameters, we ensure reliable identification of body points, providing robust fall detection independent of clothing styles.

**Reduced False Positives for Non-Fall Movements:**

Our system minimizes the common problem of false positives, where non-fall actions (like sitting or bending quickly) are misinterpreted as falls. By implementing specific pose sequences and contextual patterns, our system accurately differentiates between actual falls and sudden, non-fall activities. This enhancement improves the reliability and practical application of our system in real-world scenarios.

**Experiments and Results:**

The development and evaluation of this fall detection system involved multiple experiments to refine the detection accuracy and responsiveness in various real-world conditions. We initially aimed to employ pose estimation techniques to detect falls based on joint positions and body postures but later adapted our approach to image classification, which proved more robust in our testing scenarios.

**Initial approach with Multi-Person Pose Estimation:**

Our original methodology involved a two-step process. First, we used SSD MobileNet V3, a fast and efficient deep learning model for object detection, to locate individuals within a video frame. SSD MobileNet V3 provided bounding boxes around each detected person, effectively isolating multiple people in the frame without significantly impacting processing speed. This approach enabled the system to handle scenes with multiple individuals, which is crucial for real-world applications.

Following person detection, we employed MediaPipe for pose estimation on each detected individual. Media Pipe analyzed the bounding box regions to estimate body keypoints (e.g., elbows, knees, shoulders), allowing us to track body posture and identify falls based on changes in joint positions. However, early trials revealed significant challenges. Notably, the pose estimation model struggled to detect joint points accurately when subjects wore loose clothing, as loose garments obscured key joint positions, leading to inconsistent or missing data points.

**Transition to Image Classification with CNNs:**

Following these initial setbacks, we redesigned the system to utilize image classification instead of pose estimation. We trained a Convolutional Neural Network (CNN) specifically to classify images as "falling" or "not falling," achieving a more generalized and reliable approach. For this purpose, we used a fall detection dataset from Kaggle, which includes a diverse collection of images depicting both falling and non-falling scenarios. This dataset helped the model learn the differences between the two classes effectively. The CNN, trained using Google's Teachable Machine, was able to analyze the entire human body posture holistically rather than relying on specific joint points. During testing, this adjustment demonstrated an improvement in fall detection reliability, particularly in scenarios where pose estimation had previously failed.

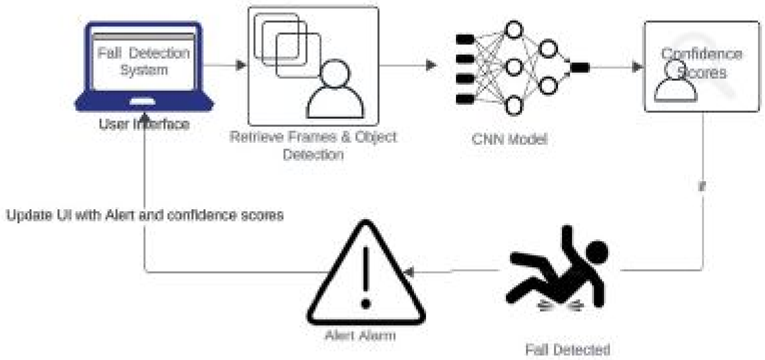


**Figure 1**

**Fall Detection using Image Classification**

**System Workflow-**

**I. Start Video Feed:**

Initialize the camera: The system begins by turning on the video feed. Start capturing frames: Once the camera is ready, the system captures the live video stream, which is a sequence of images (frames) captured at a constant rate (e.g., 30 frames per second). Each frame is processed individually for further analysis.

**II. Read Frame:**

Extract the current frame: As the video feed continues, the system reads one frame at a time from the camera. Each frame is essentially an image that represents a snapshot of the video at a specific moment.

Real-time processing: The system processes each frame in real-time or near real-time to detect whether a person is present and to predict falls, ensuring that the application remains responsive and efficient.

**III. Object Detection (YOLO):**

Detect a person using YOLO: YOLO (You Only Look Once) is a deep learning-based object detection algorithm that can detect objects in an image quickly and accurately. Here, YOLO is used to detect if there is a person in the frame.

When YOLO detects a person, it outputs a bounding box (a rectangle that surrounds the person in the frame) along with a confidence score, which indicates how certain the model is that the detected object is indeed a person. Extract the Region of Interest (ROI): The detected person's location (inside the bounding box) is extracted as the region of interest (ROI). This ROI is the portion of the frame that will be further analyzed for fall detection.

**IV. Prepare ROI for Prediction:**

Resize and normalize the ROI: Before feeding the ROI into the fall detection model, it is important to preprocess the data. The extracted ROI (image of the person) is resized to a specific resolution that the fall detection model expects. For example, if the model was trained on 128x128 images, the ROI must be resized to match.

The pixel values in the ROI are normalized, meaning they are scaled down to a range (e.g., between 0 and 1). This helps the model process the image more effectively and consistently.

**V. Predict Fall:**

Use the fall detection model: After preprocessing, the resized and normalized ROI is passed into the fall detection model. This model is trained to classify whether the person in the image is falling.

Check if the person is falling: In the fall detection system, after the model predicts a class of "falling," the algorithm checks the confidence score associated with this prediction. If the confidence score is 0.5 or higher, indicating the model is at least 50 percent confident, the system concludes that a fall has occurred and triggers an alert. Conversely, if the confidence score is below 0.5, the prediction is deemed uncertain, and the system proceeds to capture and analyze the next frame without generating any alerts. This thresholding mechanism ensures that only strong predictions result in alerts, reducing the likelihood of false alarms.

**VI. Update UI:**

Display the result: The final prediction (either "Falling" or "Not Falling") is displayed on the graphical user interface (GUI) for users to view. Along with the prediction, the confidence score is also shown to give users an idea of how certain the model is about its decision.

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**Conclusion:**

In this study, we developed a fall detection system that effectively addresses the challenges associated with traditional pose estimation methods. By transitioning to a Convolutional Neural Network (CNN) for image classification, we enhanced the system's reliability and accuracy in detecting falls. Our testing results demonstrate that the CNN model significantly improved fall detection performance, especially in conditions where pose estimation had previously encountered difficulties. Future work may focus on further enhancing model accuracy, integrating additional sensor data, and expanding the system's applicability in various environments.

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