

Sightica Pro – Intelligent Fall Detection and Monitoring System

Introduction

The Real-Time Multimodal Fall Detection and Monitoring System is designed to continuously monitor environments and accurately detect falls using parallel audio and video intelligence pipelines. Falls are among the leading causes of severe injury among elderly individuals, making rapid detection and response critical in healthcare and assisted-living environments.

The system combines computer vision, pose estimation, machine learning, contextual posture analysis, and adaptive infrared illumination to provide robust fall monitoring under both normal and low-light conditions. Unlike traditional systems that rely only on cameras or wearable devices, this architecture integrates continuous audio and visual analysis in parallel to improve reliability, environmental adaptability, and real-time responsiveness.

The system prioritizes edge-based processing, privacy-aware monitoring, asynchronous event handling, and scalable deployment across residential, hallway, assisted-living, and healthcare environments.

Tech Stack

- **Programming Language:** Python-based real-time AI inference and backend orchestration.
- **Computer Vision:** YOLO-based person detection, MoveNet pose estimation, contextual posture analysis, and motion transition verification.
- **Audio Intelligence:** MFCC feature extraction, RMS energy analysis, temporal filtering and 3-class audio classification (Fall, Scream, Non-Fall).
- **Embedded and Edge Hardware:** Raspberry Pi 5, Raspberry Camera module 3 Noir wide, custom infrared LED PCB illumination system, M305 USB microphone.
- **Backend Infrastructure:** FastAPI backend services, Laravel API integration, Twilio-based alert delivery, asynchronous queue handling, and event logging.
- **Machine Learning Frameworks:** TensorFlow Lite, TensorFlow, and YOLO-based inference pipelines optimized for edge deployment.

Understanding Fall Risk Factors

Falls in elderly individuals are influenced by biological, environmental, and behavioral factors. Common causes include imbalance, medical conditions, reduced mobility, environmental obstacles, and falls occurring in poorly lit spaces such as hallways and living rooms. Accurate fall monitoring systems must therefore operate reliably under varying environmental and lighting conditions while minimizing false positives caused by resting, sleeping, or seated postures.

Fall Detection and Prevention Approaches

Modern fall detection systems generally use wearable devices, camera-based systems, ambient sensors, or hybrid multimodal architectures. The proposed system follows a multimodal edge-AI approach where both audio and visual pipelines operate continuously and in parallel to improve detection reliability.

The camera subsystem performs person localization, pose estimation, contextual posture analysis, and motion transition verification. Simultaneously, the audio subsystem continuously analyzes acoustic patterns including screams, impact sounds, and non-fall ambient events.

Adaptive Infrared Illumination System

The system includes a custom-designed infrared LED PCB for adaptive low-light assistance. During nighttime or no-light conditions, the audio subsystem continues operating independently of environmental lighting. If a high-confidence acoustic event such as a fall-related impact or scream is detected, the infrared illumination subsystem dynamically activates IR LEDs to restore scene visibility for the camera pipeline.

This approach allows the camera subsystem to continue person monitoring and visual verification even in complete darkness without requiring constant infrared illumination. The adaptive IR mechanism improves power efficiency, hallway monitoring capability, and nighttime deployment reliability.

Performance Evaluation

The current video-based pose classification subsystem achieves approximately 92% accuracy under controlled indoor monitoring conditions, while the audio classification subsystem achieves approximately 90% accuracy for fall and scream-related acoustic event detection. The integrated multimodal system currently achieves an overall fall detection accuracy of approximately 95.45% under controlled testing environments.

Important Considerations

- Adaptive infrared illumination for low-light and no-light environments.
- Privacy-aware monitoring using skeletal overlays and masking techniques.
- Queue-based asynchronous event handling for non-blocking alerts.
- Internet connectivity checks and alert retry mechanisms.
- Temporal verification logic to reduce false positives from ambient sounds and resting postures.

System Flow

1. Video Pipeline:

- YOLO-based person detection and localization.
- MoveNet pose estimation and keypoint extraction.
- Contextual posture analysis, aspect ratio tracking, and motion transition verification.
- Multi-person monitoring and environment-aware validation.

2. Audio Pipeline:

- Continuous audio acquisition and MFCC feature extraction.
- RMS energy analysis, speech filtering, and temporal confirmation logic.
- 3-class audio classification for Fall, Scream, and Non-Fall events.

3. Adaptive IR Assistance:

- High-confidence nighttime acoustic events trigger the custom infrared PCB.
- Infrared illumination restores camera visibility during low-light conditions.
- The visual subsystem continues fall verification under enhanced visibility.

4. Alert and Logging Pipeline:

- Real-time event logging and image capture.
- Laravel API integration and Twilio-based alert delivery.
- Asynchronous event handling and queue-based processing.

Advanced Fall Verification

The system performs contextual biomechanical verification instead of relying solely on posture classification. Multiple parameters including body aspect ratio, posture transition duration, motion dynamics, vertical displacement, environmental interaction, and object-aware analysis are used to reduce false positives.

The system also differentiates between natural resting behavior, seated states, sleeping posture, and genuine fall events through temporal validation and contextual reasoning.

Privacy-Aware Monitoring

To improve deployment suitability in healthcare and assisted-living environments, the system incorporates privacy-aware visualization techniques such as skeletal overlays and privacy masking. This minimizes unnecessary visual exposure while preserving fall detection functionality.

Fall-event images viewed through the Sightica dashboard and mobile application are displayed using privacy-masked skeletal visualization to reduce unnecessary visual exposure.

Multi-Person Monitoring

The architecture supports simultaneous monitoring of multiple individuals through person-wise pose extraction and independent contextual fall analysis. This allows deployment in shared environments such as assisted-living facilities, hallways, and elderly-care centers.

Model Deployment

The system is designed for edge deployment using Raspberry Pi-based infrastructure with local inference capability. FastAPI services and backend APIs enable scalable communication, event handling, and remote alert management while preserving low latency and privacy-focused operation.

Cloud and Edge Integration

The architecture primarily emphasizes edge-based inference and privacy-preserving local processing. Optional cloud integration can be used for remote dashboards, long-term storage, analytics, and centralized monitoring when required.

Sightica Dashboard and Mobile Application

The Sightica monitoring ecosystem includes a centralized administrative dashboard for monitoring device activity, fall events, device status information, and recorded fall snapshots across deployed systems. Authorized administrators can review monitoring data, device health information, and operational activity remotely.

The Sightica mobile application allows caretakers and monitoring personnel to receive fall notifications, review fall-event history, monitor device status, and access activity-related analytics through a dedicated user interface.

Current Deployment Status

The system is currently undergoing real-world validation across multiple active deployment environments to evaluate operational stability, monitoring reliability, environmental adaptability, and low-light performance.

Three independent test deployments are currently active within controlled monitoring environments.

Conclusion

The proposed real-time multimodal fall detection system combines audio intelligence, computer vision, contextual posture verification, adaptive infrared illumination, and edge AI deployment into a unified monitoring platform. Through continuous parallel audio and video analysis, privacy-aware monitoring, and adaptive low-light assistance, the system provides robust fall detection capability suitable for elderly care, residential monitoring, hallway surveillance, and assisted-living environments.

The architecture is scalable and modular, allowing future integration of additional monitoring technologies such as radar-based sensing and enhanced multimodal analysis.