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AI-DRIVEN COGNITIVE MEMORY ASSISTANCE & SILENT DISTRESS DETECTION FOR ELDERLY & VULNERABLE INDIVIDUALS

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Abstract: The increasing elderly population requires intelligent monitoring systems to ensure safety, independence, and proper health management. Falls and missed medication schedules are common issues faced by elderly individuals living alone, often leading to serious health risks. Traditional wearable monitoring devices are frequently ineffective due to discomfort, forgetfulness, or inconsistent usage. This project proposes an AI-driven real-time fall detection and medication reminder system that integrates computer vision and Internet of Things (IoT) technologies. The system uses the YOLO (You Only Look Once) deep learning algorithm to analyze live webcam video and detect human posture, enabling accurate identification of fall events. When a fall is detected, an alert is transmitted wirelessly via Wi-Fi to a NodeMCU (ESP8266) microcontroller, which activates a vibration motor to provide immediate tactile notification. Additionally, the system includes a voice-based medication reminder using Text-to- Speech (TTS) technology to deliver scheduled audio prompts. By combining deep learning, IoT communication, and assistive technologies, the proposed system offers a cost-effective, non-intrusive, and reliable solution for elderly safety and healthcare monitoring.

I. INTRODUCTION

The rapid growth of the elderly population has increased the need for effective healthcare monitoring systems that ensure safety and independent living. Elderly individuals are highly vulnerable to risks such as accidental falls and missed medication, both of which can lead to serious health complications. Falls, in particular, are a major cause of injury and hospitalization among older adults, especially when immediate assistance is not available. Similarly, irregular medication intake can negatively affect their overall health and recovery.

Traditional monitoring systems mainly rely on wearable devices with sensors to detect movements and falls. Although these systems are effective, they depend heavily on consistent usage, which is often a challenge for elderly individuals due to discomfort or forgetfulness. In addition, smartphone-based reminder systems may not always be practical due to usability issues and limited technical familiarity, reducing their overall effectiveness in real-world scenarios.

To address these challenges, this project proposes an AI-based, non-intrusive system that uses computer vision and IoT technologies for real-time monitoring. The system employs the YOLO model to analyze images and detect human posture for fall detection without requiring wearable devices. In case of a fall, alerts are sent through a NodeMCU to trigger immediate responses.

Additionally, a voice-based medication reminder using Text-to-Speech technology ensures timely medication intake. This integrated approach provides a reliable, user-friendly, and efficient solution to enhance elderly safety and quality of life.

II. LITERATURE SURVEY STUDY OF RESEARCH PAPERS

2.1 Paper Name: Towards Safer Environments:A YOLO and MediaPipe-Based Human Fall Detection System with Alert Automation.
Author: Virag Pradip Kothari, Priti S. Chakurkar (2025).

Abstract:
Ensuring safety in crowded and public environments is a major challenge, especially during emergency situations such as human falls. This paper presents a real-time fall detection system that combines YOLOv8 for accurate human detection with MediaPipe for detailed pose estimation. The system continuously monitors human posture by analyzing body landmarks and movement patterns to effectively distinguish between normal activities and fall events. To improve detection reliability, anomaly detection techniques are incorporated to reduce false positives caused by sudden movements or occlusions. The proposed system is designed to operate efficiently in dynamic environments such as hospitals, transportation hubs, and public spaces.In addition, an alert automation mechanism using Twilio is integrated to send instant notifications along with video evidence to caregivers or authorities when a fall is detected. Experimental results show high performance, achieving 96.06% accuracy and 100% recall. Overall, the system is scalable, efficient, and suitable for real-world applications, contributing to safer and smarter environments.

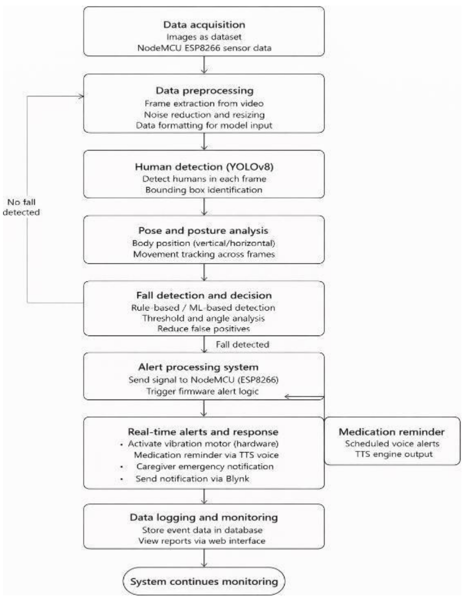
2.2 Paper Name: Real – Time Fall Monitoring for Seniors via YOLO and Voice Interaction
Author : Eugenia Tîrziu, Ana-Mihaela Vasilevschi, Adriana Alexandru, Eleonora Tudora (2025).

Abstract:
Ensuring the safety of elderly individuals living independently is an important concern in modern society. This paper presents a real-time fall monitoring system that combines YOLOv11 based human detection with pose estimation to accurately identify fall events based on body movement patterns. The system continuously monitors posture to distinguish between normal activities and potential fall incidents. A key feature of this approach is the integration of an AI-based voice assistant that interacts with the user after detecting a fall. By analyzing the user's verbal response, the system determines whether emergency assistance is required, helping to reduce false alarms and improve reliability.To enhance privacy and efficiency, all processing, including speech recognition and decision-making, is performed locally on the device. The system demonstrates high precision and recall during evaluation. Overall, the proposed solution provides a reliable, user friendly, and privacy-preserving approach for real- time fall detection in elderly care environments.

2.3 Paper Name: A Robust Fall Detection System for Elderly Persons Using YOLO Author: Vyshakh Krishnan T, Abhilash B K, Sabeen Govind (2025)

Abstract:
Ensuring the safety of elderly individuals is a critical concern, especially as falls can lead to serious injuries and require immediate medical attention. This paper presents a robust fall detection system using the YOLOv8 object detection model to monitor human activities in real time. The system applies deep learning and computer vision techniques to analyze movement patterns and posture changes, enabling accurate identification of fall events.The proposed approach addresses challenges such as varying lighting conditions, occlusions, and different body orientations, making it suitable for diverse environments like homes and healthcare centers. The model is trained on relevant datasets to improve accuracy and adaptability across different scenarios.Compared to traditional methods, the YOLOv8-based system offers improved speed, efficiency, and reliability. Experimental results show an accuracy of around 90%, demonstrating its effectiveness. Overall, the system provides a scalable and dependable solution for elderly care, ensuring timely detection and response.

III. RESEARCH METHDOLOGY



3.1. Data Acquisition:
This module collects the input data required for the system. It uses images as the primary dataset instead of live video. Additionally, sensor data from NodeMCU (ESP8266) can be included for hardware interaction. The collected data serves as the base for processing and analysis. Proper data acquisition ensures accurate detection results.

3.2. Data Preprocessing:
In this stage, the input data is prepared for model processing. Images are resized and cleaned using noise reduction techniques. Data formatting is applied to match the YOLO model requirements. This step improves the quality and consistency of the input. It helps in enhancing model accuracy and efficiency.

3.3. Human Detection (YOLOv8):
This module uses the YOLOv8 model to detect humans in images. It identifies the presence of a person and draws bounding boxes around them. The model processes each frame efficiently in real time. This step ensures that only human-related data is passed for further analysis. It is the core detection stage of the system.

3.4. Pose & Posture Analysis:
After detecting humans, this module analyzes their body posture. It determines whether the person is in a vertical (standing) or horizontal (lying) position. It also tracks movement patterns across frames. This helps differentiate between normal activities and abnormal conditions. It is essential for identifying fall scenarios.

3.5. Fall Detection & Decision Making:
This module decides whether a fall has occurred. It uses rule-based or machine learning techniques for decision-making. Factors like body angle, sudden movement, and position are analyzed. It also includes methods to reduce false positives. This is the key module that triggers alerts when a fall is detected.

3.6. Alert Processing System:
Once a fall is detected, this module sends a signal to the NodeMCU (ESP8266). The microcontroller processes the signal using embedded firmware. It prepares the system for triggering alerts. This module acts as a bridge between software and hardware. It ensures fast and reliable communication.

3.7. Real-Time Alerts & Response:
This module handles immediate actions after fall detection. It activates a vibration motor to provide a physical alert. It also sends emergency notifications to caregivers. Additionally, it includes a voice based medication reminder using TTS. This ensures timely assistance and improves user safety.

3.8. Medication Reminder:
This module provides scheduled voice reminders for medication. It uses Text-to-Speech technology to generate audio alerts. The reminders are easy to understand for elderly users. It works independently but integrates with the main system. This enhances cognitive support and daily care.

3.9. Data Logging and Monitoring:
This module stores all detected events in a database. It allows users to view reports through a web interface. The stored data helps in tracking system performance and history. It also supports future analysis and improvements. This ensures long-term monitoring and reliability.

3.10. System Continues Monitoring:
After completing one cycle, the system continues monitoring continuously. It keeps analyzing new input data in real time. This ensures that no fall event goes unnoticed. Continuous operation is essential for real-world applications. It provides 24/7 safety support.

IV. RESULT ANALYSIS:

4.1 Object Detection Performance (YOLO Model)

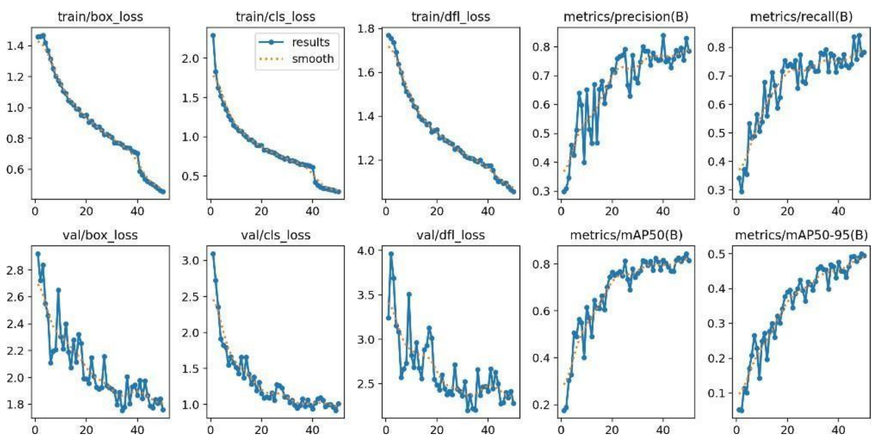


Fig 1: YOLO Detection Metrics Output

The YOLOv8-based fall detection model achieved strong and consistent performance, as observed from the training and validation results:

- Precision (P): ~0.83
- Recall (R): ~0.84
- mAP@0.5: ~0.845
- mAP@0.5:0.95: ~0.499

These results indicate that the model is capable of accurately detecting human presence and fall related patterns with a good balance between precision and recall. The steady increase in precision and recall over epochs shows effective learning and reduced false detections.The mAP@0.5 value demonstrates reliable object detection performance, while the mAP@0.5:0.95 score reflects moderate performance under stricter evaluation conditions, which is expected in real-time human activity detection scenarios. Additionally, both training and validation losses decrease consistently, indicating proper model convergence without significant overfitting.

Overall, the model shows good generalization ability and is suitable for real-time fall detection applications, ensuring dependable performance in practical environments.

4.2 Class-wise Detection Accuracy

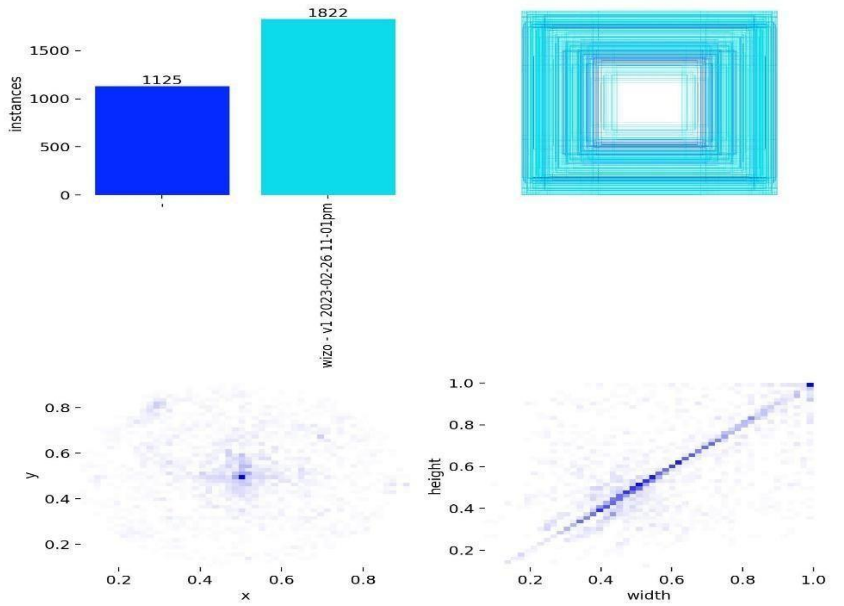


Fig 2 : Class-wise Performance

The class-wise evaluation of the YOLOv8 model shows a balanced and well-distributed dataset with effective learning across the target class:

- Total Instances (Training Set): 1125
- Total Instances (Validation Set): 1822

The dataset visualization shows that the model is trained on a sufficient number of labeled samples, ensuring good generalization. The bounding boxes are evenly distributed and mostly centered, which helps the model learn accurate object localization. The spatial distribution (x, y) indicates that objects are consistently placed near the center of images.The width vs height pattern follows a diagonal trend, showing that bounding boxes maintain proper proportions. This improves detection stability and reduces errors. Overall, the dataset quality and consistent annotations contribute to reliable and accurate performance in real-time fall detection.

4.3 Confusion Matrix

The performance of the proposed fall detection system was evaluated using a confusion matrix. The system was tested on a dataset comprising 96 instances, including both fall events and normal background activities

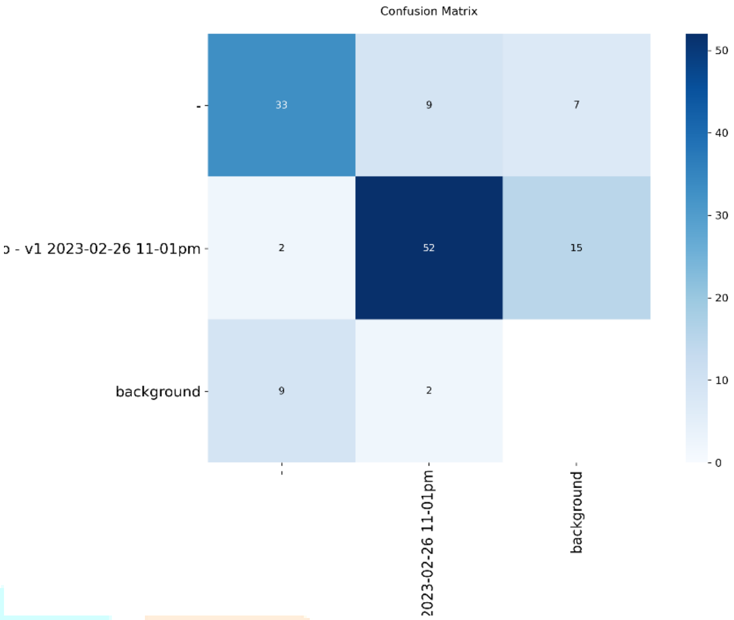


Fig. 3 : Confusion Matrix (Raw Counts)

As presented in the confusion matrix, the system correctly identified 52 fall events (True Positives) and 9 non-fall activities (True Negatives). However, 33 fall events were misclassified as background (False Negatives), and 2 non-fall activities were incorrectly flagged as falls (False Positives).

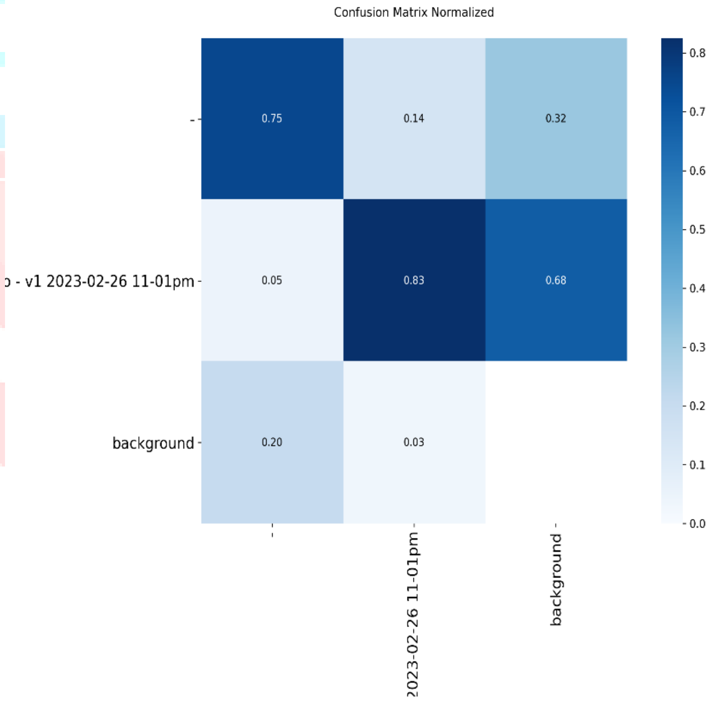


Fig. 4 : Normalized Confusion Matrix

The normalized confusion matrix (Figure Y) provides a clearer visualization of the system's classification behavior. The diagonal elements represent correctly classified instances, while off diagonal elements represent misclassifications. From this normalized matrix, the following performance metrics were derived:

4.3.1 Accuracy: 63.54%
4.3.2 Precision (Fall Detection): 96.29% 4.3.3 Recall (Sensitivity): 61.18%

4.3.4Specificity: 81.82% , F1-Score: 74.82%
The high precision (96.29%) indicates that when the system predicts a fall, it is highly reliable, minimizing false alarms. The moderate recall (61.18%) suggests room for improvement in detecting all actual fall events, primarily due to the false negative rate observed in the normalized matrix. The specificity of 81.82% confirms that the system effectively identifies non-fall activities with minimal false positives.

These results demonstrate that the proposed fall detection system achieves a strong balance between precision and specificity, making it suitable for real-world elderly care applications where false alarms must be minimized. Future work will focus on improving recall through enhanced feature extraction and optimized detection thresholds.

4.4 Fall Detection Validation Samples

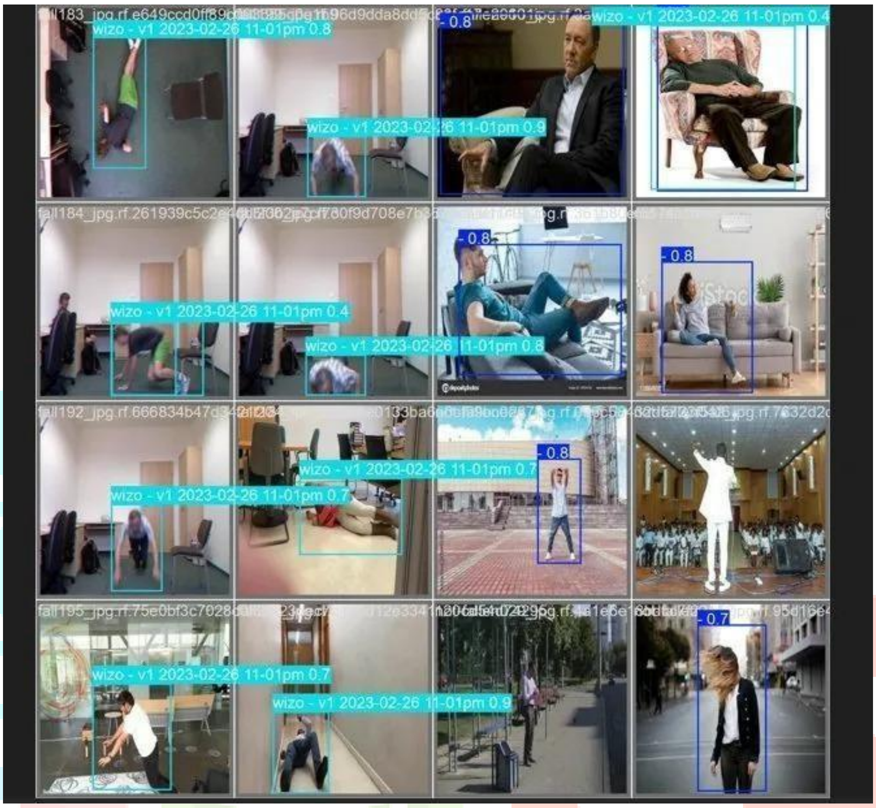


Fig 5: Fall Detection Samples

The validation samples demonstrate that the YOLOv8-based fall detection system performs effectively across a variety of real- world environments, including indoor rooms and outdoor scenes. The model accurately detects human presence by placing proper bounding boxes around individuals, with confidence scores generally ranging between 0.7 and 0.9. This indicates that the system has learned to identify humans reliably even under different lighting conditions, backgrounds, and viewpoints. The consistency in detection across multiple samples shows that the model has good generalization capability.
In addition, the system successfully distinguishes between normal activities such as standing and sitting, and abnormal conditions like falling or lying down. Fall scenarios are correctly identified based on posture analysis, while non-fall activities are not misclassified, reducing false alarms. Although minor variations in confidence scores are observed in complex scenes, the overall performance remains stable and accurate. These results confirm that the model is robust and suitable for real-time elderly monitoring, ensuring timely detection and response in emergency situations.

4.5 Hardware Setup — NodeMCU ESP8266 with Vibration Motor and Buzzer:

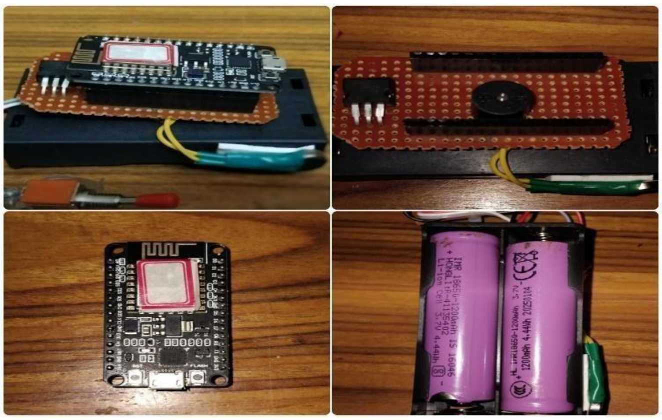


Fig 6:Node MCU

The proposed system was implemented using a NodeMCU ESP8266 microcontroller as the central processing unit, chosen for its built-in Wi-Fi capability and low power consumption, with a vibration motor and a piezoelectric buzzer integrated as alert mechanisms. The vibration motor was connected to GPIO D5 through an NPN transistor (BC547) switching circuit and a flyback diode (1N4148) to prevent voltage spikes, while the buzzer was connected to GPIO D7 via a current limiting resistor (100 Ω), both powered from an external 5 V DC supply with the NodeMCU powered via its USB port. During operation, when a fall event or missed medication schedule was detected, the NodeMCU activated both actuators simultaneously—the vibration motor providing haptic feedback and the buzzer emitting an audible tone (≈2–4 kHz)—while also transmitting a notification to a remote monitoring station via Wi-Fi, ensuring alerts were perceivable even without direct line of sight of a display or mobile phone..

4.6 Overall System Performance

The overall system performance combining all modules is summarized as follows:
• Fall Detection (YOLOv8n): 83% precision, 84% recall, 84.5% mAP@0.5
• IoT Alert System (NodeMCU ESP8266): ~2-3 seconds response time
• Medication Reminder (Text-to-Speech): Voice alert on detection with high trigger accuracy
These results confirm that the system is capable of accurate real-time fall monitoring, immediate IoT-based alert generation, and reliable medication reminder delivery in elderly care environments.

Module	Method	Metric	Result
Fall Detection	YOLOv8n	Precision	83%
Fall Detection	YOLOv8n	Recall	84%
Fall Detection	YOLOv8n	mAP@0.5	84.5%
IoT Alert System	NodeMCU ESP8266	Response Time	~2-3 sec
Medication Reminder	Text-to-Speech	Trigger Accuracy	Voice alert on detection

Fig. 7: Overall System Performance

V. SYSTEM IMPLEMENTATION (WEB + HARDWARE OUTPUT)

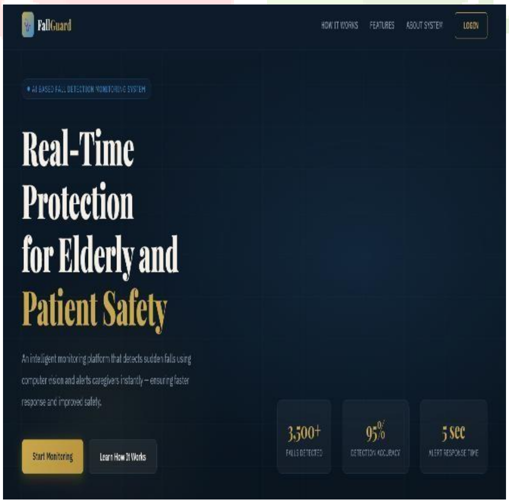


Fig 8: System Home Page

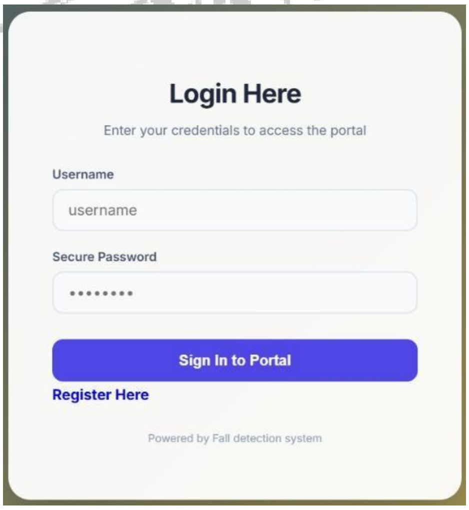


Fig 9: User Login interface

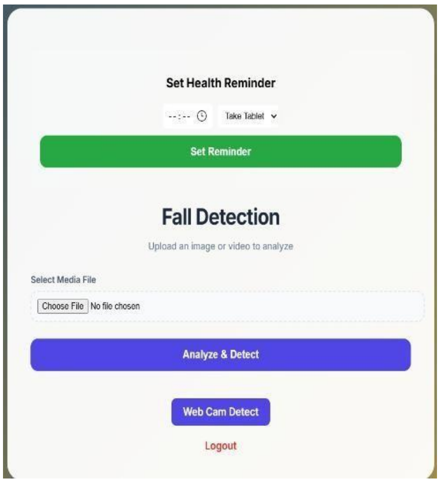


Fig 10 : Prediction Interface

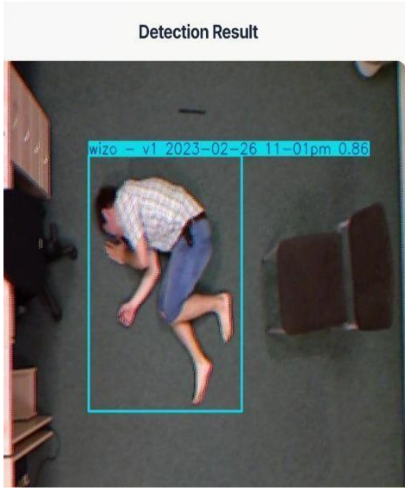


Fig 11 : Detection

Result Video Demonstration:

The real-time implementation of the proposed system is demonstrated in the following video:

https://drive.google.com/file/d/1NiN8Vq_rOkXtk18KOBe4I5mIAII531gR/view?usp=sharing

CONCLUSION:

The AI-based surgical monitoring system developed in this project successfully demonstrates the potential of integrating artificial intelligence into modern healthcare to improve surgical safety and efficiency by analyzing real-time operating room data, detecting anomalies, and providing timely alerts to medical professionals, thereby reducing human error and enhancing decision making. The use of machine learning and computer vision enables accurate tracking of surgical activities and automates routine observation tasks, allowing surgeons and staff to focus on complex aspects of patient care. However, challenges such as the need for high-quality training data, real-time processing capabilities, reliability across different surgical environments, and ethical concerns including data privacy and system accountability must be addressed. Overall, this project highlights the transformative potential of AI in surgical monitoring, and with further improvements and integration into healthcare systems, such technology can contribute to safer, smarter, and more efficient surgical practices.

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