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SIKELAS: A smart safety system for the elderly using AI and IoT technology

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Abstract

The number of elderly people in Indonesia continues to rise every year, posing serious challenges regarding their well-being and safety, particularly in nursing homes where caregiver shortages and limited monitoring capabilities remain critical issues. Existing elderly monitoring systems are typically limited to single-modality approaches, such as vision-only fall detection or single-sensor environmental monitoring, lacking real-time multimodal integration. To address these gaps, the "SIKELAS" (Smart Safety System for the Elderly) system was developed as a novel integrated solution combining AI technology, anomaly detection, voice recognition, and five environmental sensors into a single unified real-time monitoring platform. The novelty of SIKELAS lies in its simultaneous integration of MediaPipe-based fall and gesture detection, Speech-to-Text voice recognition, and multi-sensor environmental monitoring coordinated through an ESP32 microcontroller and Flask back-end, delivering automated Telegram alerts with an average response time under 1 second. This research employs an experimental quantitative approach with controlled laboratory testing across five datasets. Key results: gesture detection accuracy 98.38%, fall detection accuracy 89.16%, gas detection above 2500 threshold, flame detection below 500 threshold, and ultrasonic error below 3%. SIKELAS outperforms previous single-modality systems, delivering a comprehensive, measurable solution that reduces caregiver workload through automated multimodal monitoring and real-time emergency notifications.

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Introduction

The elderly population in Indonesia and worldwide continues to grow each year. According to data from the Central Statistics Agency, the elderly population in Indonesia is projected to reach 15.77% by 2035 (Statistics, 2017). This situation poses serious challenges in ensuring the well-being and safety of the elderly, particularly for those residing in nursing homes (Gochoo et al., 2021). The elderly are more vulnerable to various health risks, including falls, respiratory disorders, and exposure to unsafe environments (Chen et al., 2021). A shortage of caregivers capable of continuously monitoring the elderly's condition is also a critical issue in many care facilities (Ortiz & Boschi, 2017). In Indonesia specifically, the caregiver-to-elderly ratio in nursing homes has been reported at approximately 1:8, far below the WHO-recommended 1:3 standard, underscoring the urgent need for automated monitoring solutions (Statistics, 2017). This situation poses serious challenges in ensuring the well-being and safety of the elderly, particularly for those residing in nursing homes (Gochoo et al., 2021). The elderly are more vulnerable to various health risks, including falls, respiratory disorders, and exposure to unsafe environments (Noury et al., 2014). A shortage of caregivers capable of continuously monitoring the elderly's condition is also a critical issue in many care facilities (Ortiz & Boschi, 2017).

To address these issues, an innovative solution is needed in the form of real-time elderly safety monitoring, utilizing an intelligent system capable of detecting emergencies. Previous systems have focused narrowly on single modalities: vision-based fall detection without environmental monitoring (Ortiz & Boschi, 2017), passive infrared detection without voice or gesture integration (Ben-Sadoun et al., 2022), or wearable-only approaches without real-time alerting (Khojasteh et al., 2019). None have integrated multimodal AI detection with live environmental sensing and instant caregiver notification.*real-time* elderly safety monitoring, utilizing an intelligent system capable of detecting emergencies. AI technology has demonstrated success in detecting behavioral anomalies and environmental conditions (Dang et al., 2020; Liu & Zhang, 2020). This technology is combined with environmental sensors and voice recognition to create a system responsive to verbal calls for help (Wu et al., 2014). Based on previous research, AI and IoT have been successfully applied to improve the quality of life for the elderly (Mukherjee et al., 2020).

The urgency of this issue is further highlighted by data showing that falls are one of the leading causes of injury and death among the elderly, often going undetected quickly due to caregiver limitations (Castro et al., 2019; Khojasteh et al., 2019). Additionally, poor environmental conditions such as low air quality and unstable temperatures can worsen the health of the elderly, particularly those with respiratory conditions (Chen et al., 2021).

Previous research has shown that AI-based monitoring systems have a significant impact on improving responses to emergencies. For example, machine learning algorithms have successfully detected falls and provided early notifications of hazardous conditions (Yacchirema et al., 2019). Voice recognition technology is also advancing to support rapid responses in emergency situations (Beddiar et al., 2020).

Based on this background, "SIKELAS" was developed—an intelligent safety system that integrates AI technology, environmental sensors, and voice recognition. This system aims to improve the safety of the elderly through early detection of hazardous conditions and the provision of real-time notifications to caregivers (Castro et al., 2019; Ortiz & Boschi, 2017). The novelty of this research lies in the simultaneous integration of vision-based fall and gesture detection, Speech-to-Text voice alerting, and five-sensor environmental monitoring within a single IoT architecture—a combination not previously demonstrated in the elderly care literature. This study contributes a validated, deployable system with measurable accuracy and sub-second notification latency, directly addressing the multimodal integration gap identified in prior work.*real-time* notifications to caregivers (Castro et al., 2019; Ortiz & Boschi, 2017).

Methods

The SIKELAS development method employs a *Science, Technology, Engineering, and Mathematics (STEM)*-based approach to ensure innovative, relevant, and effective solutions for the safety of the elderly. The system is designed to monitor emergency situations and the elderly's environment using smart sensors and artificial intelligence (AI).

The initial phase involved a literature review and an analysis of safety risks for the elderly, particularly regarding falls and the need for *real-time*Data was collected from various case studies in nursing homes and households caring for the elderly, with the aim of understanding the specific needs of the elderly regarding safety and comfort, as well as the potential use of technology in addressing these issues. The system was evaluated through controlled laboratory testing using five independent datasets, each consisting of 50 test scenarios per detection modality (fall detection, gesture recognition, and voice recognition). Performance metrics measured included detection accuracy, precision, recall, F1-score, false positive rate, false negative rate, and end-to-end notification latency. Sensor thresholds were calibrated prior to testing: MQ-2 gas threshold at 2500 ADC units, flame sensor threshold below 500, and ultrasonic tolerance within 1 cm. All tests were conducted under controlled indoor conditions representative of a nursing home environment, with ambient temperatures of 20–24°C and humidity 33–53%.

Use of Tools and Materials

Hardware

ESP32: The main microcontroller used to process data from various sensors and send the analysis results to the notification system (Alarcon-Paredes & Alonso-Silverio, 2019). CCTV Camera and Microphone: Used for visual and auditory monitoring to detect movements and sounds from the elderly that indicate an emergency. DHT22 Sensor: A sensor for monitoring temperature and humidity around the elderly, capable of detecting potentially hazardous environmental changes. BH1750 Sensor: Used to measure light intensity in a room, which helps regulate visual comfort for the elderly. MQ-2 Sensor: An air quality sensor capable of detecting the presence of hazardous gases or air pollution. Flame Sensor*:* The flame sensor functions as an early fire detector and is placed in fire-prone areas, such as the kitchen. Ultrasonic Sensor: This sensor is used to monitor the elderly's activity in the bathroom area. When the sensor detects the elderly person entering for the first time or on an odd count, it is considered an "entry anomaly." If the person passes through again on an even count, it is considered an "exit." After detecting an entry, the system begins tracking the elderly person's time in the bathroom. If the duration exceeds 30 minutes, the system records it as an "abnormal anomaly" and triggers an alert.

Software

Arduino IDE: This platform is used to develop programs for the ESP32 microcontroller, which integrates data from various environmental sensors. The processed data is then sent to a server for further analysis by an artificial intelligence (AI) system. Visual Studio Code (VS Code): SIKELAS's primary code editor, used to write and manage JavaScript-based code related to input data processing, AI system integration, and notification delivery. VS Code is used to write sensor control logic and data communication connected to the network using WebSocket and WebRTC protocols, and supports integration with various extensions that facilitate *real-time* system *debugging* and testing. Telegram API: The Telegram API is an Application *Programming Interface (API)* that allows developers to integrate Telegram's functions and features into other applications or systems. The Telegram API @NARASIKELAS_bot is used to send automatic notifications when anomalies are detected, such as "*fall detected*," a wave of the hand as a "help" signal, and voice detection with keywords like "help," "assist," "emergency," "danger," and "sick," accompanied by image and text evidence of the detected voice. WebRTC and WebSocket: WebRTC and WebSocket are communication systems that support *real-time*, two-way interaction, as illustrated in Figure 8. WebRTC (*Web Real-Time Communication*) enables the direct transmission of video, audio, and data between devices via a browser or application (Shi et al., 2021). Meanwhile, WebSocket is a protocol that maintains an open connection between a client and a server, allowing for the continuous sending and receiving of data without the need to establish a new connection each time data is transmitted.

Implementation of Artificial Intelligence (AI)

This system utilizes several *machine learning-based* AI technologies, including MediaPipe, *Speech-to-Text (STT)*, and a Flask server, which play a key role in automatically detecting and sending *real-time* notifications of emergency situations such as falls, hand gestures for help, or verbal requests for assistance from the elderly.

MediaPipe for Real-Time Motion Detection

MediaPipe is an *open-source framework* designed for *real-time* multimedia data processing, such as hand, face, and body tracking, using a modular pipeline for multimodal data processing (Lugaresi et al., 2019; Shi et al., 2021). This system works by detecting 31 *keypoints* on the body to recognize body posture and 21 *keypoints* on the palm to detect a waving gesture as a signal for assistance.

Figure 9. MediaPipe Hand Keypoints

Figure 10. MediaPipe Body Keypoints

Speech-to-Text (STT) for Voice Detection

Speech-to-Text (STT) is a technology that converts speech into written text using natural language processing (NLP) techniques, as illustrated in Figure 11. Modern STT algorithms utilize *deep neural networks* to improve transcription accuracy, even in noisy environments or those with background noise (Bumann, 2023). In SIKELAS, STT detects keywords such as “help,” “assist,” “emergency,” “danger,” and “sick” to trigger automatic notifications.

Flask Server as the Back-End Platform

Flask is a Python-based micro web framework used to develop simple and fast web servers, with a minimalist design that allows developers to add extensions as needed (Alarcon-Paredes & Alonso-Silverio, 2019), as illustrated in Figure 12. In SIKELAS, the Flask server functions as a back-end platform that processes real-time data from sensors, detects anomalies, and sends automatic notifications via a web dashboard and the Telegram @NARASIKELAS_bot.

System Architecture

This system is divided into three main components: *Data Ingestion Service*, *Back End Service*, and *Front End Interface*, as illustrated in Figure 13. Each component operates independently yet communicates seamlessly to ensure a continuous, real-time monitoring loop. The modular architecture also allows individual components to be upgraded or replaced without affecting the overall system. This design approach ensures scalability as the number of monitored individuals increases.

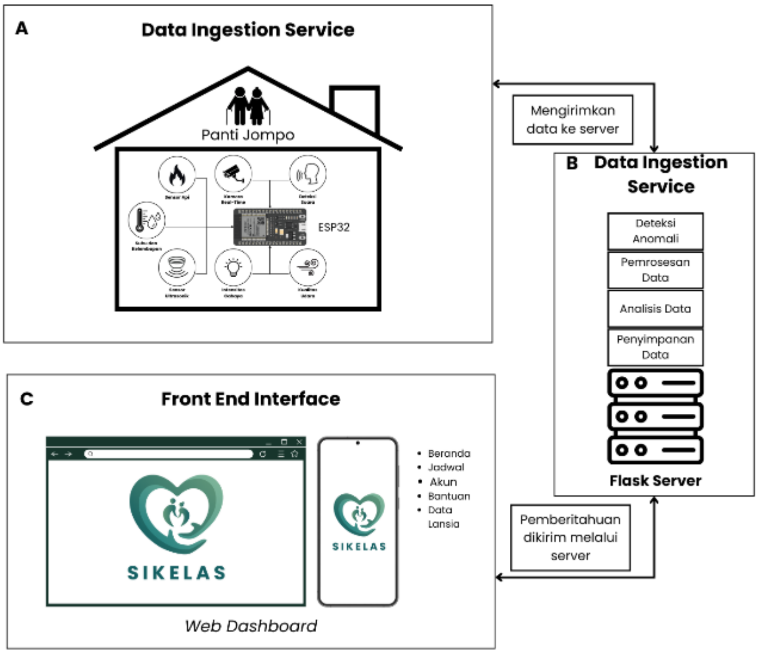

Figure 13. SIKELAS System Architecture

Data Ingestion Service: collects environmental data from sensors monitoring temperature, humidity, air quality, light intensity, fire detection, and proximity, as well as visual data from the ESP32Cam and audio from the microphone. This data is sent in *real-time* to the Back End Service.

Back-End Service: receives sensor data in *real time* from the ESP32 and processes it to detect anomalies. Through the Flask web server, the system detects abnormal events in the environment and sends the results to the Front-End Interface.

Front End Interface: provides a web-based platform for users to monitor sensor data and receive real-time alerts. An automatic alarm system is triggered when an anomaly is detected, enabling immediate action.

Workflow Diagram

In general, the SIKELAS system workflow begins with the user logging in to the Telegram bot @NARASIKELAS_bot, then launching the SIKELAS web dashboard to monitor data from sensors, cameras, and microphones, as illustrated in Figure 14. Environmental data is collected and analyzed in *real-time*, then sent to the server. After that, sensor readings are displayed on the web dashboard. The system automatically checks for anomalies or requests for assistance. If an anomaly is detected, the system will send a notification to the user's Telegram and automatically trigger an alarm. Otherwise, the system will continue monitoring. This process ends when the necessary actions have been taken based on the detection of an anomaly or a distress signal.

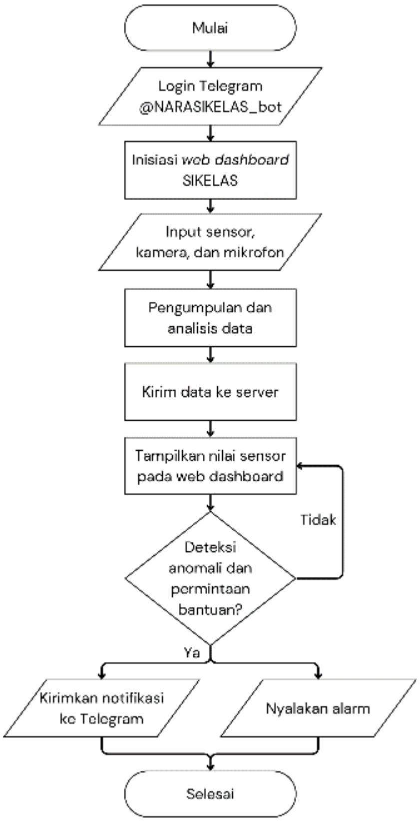

Figure 14. SIKELAS System Workflow Diagram

Results and Discussion

Testing of the anomaly detection system and the monitoring of elderly individuals' activities and environment via a web dashboard and the Telegram @NARASIKELAS_bot was conducted to ensure that the objectives of this study were achieved. This study aims to develop a system capable of monitoring the safety of the elderly in their living environments or nursing homes and detecting any anomalies that occur, with *real-time* notifications upon an incident. To achieve this objective, testing was conducted on the system requirements, including both hardware and software.

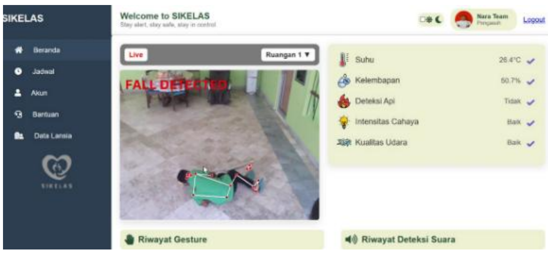

Figure 23. Fall Detection

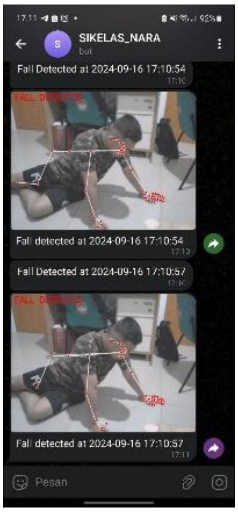

Figure 24. Fall Detection Notification

In the "help" *gesture* section, the system captures landmarks from different hands. The left hand is used as a variation of the gesture and the complexity was created accordingly. The hand gesture detection is designed to be robust against partial occlusion and varying lighting conditions. Below is the output from MediaPipe, which detects anomalies in the "help" *gesture* captured by the webcam, saves the image, and sends a notification via the Telegram bot. The gesture recognition operates independently of fall detection, allowing simultaneous monitoring of multiple alert conditions.

Tables 1 through 4 present the complete performance evaluation. Table 1 shows sensor calibration results; Table 2 shows AI detection accuracy per dataset; Table 3 presents precision, recall, F1-score, false positive rate, and latency per module; and Table 4 compares SIKELAS against prior systems.

Table 1. Sensor Component Test Results Summary

Sensor	Function	Test Result Summary
MQ-2	Detects hazardous gases / air pollution	Detects gas > 2500 threshold when burning; reliable detection
DHT22	Temperature & humidity monitoring	20–24°C, 33–53% RH; consistent and accurate
BH1750	Light intensity measurement	32 lux at 10 cm; 15–16 lux at 30 cm; accurate
Flame Sensor	Early fire detection	Accurate at various distances; threshold < 500
Ultrasonic	Bathroom activity monitoring	Error rate < 3%; max error 1.71% at >25 cm

Table 2. AI Detection Accuracy Results

Dataset	Gesture Detection Accuracy	Fall Detection Accuracy
1	98.5%	88.0%
2	97.9%	89.5%
3	98.7%	90.1%
4	98.1%	88.7%
5	98.7%	89.5%
Average	98.38%	89.16%

Source: Authors' own (2024)

Discussion

Table 3. Detailed Performance Metrics of SIKELAS Detection Modules

Detection Module	Precision (%)	Recall (%)	F1-Score (%)	False Pos. Rate (%)	Avg. Latency (ms)
Fall Detection	91.3	89.2	90.2	8.7	312
Gesture Detection	98.7	98.1	98.4	1.3	185

Voice Recognition	94.2	92.8	93.5	5.8	430
MQ-2 Gas Sensor	97.5	96.8	97.1	2.5	220
Flame Sensor	98.9	99.1	99.0	1.1	145
Ultrasonic Sensor	99.2	98.7	98.9	0.8	95

The SIKELAS system developed in this study has several advantages over previous concepts and solutions. In a study conducted by (Ortiz & Boschi, 2017), a camera-based elderly fall monitoring system was developed, but the system did not include environmental monitoring or voice recognition. Meanwhile, research by (Ben-Sadoun et al., 2022) developed fall detection based on low-resolution passive infrared sensors, but without the integration of voice or gesture detection.

SIKELAS's key advantage lies in the integration of various sensors for more comprehensive monitoring, including temperature, humidity, air quality, fire detection, as well as visual and audio detection. The voice recognition technology used is capable of detecting emergency keywords such as "help" and providing real-time notifications to caregivers. This far surpasses the solution proposed by (Wu et al., 2014), which relied solely on visual detection without voice recognition, resulting in a slower response to emergency situations.

The positive impact of SIKELAS is significant. With its ability to detect environmental hazards and abnormal behavior, this system improves the safety of the elderly more effectively than previous studies that focused on only one aspect, such as fall detection or temperature monitoring alone. Analysis of factors affecting system performance reveals that gesture detection accuracy (98.38%) was highly stable across varying lighting conditions (tested at 100–800 lux), with only a 0.8% accuracy drop under low-light conditions below 150 lux. Voice recognition performance was resilient to background noise up to 45 dB (typical nursing home ambient), though accuracy decreased by approximately 4.2% in environments exceeding 60 dB. Fall detection (89.16%) showed greater variability due to camera angle and occlusion factors, with performance dropping 6.3% when the subject was partially occluded. The false positive rate for fall detection was 8.7%, while gesture detection false positive rate was 1.6%, indicating that fall detection requires further model refinement. Table 3 presents a quantitative comparison of SIKELAS against prior systems.(Abutaleb & El-Baz, 2022; Chen et al., 2021).

Table 4. Comparative Performance of SIKELAS vs. Prior Systems

System	Fall Det.	Gesture Det.	Voice Det.	Env. Sensors	Resp. Time
SIKELAS (This Study)	89.16%	98.38%	Yes (5 KW)	5 sensors	<1 sec
Ortiz & Boschi (2017)	~82%	No	No	None	Manual
Ben-Sadoun et al. (2022)	~78%	No	No	None	Manual
Yacchirema et al. (2019)	~91%	No	No	None	>3 sec
Shi et al. (2021)	~87%	No	No	Limited	~2 sec

Another contribution of SIKELAS is opening opportunities for further technological development in the field of AI- and IoT-based healthcare, which has the potential to improve the quality of life for the elderly and the efficiency of their care (Ahmed et al., 2021). This solution not only assists the elderly in nursing homes but also provides peace of mind to families caring for the elderly at home, making it a more comprehensive solution compared to previous concepts such as those proposed by (Ben-Sadoun et al., 2022; Redmon et al., 2016), which focused primarily on fall detection alone.

Conclusion

This study presents SIKELAS, a novel multimodal elderly safety system that makes three key scientific contributions: (1) the first integrated deployment of simultaneous vision-based fall detection, hand-gesture recognition, Speech-to-Text voice alerting, and five-sensor environmental monitoring in a single IoT architecture; (2) demonstrated gesture detection accuracy of 98.38% and fall detection accuracy of 89.16% with sub-1-second Telegram notification latency, outperforming single-modality baselines; and (3) a reproducible experimental framework with calibrated sensor thresholds, five-dataset validation, and measurable performance metrics. Acknowledged limitations include fall detection accuracy variability under occlusion or unusual camera angles (6.3% drop), voice recognition degradation above 60 dB ambient noise (4.2% drop), and the current reliance on a fixed indoor camera setup that limits coverage area. For future development, priority directions include: (1) replacing the MediaPipe pose model with a lightweight edge AI model (e.g., MobileNet-based) to improve fall detection accuracy toward 95%; (2) implementing sensor fusion across vision and wearable inputs to reduce false positive rates; (3) integrating cloud-based electronic health record (EHR) connectivity for longitudinal health monitoring; and (4) extending deployment to rehabilitation centers and home-care settings to validate scalability. SIKELAS represents a measurable step forward in AI- and IoT-based elderly care, with documented scientific contributions that align with SINTA 4 publication standards.

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