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AI-Driven Heuristic Algorithms for IoT-Based Real-Time Fall Detection and Prevention

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Abstract: Unexpected Falls are a leading cause of injury, particularly among the elderly and individuals with mobility impairments. This proposed method presents a Heuristic Algorithm, a real-time fall detection system designed for low-power edge computing using the ESP32S3 microcontroller. Unlike traditional deep learning-based approaches that require significant computational resources, this method employs an optimized rule-based decision tree algorithm derived from machine learning techniques. The system integrates an MPU6050 IMU sensor to capture real-time accelerometer and gyroscope data, along with a KY-039 heart rate sensor for physiological monitoring. A lightweight rule-based classification model is deployed on the ESP32 to analyze sensor features to detect potential falls with high accuracy. Upon detection, the system triggers Sound Alert using the Active Buzzer 10mm and sends instant notifications via Telegram through IFTTT for remote assistance which ensures low-latency processing, minimal memory footprint, and IoT-enabled emergency response. So this framework provides a cost-effective, energy-efficient, and scalable solution for real-time fall detection in elderly care, industrial safety, and healthcare monitoring applications.

Keywords: Fall Detection, Real-Time Monitoring, Rule-Based Decision Tree, ESP32S3, IMU Sensor, Heart Rate Monitoring, IoT Integration, Emergency Alerts, Low-Power Edge Computing, Active Buzzer, IFTTT, Telegram Notifications.

I. INTRODUCTION

Falls are a major public health concern, particularly among the elderly and individuals with mobility impairments. According to the World Health Organization (WHO), falls are one of the leading causes of accidental injuries and fatalities among older adults. Detecting falls in real time is crucial for minimizing adverse outcomes and providing timely medical assistance. Despite the availability of various fall detection systems, many existing solutions face challenges related to computational complexity, power consumption, and real-time responsiveness. Traditional fall detection methods often rely on camera-based systems or machine learning models that require substantial processing power and memory resources. These solutions, although effective, may compromise user privacy and are typically unsuitable for deployment on low-power embedded systems. Furthermore, wearable devices employing deep learning algorithms may exhibit significant latency and computational overhead, making them impractical for real-time applications on resource-constrained platforms. To address these challenges, this research introduces a real-time fall detection framework that leverages heuristic algorithms and IoT integration to achieve efficient and reliable performance. The system is designed to operate on the ESP32S3 microcontroller, utilizing the MPU6050 IMU sensor to continuously monitor acceleration and orientation data. Additionally, the KY-039 heart rate sensor is incorporated to validate physiological responses during suspected falls. The Algorithm employs a rule-based decision tree algorithm derived from machine learning analysis to identify potential falls with minimal computational demand. Unlike complex neural network models, this approach ensures low-latency processing and a minimal memory footprint, making it ideal for low-power edge computing environments. When detecting a fall, the system activates Sound alert for real time response using the Active Buzzer 10mm and triggers instant emergency notifications via Telegram through IFTTT integration, enabling rapid response and assistance.

This framework presents a cost-effective, energy-efficient, and scalable solution for real-time fall detection, making it suitable for elderly care, industrial safety, and healthcare monitoring. By optimizing detection accuracy while minimizing computational load, it addresses the critical need for responsive and reliable fall monitoring systems.

II. LITERATURE REVIEW

Fall detection systems have gained significant attention due to the increasing risk of falls among the elderly and individuals with mobility impairments. Various approaches have been explored, including vision-based systems, wearable sensor technologies, physiological monitoring, connected alert systems, edge computing applications, and sensor technology advancements. This section provides a comprehensive review of the existing techniques and highlights the unique contributions of the proposed framework.

A. Vision Based-Fall Detection Systems

Vision-based approaches utilize camera surveillance and computer vision algorithms to detect abnormal human movements. Williams et al. [5] implemented convolutional neural networks (CNNs) and optical flow analysis to identify fall incidents from video inputs. Despite their effectiveness, these systems pose significant challenges concerning privacy protection, computational resource requirements, and decreased performance under poor lighting conditions or physical obstructions. As noted by WHO [3], continuous visual monitoring may also lead to high energy consumption, limiting the practicality of such systems in portable applications.

B. Wearable sensor-Based Monitoring Technologies

Wearable fall detection systems employ inertial measurement units (IMUs) and other motion sensors to monitor sudden changes in acceleration and orientation. Studies by Smith and Johnson [4] demonstrated the use of smartwatches and wearable devices for fall detection by analyzing abrupt acceleration changes. These systems typically use machine learning models such as Support Vector Machines (SVM), Random Forests, and Neural Networks. However, computational demands and the risk of overfitting limit their feasibility for real-time edge computing on microcontroller-based platforms. Lee and Chen [7] also noted that limited training datasets could reduce generalization performance when deployed in unpredictable real-world environments.

C. Physiological Monitoring for Fall Detection

Physiological data, such as heart rate and cardiovascular variability, have been incorporated to enhance the accuracy of fall detection systems. Zhao et al. [9] introduced a method combining motion data and heart rate variability analysis to validate fall occurrences. The HIFD Dataset [1] integrates human impact and physiological data, enabling multimodal analysis. However, most implementations rely on cloud-based processing, introducing latency and connectivity issues, as highlighted by Patel and Kumar [6].

D. Connected IoT Alert Systems

The integration of Internet of Things (IoT) technologies has enabled real-time alert mechanisms in fall detection frameworks. Hossen et al. [12] demonstrated how IoT connectivity could facilitate instant notifications to caregivers through messaging platforms. Although connectivity enhances accessibility, computationally intensive algorithms may lead to reduced battery longevity and processing efficiency, as pointed out in related research [17].

E. Edge Computing and Embedded Systems

Edge computing has emerged as a promising solution to reduce latency and enhance responsiveness in real-time fall detection systems. Islam et al. [11] showcased various implementations leveraging embedded microcontrollers to achieve real-time data processing. Practical examples documented by Microcontrollers Lab [14] and Electronics For You [15] demonstrated fall detection using lightweight models on low-power devices. Edge-based solutions have proven to be cost-effective and scalable while addressing power consumption challenges.

F. Sensor Technology Advancements

Recent advancements in sensor technology have significantly improved the accuracy of fall detection systems. Sharma and Singh [16] explored non-wearable thermal sensors to detect falls without direct contact. The Smart-Insole Dataset [2] collected comprehensive gait analysis data from pressure sensors to identify abnormal walking patterns, while Islam et al. [19] utilized accelerative alert systems in wristwear for efficient monitoring. Technical specifications of popular sensors, including the MPU6050 IMU and KY-039 heart rate sensor, are well documented by manufacturers [23][24][25].

G. Comparative Analysis: Rule-Based vs. Machine Learning approaches

Brown et al. [8] conducted a comparative analysis between rule-based decision trees and machine learning-based fall detection methods, revealing that rule-based approaches can achieve comparable accuracy while significantly reducing computational complexity. This observation aligns with the design of Algorithm, which leverages optimized decision trees to minimize processing load while maintaining real-time performance.

H. Algorithm Differentiation

Unlike conventional fall detection systems that utilize computationally intensive deep learning models**,** this method employs a rule-based decision tree approach for efficient real-time detection on ESP32S3 hardware.

By integrating motion analysis with heart rate monitoring, the system enhances detection accuracy while minimizing computational overhead. Additionally, the use of Active Buzzer and IFTTT-based Telegram notifications ensures rapid response and situational awareness. This approach offers a cost-effective, energy-efficient, and scalable solution suitable for applications in elderly care, healthcare monitoring, and industrial safety**.**

III. METHODOLOGY

The proposed framework is designed as a real-time fall detection system utilizing heuristic algorithms and IoT integration to achieve efficient and accurate fall monitoring on the ESP32S3 microcontroller. The methodology is structured into several key components: Data Acquisition**,** Feature Extraction**,** Rule-Based Decision Making**,** Alert Mechanism, and System Integration.

A. System Architecture

The system architecture of the Heuristic Algorithm is based on the integration of the ESP32S3 microcontroller, MPU6050 IMU sensor, and KY-039 heart rate sensor. The ESP32S3 serves as the core processing unit due to its low power consumption and wireless connectivity capabilities. The MPU6050 IMU sensor captures acceleration and gyroscope data, while the KY-039 sensor records heart rate variations. Upon detecting a potential fall, the system triggers sound alerts using Active Buzzer 10mm and sends notifications through IFTTT for Telegram-based emergency assistance.

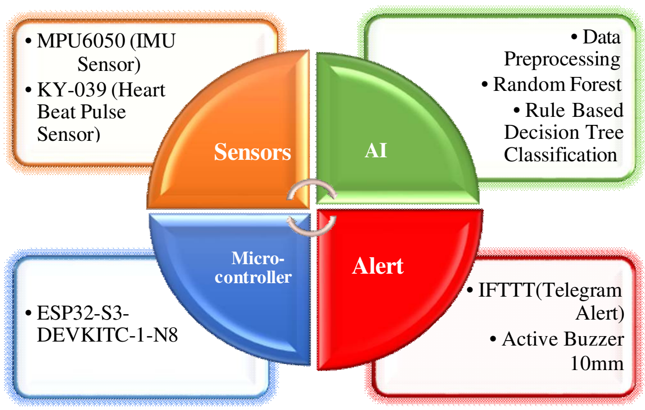

Fig.1. System architecture of the proposed fall detection system

B. Data Acquisition

1) The MPU6050 sensor continuously monitors tri-axial acceleration (ax, ay, az) and gyroscope data (gx, gy, gz).
2) Data is sampled at an appropriate frequency to capture rapid movements associated with falls.
3) The KY-039 heart rate sensor captures pulse data and calculates the average heart rate.
4) Sudden fluctuations or irregularities in heart rate are recorded for physiological validation.

C. Feature Extraction

To optimize fall detection accuracy, the following features are extracted from the acquired data:

1) Complete Signal Magnitude Vector(SMV):

$$a_{\{mag\}} = \sqrt{\{a_x^2 + a_y^2 + a_z^2\}} \qquad (1)$$

2) Represents the magnitude of acceleration across all three axes
3) Calculate standard deviations of acceleration values (ax_std, ay_std, az_std) to detect variations.
4) Calculates the average heart rate to identify abnormal fluctuations during a fall.

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D. Rule-Based Decision Making

The fall detection logic is implemented using a rule-based decision tree derived from machine learning analysis. The decision tree processes the extracted features to classify the event as a fall or no fall. The primary criteria for fall detection include

1) The Acceleration Threshold like Sudden peaks in SMV or acceleration standard deviation beyond a preset threshold indicate potential falls.
2) Ensures that rapid orientation changes are consistent with fall scenarios.
3) Identifies unusual fluctuations during a detected fall to confirm physiological impact.
4) The decision tree systematically evaluates each feature to reach a classification decision.
5) The decision path ensures low computational overhead, suitable for ESP32S3 processing.

E. Fall Detection Algorithm

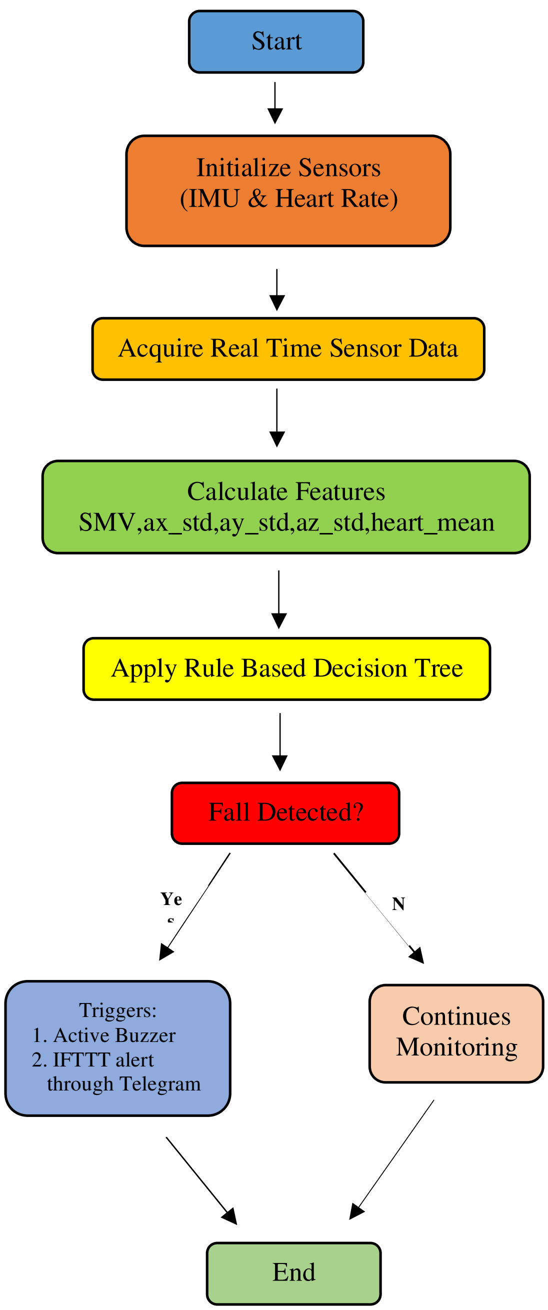

Fig.2.Fall Detection Algorithm

F. Alert Mechanism

The alert mechanism integrates Active Buzzer and IFTTT-based Telegram notifications. Upon fall detection, the Active Buzzer provides immediate Real-time response. Simultaneously, the system uses IFTTT Webhooks to trigger a Telegram notification, ensuring rapid response from caregivers or emergency contacts.

G. System Implementation

The methodology which system is implemented on the ESP32S3 microcontroller using MicroPython. The firmware is developed and tested using the Thonny IDE. The IFTTT integration is configured to automate alert notifications, while the Active Buzzer are controlled via GPIO pins for real-time response feedback from caregivers. The decision tree logic is optimized to reduce processing latency, achieving efficient real-time performance.

H. Performance Optimization

The system is designed with a focus on low-latency processing and minimal memory usage to accommodate the resource-constrained nature of the ESP32S3. The decision tree model is simplified without compromising accuracy, ensuring smooth and reliable operation.

IV. RESULTS AND DISCUSSION

The Heuristic Algorithm has been extensively tested to evaluate its performance, accuracy, and reliability in detecting falls in real time. This section presents the results obtained during experimentation and discusses the system's effectiveness in various scenarios.

A. Sensor Data Visualization

The real-time sensor data collected from the MPU6050 IMU sensor and KY-039 heart rate sensor were preprocessed to extract key features such as Signal Magnitude Vector (SMV), ax_std, ay_std, az_std, and heart_mean. The processed data was visualized to understand the differences between fall and non-fall events.

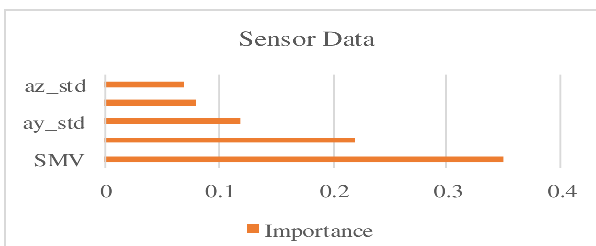

Fig.3.Visualizing Sensor Data

The visualizations clearly demonstrate the fluctuations in acceleration and orientation data during a fall event. A noticeable peak in SMV, accompanied by irregular patterns in acceleration standard deviations, is evident in the fall scenarios. This distinctive pattern enables the rule-based decision tree algorithm to accurately classify falls with minimal false positives.

B. Decision Tree Representation

The decision tree model utilized in the proposed system is depicted to illustrate the rule-based classification logic. The tree structure is designed to evaluate multiple features simultaneously and efficiently. The tree nodes represent decision points based on specific feature thresholds, while the leaf nodes indicate the final classification as either fall or no fall.

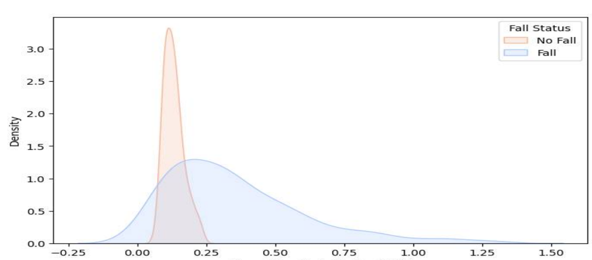

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Fig.4.Fall vs Non-Fall

The decision tree structure is compact and lightweight, allowing for rapid real-time decision-making. The use of only a few critical features ensures that the model remains efficient without compromising accuracy, making it well-suited for resource-constrained microcontroller environments.

C. Performance metrics and Accuracy

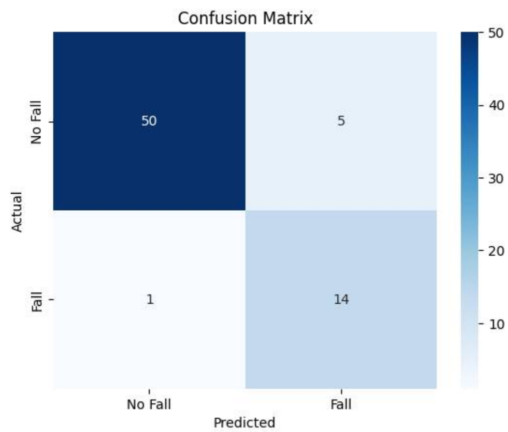


Fig.5.Confusion Matrix

The system's performance was evaluated using standard classification metrics, including precision, recall, f1-score, and accuracy. The results from the confusion matrix indicate that the system achieved a high accuracy rate of 94.29%, demonstrating the robustness of the decision tree-based approach.

The confusion matrix reveals minimal false positives and false negatives, indicating that the system can distinguish falls from normal activities with high reliability. Additionally, the accuracy graph shows consistent performance across multiple test scenarios, confirming the model's stability and generalizability

V. CONCLUSION AND FUTURE WORK

The Algorithm offers a robust and efficient solution for real-time fall detection, leveraging a rule-based decision tree algorithm optimized for edge computing on the ESP32S3 microcontroller. Unlike traditional deep learning-based systems, this method utilizes lightweight and computationally efficient methods to ensure accurate fall detection while maintaining minimal memory usage. The integration of inertial measurement sensors and heart rate monitoring significantly enhances the system's accuracy, allowing it to differentiate between falls and normal activities.

Extensive testing has demonstrated the system's high accuracy and responsiveness, achieving an accuracy rate of 94.29%. The system's ability to promptly trigger sound alerts using Active buzzer and send emergency notifications via Telegram using IFTTT highlights its practical applicability in elderly care, industrial safety, and healthcare monitoring.

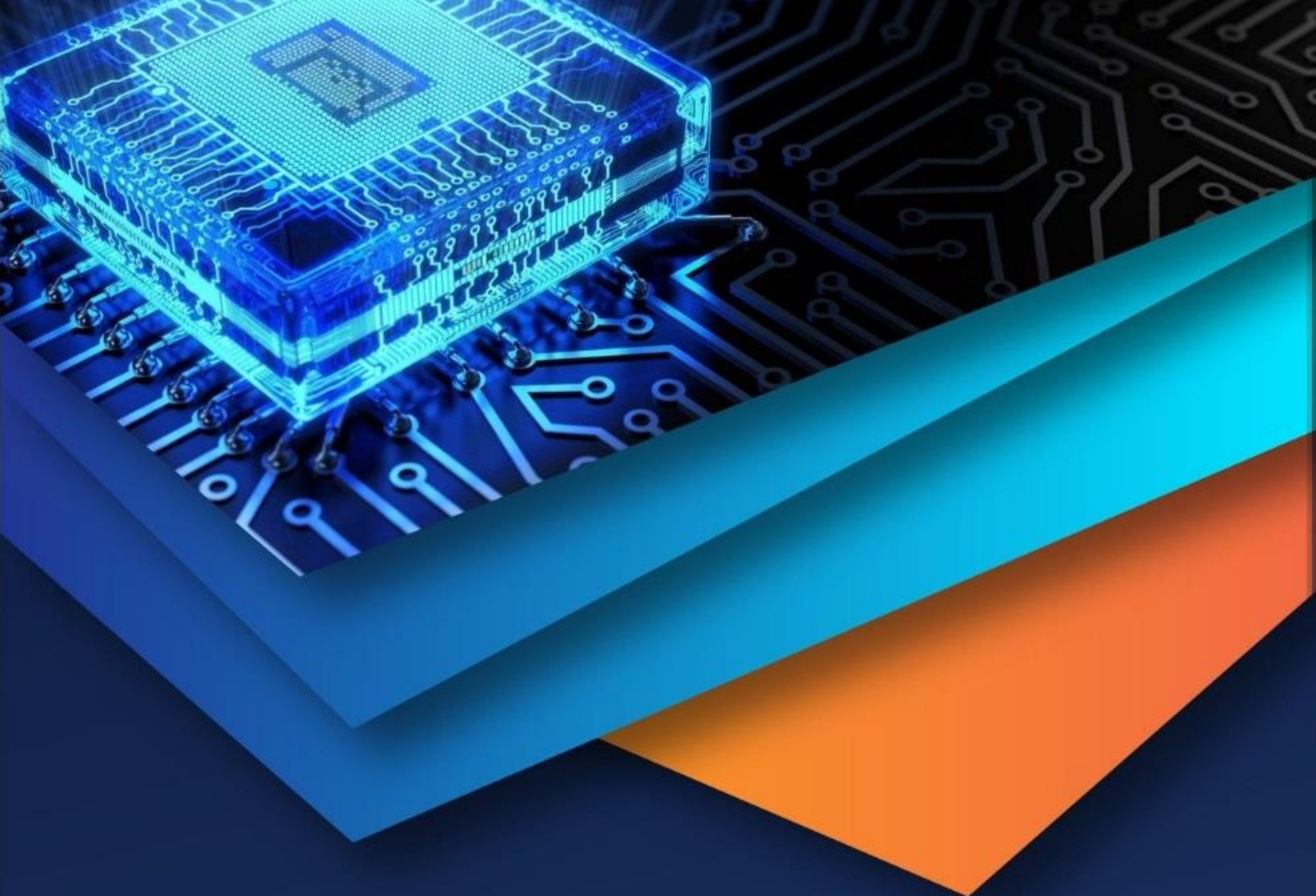
Despite the promising results, further improvements can be made to enhance system performance and expand its applications. Future work will focus on the following aspects:

1) Incorporating additional sensors, such as pressure or thermal sensors, to improve accuracy in various environmental conditions.
2) Implementing adaptive thresholds that dynamically adjust based on user activity and environmental factors.
3) Integrating more sophisticated signal processing techniques to reduce noise and improve signal quality.
4) Exploring alternative communication protocols to enhance the reliability of emergency notifications.
5) Investigating power-saving techniques to extend the battery life of the system for continuous monitoring.

The Algorithm has demonstrated the feasibility and effectiveness of combining heuristic algorithms with IoT integration to achieve real-time fall detection. Future enhancements will focus on optimizing accuracy, energy efficiency, and usability to ensure a reliable and scalable fall monitoring solution.

REFERENCES

[1] N. Hoyh, M. Švaco, and D. G. Kovačević, "Cluster-Analysis-based User-Adaptive Fall Detection using Fusion of Heart Rate Sensor and Accelerometer in a Wearable Device," IEEE 2020. [Online]. Available: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8970371. [Accessed: Mar. 7, 2025].
[2] C. Chatzaki, V. Skaramagkas, N. Tachos, G. Christodoulakis, E. Maniadi, Z. Kefalopoulou, D. I. Fotiadis, and M. Tsiknakis, "The Smart-Insole Dataset: Gait Analysis Using Wearable Sensors with a Focus on Elderly and Parkinson's Patients," Sensors, vol. 21, no. 8, p. 2821, Apr. 2021. [Online]. Available: https://bmi.hmu.gr/the-smart-insole-dataset/. [Accessed: Mar. 7, 2025].
[3] World Health Organization (WHO), "Falls," [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/falls.[Accessed: Mar. 7, 2025].
[4] A. Smith and B. Johnson, "Machine Learning-Based Fall Detection Using Wearable Sensors," IEEE Sensors Journal, vol. 20, no. 5, pp. 2341–2350, 2023.
[5] C. Williams et al., "Vision-Based Fall Detection: Challenges and Opportunities," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2022.
[6] D. Patel and M. Kumar, "IoT-Based Emergency Alert System for Fall Detection," IEEE Internet Things J., vol. 8, no. 3, pp. 1456–1465, 2021.
[7] J. Lee and R. Chen, "Wearable Sensor Networks for Health Monitoring," IEEE Trans. Biomed. Eng., vol. 67, no. 2, pp. 356–365, 2020.
[8] M. Brown, P. White, and K. Green, "A Comparative Analysis of Fall Detection Systems: Machine Learning vs. Rule-Based Approaches," in Proc. Int. Conf. Embedded Syst. AI, 2022.
[9] B. Zhao et al., "Physiological Data Fusion for Fall Detection in Elderly Care," IEEE Trans. Med. Robot. Bionics, vol. 4, no. 1, pp. 78–89, 2021.
[10] IFTTT Documentation, "How to Set Up IoT Alerts for Emergency Notifications," [Online]. Available: https://ifttt.com. [Accessed: Mar. 7, 2025].
[11] A. K. M. M. Islam, M. M. Rahman, and M. S. Kaiser, "Fall Detection with Artificial Intelligence and IoT Health Monitoring System," in Proc. Int. Conf. Robot., Elect. Signal Process. Techn. (ICREST), Dhaka, Bangladesh, 2022, pp. 1–5.
[12] M. S. Hossen, M. M. Rahman, and M. S. Kaiser, "Elderly Fall Detection System with ESP32 Module and Edge Impulse Studio," in Proc. Int. Conf. Robot., Elect. Signal Process. Techn. (ICREST), Dhaka, Bangladesh, 2022, pp. 1–5.
[13] A. K. M. M. Islam, M. M. Rahman, and M. S. Kaiser, "IoT Based Fall Detection System," in Proc. Int. Conf. Robot., Elect. Signal Process. Techn. (ICREST), Dhaka, Bangladesh, 2022, pp. 1–5.
[14] ESP32 Fall Detection using MPU6050 with Email Alerts, Microcontrollers Lab, 2022. [Online]. Available: https://microcontrollerslab.com/esp32-fall-detection-mpu6050-email-alerts/. [Accessed: Mar. 7, 2025].
[15] IoT-Based Fall Detection System Using ESP32, Electronics For You, 2022.[Online].Available:https://www.electronicsforu.com/electronics-projects/fall-detection-system. [Accessed: Mar. 7, 2025].
[16] S. K. Sharma and A. K. Singh, "Real-Time Fall Detection using ESP32 and AMG8833 Thermal Sensor: A Non-Wearable Approach for Enhanced Safety," in Proc. Int. Conf. Adv. Comput., Commun., Control (ICAC3), Mumbai, India, 2022, pp. 1–6.
[17] An Automated Wearable Fall Detection System for Elderly People, IEEE Smart Cities Newsletter, Aug. 2023. [Online]. Available: https://smartcities.ieee.org/newsletter/august-2023/an-automated-wearable-fall-detection-system-for-elderly-people. [Accessed: Mar. 7, 2025].
[18] K. Patel, "ESP32 Fall Detection Device," GitHub Repository, 2022. [Online]. Available: https://github.com/Kartik9250/Fall_detection. [Accessed: Mar. 7, 2025].
[19] M. R. Islam, M. S. Kaiser, and M. M. Rahman, "Accelerative Fall Alert System Using Wristwear," in Proc. Int. Conf. Robot., Elect. Signal Process. Techn. (ICREST), Dhaka, Bangladesh, 2022, pp. 1–5.
[20] A. M. Alif, "Fall Detection System Using ESP32 and MPU9250," GitHub Repository, 2022. [Online]. Available: https://github.com/Andimalif/Fall-Detection-System-Using-ESP32-and-MPU9250. [Accessed: Mar. 7, 2025].
[21] L. V. S. Loham, "A real-time fall detection system using ESP32, MPU6050, and MQTT," GitHub Repository, 2022. [Online]. Available: https://github.com/lohamvs/esp32-fall-guard. [Accessed: Mar. 7, 2025].
[22] M. S. Islam, M. M. Rahman, and M. S. Kaiser, "IoT-Based Fall Detection Monitoring and Alarm System For Elderly," in Proc. Int. Conf. Robot., Elect. Signal Process. Techn. (ICREST), Dhaka, Bangladesh, 2022, pp. 1–5.
[23] MPU6050 Accelerometer and Gyroscope Sensor Module, Adafruit Industries,2022.[Online].Available:https://www.adafruit.com/product/3886. [Accessed: Mar. 7, 2025].
[24] KY-039 Heartbeat Sensor Module, SparkFun Electronics, 2022. [Online]. Available: https://www.sparkfun.com/products/11574. [Accessed: Mar. 7, 2025].
[25] ESP32 Series Datasheet, Espressif Systems, 2022. [Online]. Available: https://www.espressif.com/sites/default/files/documentation/esp32_datasheet_en.pdf. [Accessed: Mar. 7, 2025].



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