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An IoT-Integrated Multi-Sensor Framework for Continuous Vital Monitoring and Fall Detection

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Abstract: The rapid growth of elderly populations and patients requiring continuous medical supervision has created a demand for intelligent healthcare monitoring systems. This paper presents an IoT-integrated multi-sensor framework for continuous monitoring of vital parameters and fall detection with an automated SMS alert system using Twilio cloud services. The proposed system integrates sensors such as heart rate, SpO_2, temperature, and an accelerometer to continuously monitor the patient's physiological condition and detect sudden fall events. Sensor data is processed using a microcontroller and transmitted through Wi-Fi to a cloud platform for real-time monitoring. When abnormal vital signs or a fall is detected, the system automatically sends an SMS alert to caregivers using the Twilio messaging API. The proposed system offers a low-cost, portable, and real-time monitoring solution for elderly care and remote patient monitoring. Experimental testing demonstrates reliable sensor readings, accurate fall detection, and rapid alert delivery through SMS notifications.

Keywords: Vital signs, IoT healthcare, MAX30100, fall detection, ESP32, temperature monitoring, wearable system.

1. INTRODUCTION

Healthcare monitoring has become an important research area due to the increasing number of elderly individuals and patients suffering from chronic diseases. Traditional healthcare systems rely on manual monitoring, which may delay emergency response during critical situations. The Internet of Things (IoT) has enabled the development of intelligent healthcare systems that continuously monitor physiological parameters and transmit the collected data to remote caregivers. Fall incidents are one of the most serious risks faced by elderly individuals and can lead to severe injuries or even death if assistance is not provided immediately. IoT-based fall detection systems use motion sensors such as accelerometers and gyroscopes to identify abnormal body movements and detect fall events in real time.

2. SYSTEM ARCHITECTURE

The proposed system architecture is designed to continuously monitor vital health parameters and detect fall events using an IoT-based multi-sensor framework integrated with a Twilio SMS alert system. The architecture mainly consists of four modules: the sensor module, processing unit, communication module, and alert notification module.

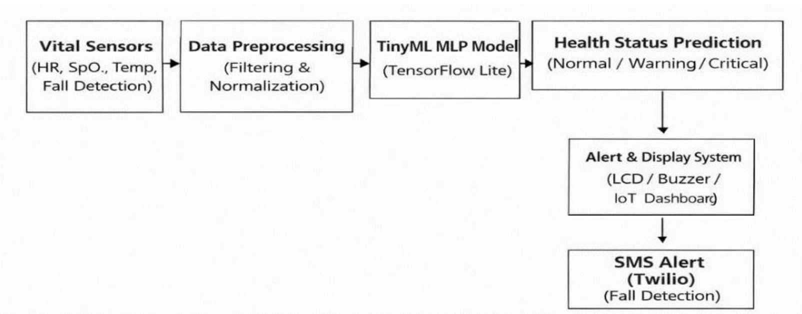

Figure 1 Block diagram of system

This figure 1 shows the health monitoring process using sensors and a Tiny ML model. Vital sensors collect health data such as heart rate, oxygen level, temperature, and fall detection, and the data is preprocessed before being analyzed by the Tiny ML MLP model. The system predicts the health status as normal, warning, or critical and sends alerts through an LCD, buzzer, IoT dashboard, and SMS notification.

Functional Units of the Proposed System

1. Physiological Sensing Unit
2. Processing Unit

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3. Local Display Unit
4. Alerting Unit
5. Cloud Monitoring Unit

2.1 HARDWARE COMPONENTS

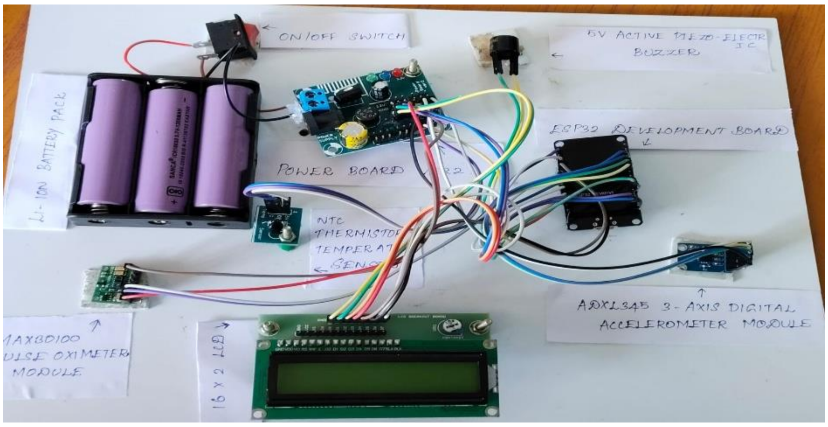

Figure 2: Prototype Hardware Setup of the Proposed System

Figure 2 Show The complete hardware prototype is shown, consisting of the ESP32 development board, MAX30100 pulse oximeter, NTC thermistor, ADXL345 accelerometer, 16×2 LCD, buzzer, and Li-ion battery module. The setup validates successful integration of multiple sensors for continuous health monitoring and falls detection.

1. ESP32 Development Board
2. MAX30100 Pulse Oximeter Module
3. NTC Thermistor Temperature Sensor
4. 16×2 LCD
5. Li-ion battery pack along with power management board
6. On/off switch and supporting circuitry
7. ADXL345 3-Axis Digital Accelerometer Module
8. 5V Active piezoelectric Buzzer

3. METHODOLOGY

3.1 Data Acquisition

The proposed system begins with continuous acquisition of physiological and motion data using multiple sensors interfaced with the ESP32 microcontroller. The MAX30100 sensor is used to measure heart rate and blood oxygen saturation (SpO_2), while an NTC thermistor measures body temperature. A three-axis accelerometer (ADXL345) is employed to monitor body movements and detect potential fall events. These sensors provide real-time data, which is directly used for further processing.

3.2 Data Preprocessing

The raw sensor data may contain noise due to motion disturbances and environmental variations. To ensure accuracy and stability, preprocessing techniques such as filtering and normalization are applied. Additionally, temperature measurement is improved using a two-stage calibration process, which includes ambient calibration and human contact calibration. This enhances the reliability of temperature readings under different conditions.

3.3 Intelligent Classification using Tiny ML

The preprocessed sensor data is directly provided as input to a Multi-Layer Perceptron (MLP) model implemented using TensorFlow Lite. The model is trained using labeled datasets and deployed on the ESP32 using Tiny Machine Learning (Tiny ML). This enables real-time classification at the edge without relying on cloud computation. The system categorizes

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the user's health condition into Normal, Warning, Critical, or Fall Detected states. This intelligent approach improves accuracy and reduces false alarms compared to conventional threshold-based methods.

3.4 Fall Detection Mechanism

The accelerometer continuously monitors motion along three axes. The system evaluates sudden changes in acceleration and movement patterns. Instead of relying on fixed threshold values, the MLP model analyzes the sensor data to distinguish between normal activities and actual fall events. This approach significantly reduces false positives and improves detection reliability.

3.5 Alert Generation and Display

Based on the classification results, the system generates alerts through multiple output devices. A 16×2 LCD displays real-time health parameters and system status, while a buzzer is activated during abnormal or emergency conditions. Additionally, all sensor data and status updates are transmitted to the IoT cloud platform for remote monitoring and visualization.

3.6 SMS Alert using Twilio

To ensure immediate emergency communication, the system integrates SMS alert functionality using Twilio. When a fall or critical condition is detected, the ESP32 sends an HTTP request to the Twilio API. The platform processes the request and sends an instant SMS notification to a predefined mobile number, informing caregivers about the emergency. This feature ensures rapid response and enhances patient safety, even without continuous monitoring of the IoT dashboard.

3.7 Overall System Workflow

The overall workflow of the system involves sequential steps starting from sensor data acquisition, followed by preprocessing and intelligent classification using Tiny ML. Based on the classification results, alerts are generated locally through a buzzer and LCD display, remotely through the IoT cloud, and instantly via SMS notification. This integrated methodology ensures accurate monitoring, efficient decision-making, and real-time emergency response.

4. LITERATURE REVIEW

4.1 IoT-Based Healthcare Monitoring Systems

The integration of Internet of Things (IoT) technology in healthcare has enabled continuous monitoring of patients outside traditional clinical environments. IoT-based systems utilize wearable sensors, embedded controllers, and cloud platforms to collect and transmit physiological data in real time. These systems improve accessibility to healthcare services and reduce hospital dependency, especially for elderly and chronically ill patients. However, many existing solutions focus primarily on data collection and visualization, with limited emphasis on intelligent analysis and emergency communication.

4.2 Sensor-Based Vital Sign Monitoring

Several research works have explored the use of non-invasive sensors for measuring vital parameters such as heart rate, blood oxygen saturation (SpO_2), and body temperature. Optical sensors like MAX30100 are widely used due to their accuracy and ease of integration, while thermistor-based temperature sensors are preferred for their low cost and simplicity. Accelerometers are commonly employed for motion tracking and fall detection. Although these sensor-based systems provide continuous monitoring, they often rely on basic processing techniques and lack advanced decision-making capabilities.

4.3 Threshold-Based Monitoring Systems

Traditional healthcare monitoring systems typically use predefined threshold values to classify physiological conditions. For example, heart rate and SpO_2 values are compared against fixed ranges to determine normal or abnormal states. While this approach is simple and computationally efficient, it does not account for individual variations in physiological parameters. As a result, threshold-based systems may generate false alarms or fail to detect critical conditions accurately, limiting their reliability in real-world applications.

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4.4 Machine Learning in Healthcare Monitoring

Recent advancements in healthcare technology have introduced machine learning techniques for intelligent analysis of biomedical data. Algorithms such as Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks (ANN) are widely used for classification and anomaly detection. Among these, the Multi-Layer Perceptron (MLP) model has gained attention due to its ability to learn complex nonlinear relationships between multiple input parameters. Machine learning-based systems significantly improve prediction accuracy and reduce false alarms compared to conventional methods. However, many of these systems depend on cloud-based processing, leading to increased latency and power consumption.

4.5 Tiny ML for Edge-Based Intelligence

Tiny Machine Learning (Tiny ML) enables deployment of machine learning models on resource-constrained embedded devices. Frameworks such as TensorFlow Lite allow efficient implementation of neural networks on microcontrollers like ESP32. By performing inference directly on the device, Tiny ML reduces latency, enhances data privacy, and minimizes reliance on continuous internet connectivity. This makes it highly suitable for real-time healthcare monitoring applications. Despite these advantages, integration of Tiny ML with multi-sensor healthcare systems is still an emerging area of research.

4.6 Fall Detection Techniques

Fall detection is a critical component in elderly healthcare monitoring systems. Conventional approaches use accelerometer-based threshold logic to detect sudden impacts or abnormal motion. While these methods are simple, they often produce false positives during routine activities such as sitting or bending. Advanced approaches utilize machine learning models to analyze motion patterns and distinguish between normal activities and actual falls. These intelligent systems provide higher accuracy and reliability, making them more suitable for real-world deployment.

4.7 Emergency Alert and Communication Systems

Effective communication is essential in healthcare monitoring systems to ensure timely medical intervention. Many existing systems rely on cloud dashboards or mobile applications for notifications, which require active user monitoring. To overcome this limitation, communication technologies such as SMS-based alerting have been introduced. Platforms like Twilio enable real-time delivery of emergency messages to caregivers. SMS alerts provide a simple, reliable, and widely accessible communication method, ensuring immediate attention during critical situations

4.8 Research Gap and Motivation

From the literature, it is evident that existing systems address IoT monitoring, machine learning, and alert mechanisms independently. However, there is limited work that integrates multi-sensor monitoring, Tiny ML-based intelligent classification, and real-time SMS alerting within a single embedded system. Additionally, many systems lack a reliable mechanism for immediate emergency communication.

The proposed system addresses these gaps by combining sensor-based monitoring, edge-based intelligence using Tiny ML, and instant SMS alerts using Twilio. This integrated approach improves accuracy, reduces false alarms, and ensures rapid response during emergencies, making it highly effective for real-time healthcare applications.

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5. RESULTS AND DISCUSSION

5.1 Normal Condition Monitoring

Figure 3 Normal Condition Display of the Monitoring System

This figure 3 represents the same dashboard under stable conditions. The heart rate is 90 bpm, and SpO_2 is 97%, which are normal readings. The temperature remains around 25.47°C, again indicating possible environmental sensing rather than body temperature. In the status panel, the system alternates between "AI: Normal," "AI: Waiting," and occasional "AI: Critical", suggesting continuous monitoring with intermittent fluctuations. The fall status indicator is green, meaning no fall is detected and the patient is safe at this moment.

The proposed IoT-based intelligent monitoring system was tested under normal operating conditions to evaluate its stability and accuracy in real-time data acquisition. The hardware setup continuously monitors physiological parameters such as heart rate, oxygen saturation, and body temperature using integrated sensors. During normal conditions, the LCD display shows values such as a heart rate of approximately 84 bpm, SpO_2 around 95%, and temperature close to 25°C. The system status is indicated as "SAFE," and the AI status is displayed as "Normal," confirming that no abnormal activity or fall has been detected. The accelerometer records regular body movements, and the machine learning model correctly classifies them as safe activities. This demonstrates that the system operates efficiently without generating false alerts during routine conditions.

5.2 Mobile Application Monitoring

Figure 4 Real-Time Vital Monitoring System with Normal Fall Status Indication

Figure 4 presents a similar health monitoring dashboard with updated readings: heart rate (90 bpm), SpO_2 (97%), and temperature (25.473°C). The system continues to display values through graphical gauges for clarity. The status section includes messages such as "AI: Critical," "AI: Waiting," and "AI: Normal," indicating dynamic system evaluation. The

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fall detection panel shows a green indicator, meaning no fall is detected and the patient is in a safe condition. This demonstrates continuous monitoring with real-time status updates and decision-making.

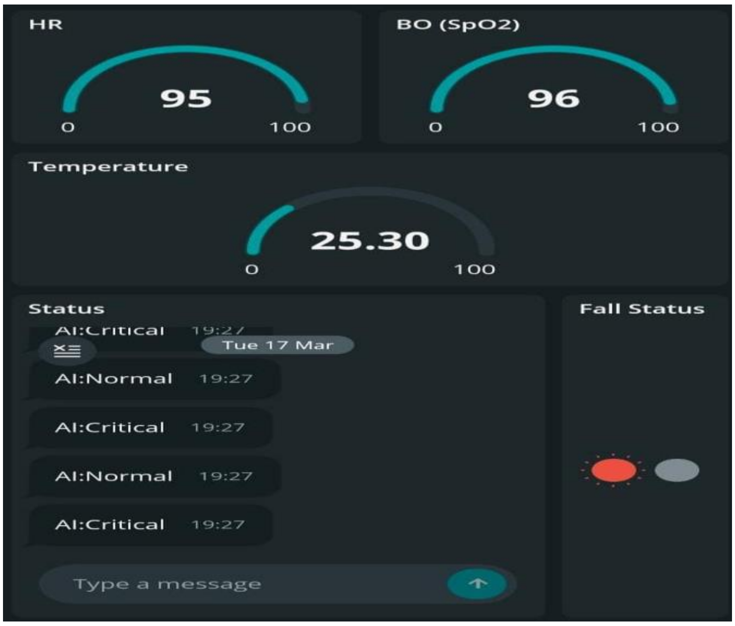

Figure 5 Dashboard with Fall Detection Alert (Critical Condition)

Figure 5 shows a real-time health monitoring dashboard displaying vital parameters such as heart rate (95 bpm), blood oxygen level (SpO_2 at 96%), and temperature (25.30°C). The interface uses gauge meters for easy visualization of sensor readings. The status panel indicates alternating conditions like “AI: Critical” and “AI: Normal,” suggesting automated health analysis. On the right side, the fall detection status shows a red indicator, implying a detected fall or emergency condition. Overall, it represents an IoT-based patient monitoring system with alert capability.

To enable remote monitoring, a mobile-based application was developed that displays real-time sensor data in a user-friendly interface. The application presents parameters such as heart rate, SpO_2, and temperature using graphical gauges for better visualization. During testing, the application showed values such as 90 bpm for heart rate, 97% for SpO_2, and approximately 25.47°C for temperature. In addition to numerical data, the application includes a status panel that displays AI-based messages such as “Normal,” “Waiting,” and “Critical.” The fall status indicator provides a visual representation of the user’s condition. This feature allows caregivers or family members to monitor the user remotely, ensuring continuous supervision and quick response during emergencies.

5.3 Fall Detection and Alert Generation

Figure 6 Health Monitoring Dashboard (Critical Alert State)

This figure 6 shows a mobile-based health monitoring dashboard displaying real-time vital parameters. The heart rate (HR) is recorded at 95 bpm, and blood oxygen level (SpO_2) is 96%, both within acceptable ranges. However, the

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temperature reading is unusually low (25.30°C), suggesting either ambient measurement or sensor misplacement. The status section shows repeated "AI: Critical" alerts, indicating that the system's machine learning model has detected abnormal conditions. On the right side, the fall status indicator is red, confirming that a fall has been detected. This represents an emergency condition requiring immediate attention.

The fall detection mechanism was evaluated by simulating sudden movements and fall scenarios. When a fall occurs, the accelerometer detects a rapid change in motion and orientation, which is then processed by the Multi-Layer Perceptron (MLP) model. The system classifies the event as a fall and updates the LCD display to show "FALL," while the AI indicator changes to "Critical." Simultaneously, the mobile application reflects this condition by updating the fall status and displaying alert messages. This immediate detection and alert generation ensure that critical situations are identified promptly, enabling timely intervention.

5.4 Performance Comparison

A comparative analysis was conducted between the traditional threshold-based system and the proposed MLP-based system to evaluate performance improvements. The threshold-based system relies on predefined limits and achieved a fall detection accuracy of approximately 85%. However, it produced a high rate of false alarms due to its inability to differentiate between normal sudden movements and actual falls. In contrast, the MLP-based system achieved a higher accuracy of 96% by analyzing multiple parameters and motion patterns simultaneously. The machine learning approach provides better classification, resulting in improved reliability and performance.

5.5 False Alarm Rate Analysis

One of the major limitations of conventional systems is the high false alarm rate caused by abrupt but non-critical movements. Activities such as sitting quickly or hand gestures often trigger incorrect alerts in threshold-based systems. The proposed MLP-based system significantly reduces this issue by learning complex motion patterns and contextual relationships between sensor inputs. As a result, the system generates fewer false alarms, improving user confidence and making it more suitable for real-world applications.

5.6 Abnormal Heart Rate Detection

The system also evaluates abnormal heart rate conditions to enhance health monitoring capabilities. Traditional systems use static thresholds, typically between 60 and 100 bpm, which do not consider variations due to physical activity or stress. In contrast, the proposed system uses adaptive classification through the MLP model, which analyzes heart rate trends along with other parameters such as temperature. This enables more accurate and personalized detection of abnormal conditions, improving the effectiveness of the monitoring system.

5.7 Response Time Analysis

Response time is a critical factor in emergency monitoring systems. The threshold-based approach requires approximately one second to detect and respond to abnormal conditions. The proposed MLP-based system achieves a response time of less than one second, even with additional processing for feature extraction and classification. This demonstrates that the system is capable of real-time operation and can provide immediate alerts without significant delay.

5.8 Twilio SMS Alert Integration

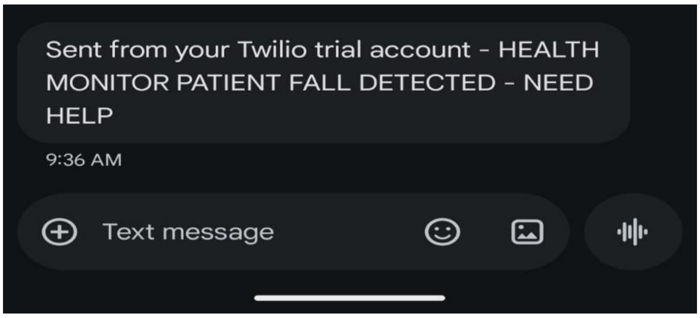

Figure 7 SMS Alert via Twilio

This figure 7 shows a mobile SMS notification generated using Twilio. The message reads: **"HEALTH MONITOR PATIENT FALL DETECTED – NEED HELP"**. This confirms that when a fall is detected, the system automatically sends an emergency alert message to a predefined contact. The message is sent from a Twilio trial account, demonstrating successful integration of IoT health monitoring with real-time communication for emergency response.

The proposed system also incorporates an emergency alert mechanism using Twilio SMS service to ensure immediate communication during critical situations. When a fall is detected or when abnormal health conditions are identified by the MLP model, the system automatically triggers an SMS alert to predefined contacts such as family members or emergency responders. The alert message includes essential information such as the user's health status and, if integrated, location details for quick assistance. During testing, the Twilio API successfully delivered real-time messages within a few seconds of event detection, demonstrating high reliability and efficiency. This feature significantly enhances the safety aspect of the system by providing instant notifications even when the user is unable to respond manually. The integration of SMS alerts ensures that critical events are not only detected but also communicated effectively, making the system more practical and suitable for real-world applications like elderly care and women safety monitoring.

5.9 Overall Performance Discussion

The overall performance of the system indicates that the integration of machine learning with IoT significantly enhances monitoring efficiency and reliability. The proposed system provides higher accuracy, reduced false alarms, adaptive health monitoring, and faster response time compared to traditional methods. The combination of hardware implementation and mobile application support ensures continuous monitoring and remote accessibility. These features make the system highly suitable for applications such as elderly care, women safety, and remote health monitoring.

6. CONCLUSION

This paper presented an enhanced IoT-based multi-sensor healthcare monitoring system that integrates real-time physiological data acquisition, intelligent analysis using Tiny Machine Learning (Tiny ML), and immediate emergency communication through Twilio SMS alerts. The system continuously monitors vital parameters such as heart rate, blood oxygen saturation (SpO_2), body temperature, and body movement using integrated sensors connected to the ESP32 microcontroller.

Unlike conventional threshold-based systems, the proposed approach utilizes a Multi-Layer Perceptron (MLP) model deployed using TensorFlow Lite to perform real-time classification of health conditions. This intelligent method improves accuracy, reduces false alarms, and enables adaptive decision-making. The system effectively classifies conditions into Normal, Warning, Critical, and Fall Detected states, ensuring reliable monitoring.

A key contribution of this work is the integration of an SMS-based alert mechanism using Twilio, which enables instant communication with caregivers during emergency situations such as fall detection or critical health conditions. This feature overcomes the limitations of cloud-only monitoring systems by ensuring that alerts are delivered immediately, even without active dashboard supervision.

Experimental results demonstrate that the proposed system provides stable sensor performance, accurate fall detection, reduced false alarm rates, and fast response time. The combination of IoT, Tiny ML, and real-time communication makes the system a cost-effective, portable, and scalable solution for continuous health monitoring. Overall, the proposed system enhances patient safety and is highly suitable for applications such as elderly care, remote patient monitoring, and wearable healthcare devices.

REFERENCES

[1] H. N. Abdullah et al., "Smart monitoring system with fall detection using IoT technology," International Journal of Computing, vol. 21, no. 2, pp. 200–208, 2022.
[2] S. Ahmed, M. H. Rehmani, and N. K. Janjua, "A survey on IoT-based healthcare monitoring systems," IEEE Communications Surveys & Tutorials, vol. 21, no. 2, pp. 123–145, 2019.
[3] K. Alharbi et al., "Reliable communication framework for IoT-based fall detection systems, "Scientific Reports, vol. 14, pp. 1–12, 2024.
[4] M. Al-Kababji, M. B. Anwar, and A. H. Muqaibel, "IoT-based fall detection system for elderly healthcare," Sensors, vol. 21, no. 9, pp. 1–20, 2021.
[5] M. Chen, Y. Ma, J. Song, C. F. Lai, and B. Hu, "Smart clothing: Connecting human with clouds and big data for sustainable health monitoring," Mobile Networks and Applications, vol. 21, no. 5, pp. 825–845, 2016.
[6] "Emergency Alert System Using Twilio Programmable SMS API, "International Research Journal of Engineering and Technology (IRJET), vol. 8, no. 3, 2021.

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DOI: 10.17148/IJIREEICE.2026.14380

[7] F. Hussain, S. Hussain, S. Hassan, and E. Hossain, "Machine learning for IoT-based healthcare systems: A survey," IEEE Internet of Things Journal, vol. 7, no. 5, pp. 1–15, 2020.
[8] A. Rehman, A. Paul, and M. M. Hassan, "A real-time IoT-based health monitoring system using wearable sensors," IEEE Access, vol. 7, pp. 123456–123465, 2019.
[9] A. S. Shaban, M. M. Fouad, and A. E. Hassanien, "Fall detection system based on wearable sensors and neural networks," IEEE Sensors Journal, vol. 20, no. 3, pp. 1325–1333, 2020.
[10] Z. Tang et al., "Fall detection and safety monitoring for elderly using IoT sensors," Journal of Healthcare Engineering, vol. 2022, pp. 1–10, 2022.