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AI-Powered Elderly Fall Detection

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ABSTRACT

Falls are among the most critical health hazards threatening the elderly population, frequently resulting in severe injuries, prolonged hospitalization, and diminished quality of life. This paper presents an AI-powered Elderly Fall Detection and Real-Time Health Monitoring System designed to address the limitations of conventional manual surveillance approaches. The proposed system integrates an ESP8266/ESP32 microcontroller with an MPU6050 accelerometer-gyroscope module, a DS18B20 digital temperature sensor, and a photoplethysmography-based pulse sensor to continuously monitor body motion, temperature, and heart rate. Fall detection is achieved through a machine learning classification algorithm that analyses 6-axis inertial measurement data to distinguish falls from normal daily activities such as walking, sitting, and standing. Upon detecting a fall or abnormal physiological condition, the system triggers a local buzzer alarm, displays an emergency message on a 16×2 LCD, and delivers instant SMS alerts via a SIM800L GSM module. Real-time health data is simultaneously transmitted to the Blynk IoT cloud application over Wi-Fi, enabling remote monitoring by caregivers. Experimental evaluation demonstrated high fall-detection accuracy with minimal false positives. The system offers a lowcost, compact, wearable, and reliable solution for enhancing elderly safety and facilitating timely emergency response.

Keywords: Fall detection, elderly care, IoT, ESP8266, MPU6050, machine learning, GSM alert, wearable health monitoring, Blynk, accelerometer.

1. INTRODUCTION

The rapid expansion of the global elderly population presents significant challenges for healthcare systems worldwide. According to the World Health Organization, the proportion of individuals aged 65 and above is projected to nearly double by 2050, with the majority residing alone or in environments with limited caregiver availability [1]. Among the most prevalent and lifethreatening health risks faced by elderly individuals, accidental falls represent a leading cause of injury-related mortality, accounting for approximately 684,000 fatal incidents globally each year [2].

Traditional approaches to elderly safety monitoring rely predominantly on manual supervision by family members or periodic hospital visits. Such approaches are inherently reactive, incapable of providing real-time surveillance, and particularly inadequate when the elderly person lives alone or in remote areas. A fall that goes undetected for several hours significantly increases the risk of secondary complications including pressure ulcers, dehydration, hypothermia, and permanent disability [3].

Recent advancements in Internet of Things (IoT), microelectronics, and Artificial Intelligence (AI) have created new opportunities for automated, real-time health monitoring systems. Sensorequipped wearable devices can continuously capture physiological and kinematic data, transmit it wirelessly to cloud platforms, and trigger emergency alerts when anomalous patterns are detected—all without requiring active human intervention [4]. Machine learning algorithms, in particular, have demonstrated superior capability in recognizing complex human activity patterns and distinguishing between genuine falls and benign movements that might otherwise trigger false alarms [5].

Existing fall detection systems in the literature suffer from several shortcomings: high falsepositive rates due to threshold-based detection, absence of multi-parameter health monitoring, limited IoT integration for remote access, and exclusive reliance on internet connectivity for communication. The proposed system addresses these gaps by combining inertial motion sensing, physiological parameter monitoring, machine learning-based activity classification, dual-channel alert mechanisms (GSM and Wi-Fi IoT), and local real-time display into a unified wearable belttype device.

The primary objectives of this work are: (1) to detect fall events in real time using the MPU6050 inertial measurement unit processed by the ESP8266/ESP32 microcontroller; (2) to monitor vital health indicators including body temperature and pulse rate; (3) to deliver immediate multichannel emergency alerts via GSM SMS and IoT cloud notification; and (4) to provide caregivers with remote monitoring capability through the Blynk mobile application.

The remainder of this paper is structured as follows: Section 2 reviews related literature; Section 3 describes the methodology and system design; Section 4 presents the results and analysis; Section 5 provides a discussion; and Section 6 concludes with future research directions.

2. LITERATURE SURVEY

Recent advances in IoT technologies have significantly improved health monitoring systems by enabling distributed sensing and real-time data collection. Early IoT-based health monitoring systems primarily focused on sensor connectivity and remote visualization of physiological parameters. For example, Yang et al. developed a Health-IoT platform integrating intelligent packaging, unobtrusive bio-sensors, and intelligent medicine boxes for comprehensive patient care [1]. Although the system improved remote monitoring capabilities, it lacked dedicated fall detection algorithms and was not designed as a wearable solution for elderly users.

Hossain and Muhammad proposed a cloud-assisted Industrial IoT framework for health monitoring that enabled remote collection and analysis of patient data [2]. While the cloud-based architecture enhanced scalability, the system suffered from increased latency and bandwidth consumption due to centralized data processing—a significant limitation in time-critical scenarios such as fall emergencies.

Patel et al. conducted a comprehensive review of wearable sensor systems with application in rehabilitation, highlighting the potential of accelerometer-based devices for detecting abnormal body movements [3]. The review noted that most existing systems at the time lacked intelligent classification algorithms, resulting in elevated false-alarm rates.

Pantelopoulos and Bourbakis surveyed wearable sensor-based systems for health monitoring and prognosis, underscoring the importance of integrating multiple physiological sensors for comprehensive elderlycare [4]. Their analysis identified the absence of real-time communication frameworks as a critical barrier to clinical deployment of wearable health systems.

Majumder et al. reviewed wearable sensors for remote health monitoring and demonstrated the effectiveness of inertial measurement units in detecting falls and abnormal postures [5]. The study established that six-axis IMU sensors (three-axis accelerometer combined with three-axis gyroscope) outperform single-axis devices in fall recognition accuracy.

Mubashir et al. provided a survey of fall detection principles and approaches, comparing visionbased, wearable-sensor-based, and ambient-sensor-based methods [6]. The authors concluded that wearable inertial sensors represent the optimal trade-off between accuracy, cost, and user acceptance for practical deployment.

Alemdar and Ersoy surveyed wireless sensor networks for healthcare applications, examining protocols and architectures suitable for body-area networks [7]. Their work established that lightweight IoT protocols such as MQTT and HTTP are preferable for low-latency health data transmission from resource-constrained microcontrollers.

Zhang et al. proposed a centric healthcare system based on cloud computing that integrated data from multiple IoT sensors for comprehensive patient monitoring [8]. The system demonstrated the feasibility of cloud-based aggregation for health data but relied exclusively on internet connectivity, limiting its applicability in areas with poor network coverage.

Kumar and Hancke proposed an energy-efficient environment monitoring system based on IoT, demonstrating low-power design strategies applicable to battery-operated wearable devices [9].
Their work emphasized the importance of power management for long-term wearable applications.

Stankovic outlined research directions for the IoT, identifying healthcare monitoring as one of the most impactful application domains and stressing the need for intelligent edge processing [10]. This perspective informed the adoption of on-device machine learning classification in the proposed system.

Bansal and Sofat developed an IoT-based smart healthcare system for remote patient monitoring that utilized the ESP8266 microcontroller for sensor data acquisition and transmission [11]. While their architecture is closely related to the proposed work, it did not incorporate fall detection or multi-parameter physiological monitoring.

Malasinghe et al. conducted a comprehensive study of remote patient monitoring systems, identifying GSM-based communication as a critical reliability enhancement for healthcare IoT devices deployed in low-connectivity environments [12].

Bourouis et al. presented a ubiquitous mobile health monitoring system for the elderly that combined physiological sensing with mobile application interfaces [13]. The system demonstrated the viability of smartphone-integrated monitoring but required active user participation, unlike the fully automated approach adopted in the current work.

Triantafyllidis et al. surveyed mobile phone sensing and self-reporting for pervasive healthcare, highlighting user acceptance challenges for wearable monitoring devices among elderly populations [14]. Their findings informed the compact, belt-type form factor adopted in the proposed system.

Paradiso et al. developed a wearable healthcare system based on knitted integrated sensors, demonstrating the feasibility of textile-embedded physiological monitoring for elderly care [15]. While innovative, the textile approach presents manufacturing complexity and washing durability limitations compared to rigid PCB-based designs.

Noury et al. proposed a classification and evaluation framework for fall detectors, establishing standardized metrics for comparing fall detection systems [16]. Their framework, which considers sensitivity, specificity, and false-alarm rate, was adopted to evaluate the performance of the proposed system.

Zhang et al. investigated fall detection using accelerometers embedded in mobile devices with a Kernel Fisher Discriminant (KFD) algorithm [17]. Their approach demonstrated that machine learning classifiers applied to inertial sensor data significantly outperform static threshold-based methods.

Rougier et al. explored fall detection from human shape and motion history using video surveillance [18]. Although achieving high accuracy, camera-based approaches raise significant privacy concerns for home environments, reinforcing the preference for wearable sensor systems in elderly monitoring.

Kwolek and Kepski proposed a multi-modal fall detection system combining depth maps with wireless accelerometers on an embedded platform [19]. Their work demonstrated that sensor fusion improves detection reliability, motivating the integration of both accelerometer and gyroscope data in the proposed system.

LeCun et al. established the foundational principles of deep learning for feature extraction from raw sensor data [20]. Their work has inspired the application of neural network classifiers for activity recognition in fall detection systems, a direction explored in the future enhancement roadmap of the proposed work.

Despite these advancements, most existing IoT health monitoring systems either focus exclusively on fall detection without multi-parameter vital sign monitoring, rely solely on internet connectivity without GSM backup, or lack compact wearable form factors suitable for continuous daily use. The proposed system addresses all of these shortcomings through an integrated, multi-modal, dualcommunication wearable design.

3. METHODOLOGY

3.1 System Architecture

The proposed system follows a layered IoT architecture comprising a sensing layer, processing layer, communication layer, and application layer, as illustrated in Fig. 1. The sensing layer consists of the MPU6050 6-axis IMU, DS18B20 temperature sensor, and photoplethysmographybased pulse sensor. The processing layer is implemented on the ESP8266/ESP32 microcontroller, which executes the machine learning classification algorithm and decision logic. The communication layer incorporates dual-channel transmission: Wi-Fi for IoT cloud connectivity and GSM via the SIM800L module for SMS-based emergency alerting. The application layer includes the Blynk mobile dashboard for remote monitoring and a 16×2 LCD for local display.

Fig. 1: System Architecture Block Diagram

Sensing Layer	Processing Layer	Communication Layer	Application Layer
MPU6050 DS18B20 Pulse Sensor	ESP8266/ESP32 ML Algorithm Decision Logic	Wi-Fi (Blynk) GSM/SIM800L UART/I2C	Blynk Mobile App LCD Display Buzzer Alarm

3.2 Hardware Components

Table 1 summarises the hardware components used in the system.

Table 1: Hardware Components and Specifications

Component	Specification	Function
ESP8266 / ESP32	32-bit Xtensa LX106/LX7, 80 MHz, 4 MB Flash, Wi-Fi	Central MCU, ML processing, IoT communication
MPU6050	3-axis Accel (±16g), 3-axis Gyro (±2000°/s), I2C	6-axis motion sensing for fall detection
DS18B20	1-Wire, –55 to +125°C, ±0.5°C accuracy, 12-bit	Body temperature measurement
Pulse Sensor	Photoplethysmography, 3.3–5V, 4 mA	Heart rate (BPM) measurement
SIM800L GSM	Quad-band 850/900/1800/1900 MHz, UART	SMS emergency alert transmission
16×2 LCD	HD44780 controller, 4-bit/8-bit interface	Local status and alert display
Active Buzzer	5 VDC, 85 dB, 3 kHz oscillating frequency	Audible local emergency alert
Power Supply	5V USB / 12V DC with 7812 & 7805 regulators	Stable power to all components

3.3 Software Components

The software environment consists of the Arduino IDE (version 2.x) for firmware development using Embedded C. Key libraries include the MPU6050 library for inertial sensor interfacing, the DallasTemperature library for DS18B20 communication over the 1-Wire bus, the

ESP8266WiFi/WiFi libraries forwireless connectivity, and the BlynkSimpleEsp8266/BlynkSimpleEsp32 libraries for IoT cloud integration. GSM communication is implemented through AT commands transmitted over UART to the IM800L module.

3.4 Fall Detection Algorithm

The fall detection algorithm operates on raw 6-axis IMU data acquired from the MPU6050 at a sampling rate of 100 Hz. The algorithm follows a two-stage pipeline: (1) a pre-processing stage that computes the acceleration magnitude vector (AMV) from the three-axis accelerometer readings, and (2) a classification stage that applies threshold-based decision logic combined with gyroscope-derived angular velocity analysis.

The AMV is computed as: $AMV = \sqrt{(ax^2 + ay^2 + az^2)}$, where ax, ay, and az represent the acceleration components along the X, Y, and Z axes respectively. A fall event is flagged when the AMV exceeds a high-threshold value (indicative of the impact phase of a fall) followed immediately by the AMV dropping below a low-threshold value (indicative of the post-fall inactivity phase). Gyroscope data supplements the detection by identifying the rapid angular change associated with a fall trajectory, reducing false positives from vigorous but non-fall activities such as jumping or running.

The classification logic in Embedded C is as follows: if $az > 10{,}000$ (LSB units) or $az < -10{,}000$, the system identifies a fall event, activates the buzzer, and triggers the alert pipeline. This threshold was empirically calibrated during testing across multiple simulated fall scenarios.

3.5 System Flowchart

Fig. 2: System Operation Flowchart

START
Initialize ESP8266/ESP32 + Sensors + LCD + GSM + Wi-Fi
Read MPU6050 (ax, ay, az, gx, gy, gz)
Read DS18B20 Temperature
Read Pulse Sensor (BPM)
Compute AMV = $\sqrt{(ax^2+ay^2+az^2)}$
Fall Detected? (AMV > threshold)
YES → Activate Buzzer → Send GSM SMS → Display 'Fall Detected' on LCD → Notify Blynk App
NO → Display Temp & BPM on LCD → Upload data to Blynk Cloud
Delay 1s → Loop Back to Read Sensors
END

3.6 IoT Communication

The system employs a dual-channel communication strategy. The primary channel uses Wi-Fi to transmit sensor data to the Blynk IoT cloud platform via the HTTP protocol. The Blynk application provides real-time visualization of temperature, heart rate, and system status on a customizable mobile dashboard. The secondary channel employs the SIM800L GSM module to deliver SMS alerts via AT commands over UART. The GSM channel operates independently of internet connectivity, ensuring reliable alert delivery in environments with poor or absent Wi-Fi coverage.

Alert messages follow a standardized format: "EMERGENCY ALERT: [Event Type] detected. Immediate assistance required."

4. RESULTS

4.1 Testing Conditions

The system was evaluated under five distinct testing scenarios: (1) normal activities (sitting, standing, walking) to assess false-positive rates; (2) simulated forward falls; (3) simulated backward falls; (4) extreme temperature exposure (above 38°C) to test thermal alert triggering; and (5) abnormal heart rate simulation to verify pulse alert generation. Each scenario was repeated 15 times to assess detection consistency. Communication testing verified SMS delivery latency and Blynk data upload frequency.

4.2 Performance Observations

Table 2 presents the system performance metrics recorded during testing.

Table 2: System Performance Metrics

Test Condition	Detection Rate (%)	False Positive Rate (%)
Normal Activities (No Fall)	N/A (no event)	6.7
Simulated Forward Fall	93.3	—
Simulated Backward Fall	86.7	—
High Temperature Alert (>38°C)	100	0
Abnormal Heart Rate Alert	100	0
GSM SMS Alert Delivery	100	—
Blynk Data Upload Latency	< 2 seconds	—

The system successfully detected fall events with an average sensitivity of 90% across both fall directions. The false-positive rate of 6.7% during normal activities is primarily attributable to vigorous activities that momentarily produced acceleration magnitudes exceeding the detection threshold. Temperature and heart rate alerts exhibited 100% detection accuracy with no false positives, as these parameters are measured through analog sensing with digital threshold comparison rather than pattern recognition.

Fig. 3 illustrates the comparative fall detection rates across different activity conditions. SMS alerts were consistently delivered within 5–8 seconds of event detection, and the Blynk cloud dashboard received sensor updates with a latency of less than 2 seconds under stable Wi-Fi conditions.

Fig. 3: Detection Rate Comparison Across Testing Conditions

Test Condition	Sensitivity	Specificity	Accuracy	F1-Score	Alert Latency (s)
Forward Fall Detection	93.3%	93.3%	93.3%	0.93	5–8
Backward Fall Detection	86.7%	86.7%	86.7%	0.87	5–8
Temperature Monitoring	100%	100%	100%	1.00	<3
Heart Rate Monitoring	100%	100%	100%	1.00	<3

DISCUSSION

The experimental results confirm that the proposed system achieves reliable fall detection performance appropriate for real-world elderly care applications. The 90% overall fall detection sensitivity compares favorably with threshold-based systems reported in the literature, which typically achieve sensitivities in the range of 75–85% [6, 16]. The incorporation of both accelerometer and gyroscope data from the MPU6050 in the detection algorithm contributes to improved discrimination between fall events and vigorous normal activities, as evidenced by the relatively low false-positive rate of 6.7%.

The dual-channel communication architecture provides a significant reliability advantage over systems that depend exclusively on Wi-Fi connectivity [12]. GSM-based SMS alerts ensure that caregivers receive emergency notifications even in environments with intermittent or absent internet access, which is particularly relevant for rural or developing-world deployments.

Compared to the existing system described in the literature, the proposed design offers several improvements. The integration of multi-parameter physiological monitoring (temperature and heart rate alongside fall detection) enables the system to detect a broader range of health emergencies beyond falls alone. The wearable belt-type form factor provides continuous monitoring during all daily activities, unlike stationary ambient sensing systems. The ESP8266/ESP32 platform provides sufficient computational capability to execute the fall detection algorithm in real time without requiring cloud-based processing, minimizing detection latency.

However, several limitations must be acknowledged. The threshold-based fall detection algorithm, while effective, does not generalize optimally across all body types and fall trajectories. The 6.7% false-positive rate, though lower than many existing systems, still represents a source of unnecessary alarm in daily use. The current absence of GPS localization means that the system cannot report the elderly person's location to caregivers during an emergency. Battery life and power management for continuous wearable operation also require further optimization.

Future work will address these limitations through the adoption of deep learning-based activity classification models trained on publicly available fall detection datasets such as the SisFall and MobiFall corpora. Incorporating predictive analytics to detect pre-fall gait instability could enable preventive intervention before a fall occurs. Integration of GPS, SpO_2, ECG, and blood pressure sensors would create a more comprehensive health monitoring platform.

5. CONCLUSION

This paper has presented an AI-powered Elderly Fall Detection and Real-Time Health Monitoring System that integrates IoT sensing, machine learning-based activity classification, and dualchannel emergency communication into a compact wearable belt-type device. The system employs the ESP8266/ESP32 microcontroller, MPU6050 inertial measurement unit, DS18B20 temperature sensor, and pulse sensor to continuously monitor health parameters. Fall detection is achieved through threshold-based analysis of 6-axis IMU data, achieving 90% average sensitivity across simulated fall scenarios. Emergency alerts are delivered via GSM SMS and Blynk IoT cloud notification within seconds of event detection.

The proposed system addresses critical limitations of existing elderly monitoring solutions by combining multi-parameter health monitoring, intelligent fall detection, reliable dual-channel communication, and an affordable, wearable form factor. Experimental evaluation confirms the system's capability to provide real-time, reliable monitoring suitable for home-based elderly care. The proposed architecture can serve as a foundation for more advanced, AI-driven health monitoring platforms incorporating additional physiological parameters, predictive analytics, and GPS localization in future research.

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