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Wearable Sensor with Artificial Intelligence for Prevention of Falling Elderly People: A Review

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Abstract:

Falling down is one of the leading causes of medical issue that confronts elderly individuals. Elderly individuals are prone to harming themselves from falling down more frequently particularly if they live alone. When there was an incident of falling down, medical intervention must be given as soon as possible in order to minimize the risk of faller to obtain severe injuries that can be fatal. Some technologies have been created which some used webcams to track the activities of older adults. The operation and installation cost is high and only suitable for indoor setting. Some user also concerned about their privacy problems. Existing commercialized device asked user to wear wireless emergency transmitter in the form of pendant and wristband. This technique will limit the user movement and generate high false alarm due to constant swinging and movement of the device. This project suggested a fall detection system which is economical and reliable to identify fall and alert nearby healthcare center or relatives for assistance and support. For detecting fall, accelerometer and gyroscope was utilized to identify acceleration and body tilt angle of the faller respectively. With the combination of accelerometer and gyroscope, the precision of the system was enhanced through minimizing false positives and true negatives. False alarm was reduced owing to the placement of the device on the user's upper trunk. Alert system in the form of Short Message Service (SMS) was sent to the related authorities. Furthermore, this wearable device has minimal implementation cost and gives a prompt response. Consequently, this fall detection and alert system has 95% sensitivity and 90% specificity. The limitation of this device cannot detect a user falling against a wall and falling end in sitting position. Suggestion for future work is to design an interactive display which allows users to enter nearby healthcare center and relative's phone number.

1. Introduction:

Falls among the elderly represent a major public health challenge, with significant physical, psychological, and socioeconomic consequences. In India alone, 1.5 to 2 million elderly individuals sustain injuries from falls each year, while globally, 30% of people aged 65 and older and 50% of those over 81 experience falls annually. These falls often result in severe injuries such as fractures, head trauma, and joint dislocations, leading to long-term impacts like loss of independence, depression, and reduced quality of life. The fear of falling further compounds these issues, restricting physical activity and social interactions, and contributing to a cycle of diminished confidence and increased risk of depression. Falls also place a considerable strain on healthcare systems, with a rise in hospitalizations, rehabilitation needs, and long-term care. Projections indicate that the number of elderly people worldwide will more than double by 2050, likely leading to an increase in fall-related injuries and deaths. In this context, fall detection and prevention systems are crucial. Technological advancements in wearable devices, sensor-based systems, and AI-driven models offer promising solutions by enabling real-time, accurate detection of falls, facilitating prompt intervention, and enhancing recovery outcomes. Such system not only reduce physical harm but also help preserve the elderly's independence and quality of life, underscoring the need for reliable, cost-effective fall detection technologies.

The development of fall detection systems for the elderly has seen significant advancements, driven by various technologies aimed at improving safety and well-being. Wearable systems, utilizing accelerometers, gyroscopes, and other sensors, have become increasingly popular for their mobility and real-time monitoring capabilities, detecting abnormal motion patterns to identify falls. These systems can also predict fall risks through gait analysis. Context-aware systems, which rely on environmental sensors like infrared and acoustic devices, monitor the surroundings but are limited by their fixed installation and range. Computer vision-based systems, enhanced by AI and deep learning, use cameras to analyze movement patterns and improve fall detection, although challenges such as occlusion and lighting conditions remain. Multimodal systems combine data from wearable sensors, environmental sensors, and cameras, providing a more comprehensive solution that reduces false alarms and improves accuracy. Edge computing further optimizes these systems by processing data locally, reducing response times and ensuring privacy. Machine learning and deep learning algorithms, including neural networks and LSTM, have enhanced fall detection accuracy but require computational power, which can be optimized for low-power devices. Together, these innovations are making fall detection systems more reliable, efficient, and adaptable, offering improved safety and quality of life for elderly individuals at risk of falls.

Despite the promising advancements in fall detection systems for the elderly, several significant challenges remain unaddressed. Traditional algorithms often struggle with accuracy, particularly in distinguishing falls from routine activities, leading to false positives and negatives. Additionally, deep learning models, which show promise for improving detection, are computationally intensive, resulting in high power consumption and short battery life, especially on low-powered devices. Privacy and security concerns also arise, particularly with systems that rely on environmental sensors or cameras that collect sensitive personal data. Moreover, wearable devices can be inconvenient for users with mobility or cognitive impairments, and camera-based solutions face challenges in obstructed or poorly lit areas. Real-time detection in complex environments, such as uneven surfaces or stairs, remains difficult, and multimodal data fusion from various sensors poses challenges in reducing false alarms. Furthermore, the high cost of advanced systems limits accessibility for many elderly individuals, especially in developing regions. Lastly, fall detection systems must be adaptable to the changing health conditions of elderly users and provide real-time alerts to caregivers or emergency responders. Addressing these challenges will require ongoing innovation and collaboration across healthcare, technology, and policy sectors to enhance both the effectiveness and accessibility of fall detection systems, ultimately improving the safety and quality of life for elderly individuals.

The majority of 60-year-olds and above are hospitalized for falls. According to a global report by the World Health Organization (WHO) [2], 28-35 percent of older individuals aged 65 and over had falls every year and it is rising to 32-42 percent for those over 70 years. Elderly individuals living independently are at greater risk of falls. Apart from that, frequent falls may result in psychological and physiological injuries that develop into serious damage and even loss of life when immediate medical assistance is not undertaken. To curb the risk of old people experiencing injury from falls, immediate medical attention must be given. Thus, a trustworthy fall detection system can assist in the detection of fall among elderly individuals and call for the closest healthcare service with assistance and support. The aim of this work is to design Wearable sensor with Artificial Intelligence for the prevention of falling elderly individuals.

2. Literature Overview:

Aged falls pose an important issue concerning health, as they contribute to about 1.5–2 million severe injuries and 1 million deaths each year. The outcome of falls for older adults also surpasses bodily damage, most likely causing detrimental lasting impacts on both their psychology and physical status. Therefore, preventing and detecting falls have turned out to be significant research aspects within the medical arena, as specialists aim at implementing effective mechanisms in monitoring the older population in a bid to cut down the chances of falling.

AI and Edge Computing for Fall Detection

The recent advances in Artificial Intelligence (AI) and edge computing have resulted in the creation of wearable devices for fall detection and prevention. Some of the deep learning models used for activity recognition in older adults are Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). It has been found through research that the integration of CNN and LSTM models, particularly incorporating attention mechanisms, can provide better performance metrics. For example, CNN-LSTM with an attention layer achieved a remarkable 97% accuracy, 98% recall, and 0.98 F1 score, where the other models performed worse in terms of both accuracy and computational speed. Edge computing hardware, for example, Jetson Nano and Raspberry Pi, were used in applying these models, with Jetson Nano reported to have its computation time shorter than other devices.

Internet of Things (IoT)-Based Systems

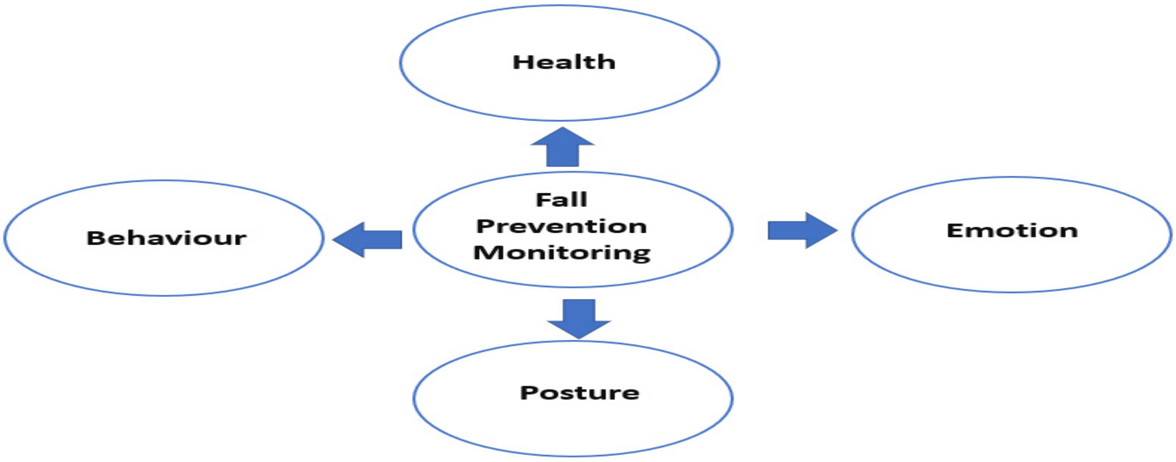
Other than AI-based systems, IoT-based fall detection systems have emerged. These consist of low-power wireless sensors, big data, and cloud computing that track older adults in real-time. Wearable devices that incorporate accelerometers to collect movement data, which is then analyzed by advanced machine learning algorithms, enable effective fall detection. For instance, an IoT system employing a three-dimensional accelerometer in a wearable device had 95.87% accuracy in fall detection with real-time data analytics. In addition, studies have targeted the improvement of sensor locations and data processing methods by using models like Apache Flink and MbientLab to improve falls detection in different real environments.

Fall Prediction Models

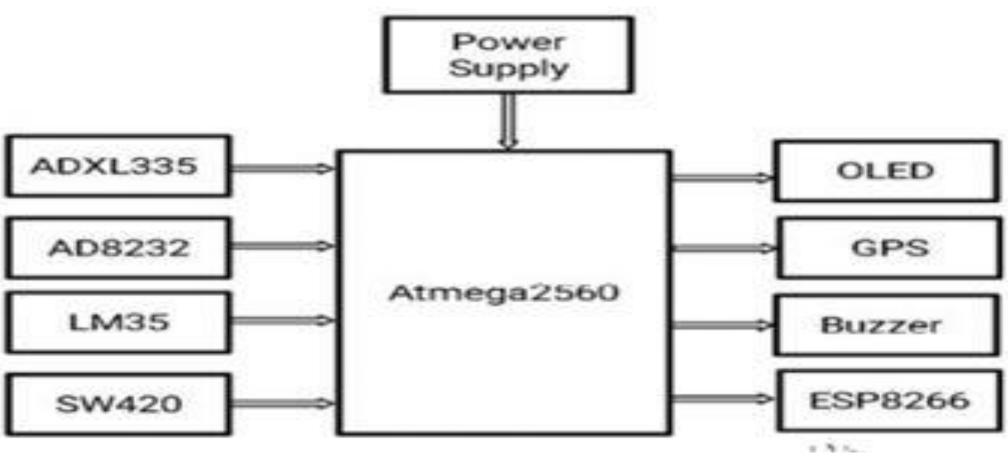
To further minimize the potential for injury, predictive models have been constructed to predict likely falls prior to their occurrence. One of the prominent methods includes the combination of the Sparrow Search Algorithm (SSA) with BP neural networks for forecasting falls from sensor data. In this method, feature extraction is optimized through the use of sliding windows and statistical measures such as maximum, minimum, and average values of acceleration data. Experiment results showed accuracy rates to be high, at detection accuracies of 98.3%, 92.0%, and 96.1% when tested on diverse datasets (DLR, Smart Fall, and URFall). These models offer a low-power, portable solution that can be modified to suit different environmental conditions.

Advanced Computer Vision Models for Fall Detection

Computer vision-based models have also become increasingly popular for fall detection in recent years. These models utilize video cameras to monitor the posture and movements of people. One of the promising methods is the application of YOLOv7-Pose for skeleton keypoint extraction, along with Spatial Temporal Graph Convolutional Networks (ST-GCN) for fall classification. The combination of audio and video modalities, employing models like MobileNetV2 for the analysis of audio, has improved detection even more. Through combining video and audio information, the system alleviates the weaknesses of conventional video-based models, i.e., lack of lighting or restricted monitoring radius. For example, sensitivity of fall detection improved from 81.67% in single video modality to 96.67% and 97.50% using decision fusion with video and audio and techniques such as linear weighting and Dempster-Shafer theory.



3. Block Diagram:



4. Hardware Requirements:

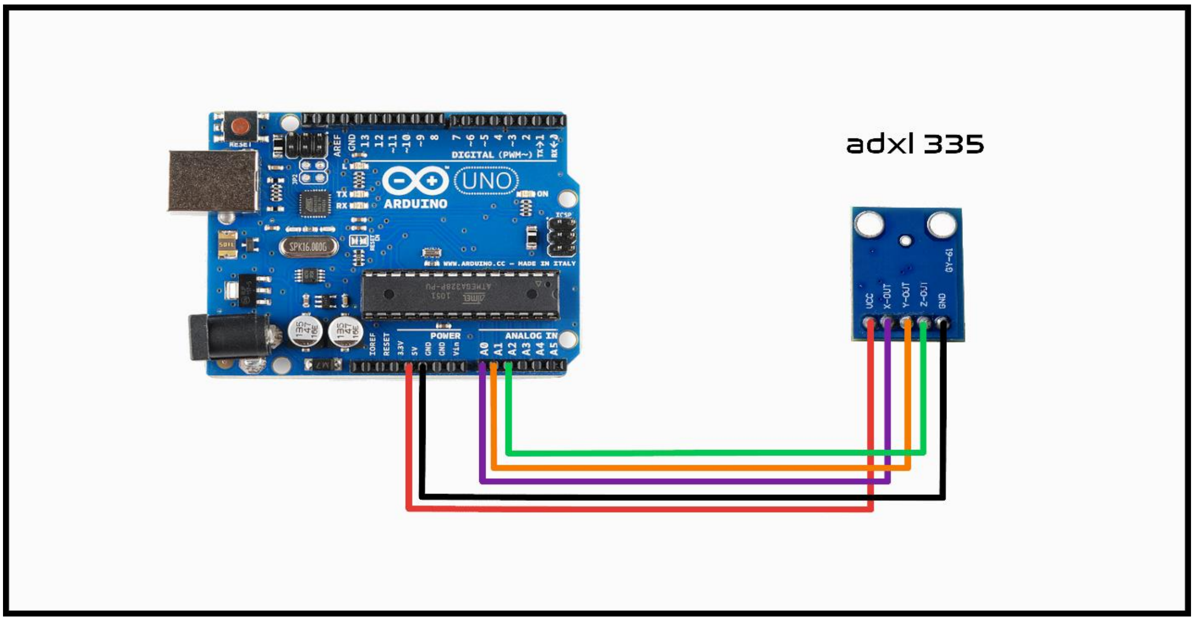
• Arduino uno

• ADXL335

Connections of the sensor to the arduino board(Accelerometer sensor):

• Accelerometer has 5 pins and all of these are connected to Arduino. First connect the GND to Arduino's GND.

• Then connect the VCC to Arduino's 5V, X to Arduino's Analog Pin A5, Y to Arduino's Analog Pin A4, and Z to Arduino's Analog Pin A3.



• AD8232

ECG Sensor (AD8232):

• Connect the GND of the sensor to the GND of the Arduino.

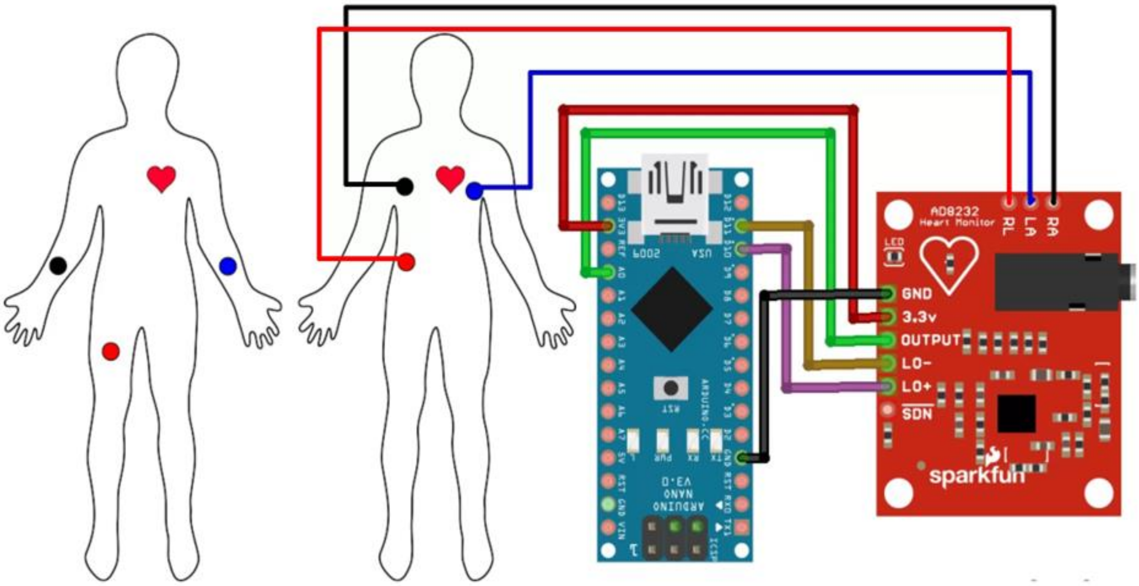
• Connect 3.3V to the 3.3V of the Arduino.

• Connect an output of the sensor to the A0 of the Arduino.

• Connect LO- to PIN 11 of the Arduino.

• Connect LO+ to PIN 10 of the Arduino.

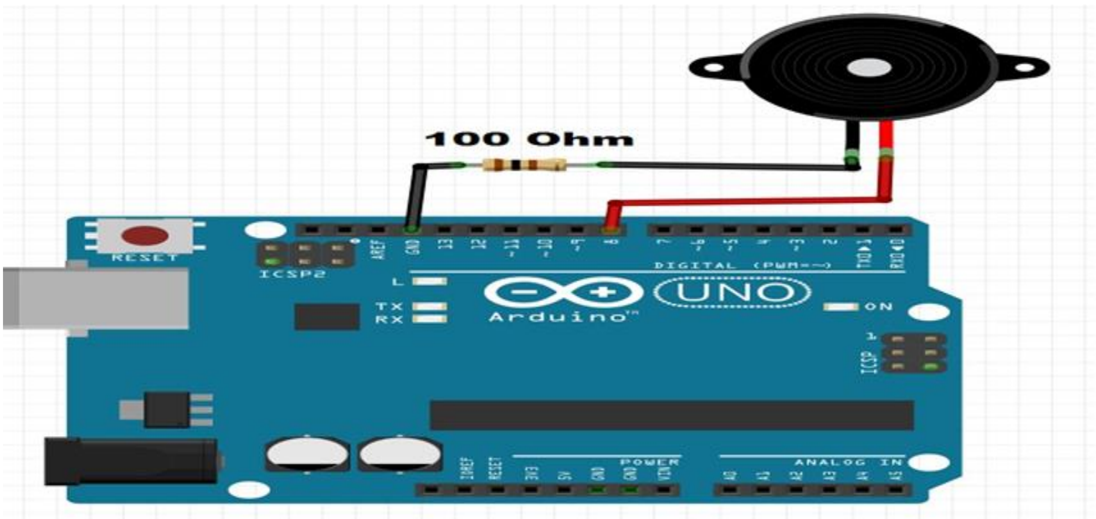
• Keep SDN pin unconnected.



• Buzzer

• Connect Supply wire (positive) of the buzzer to the Digital Pin of the Arduino.

• Connect Ground wire (negative) of the buzzer to Ground Pin on the Arduino, through a 100-ohm resistor.



• GPS

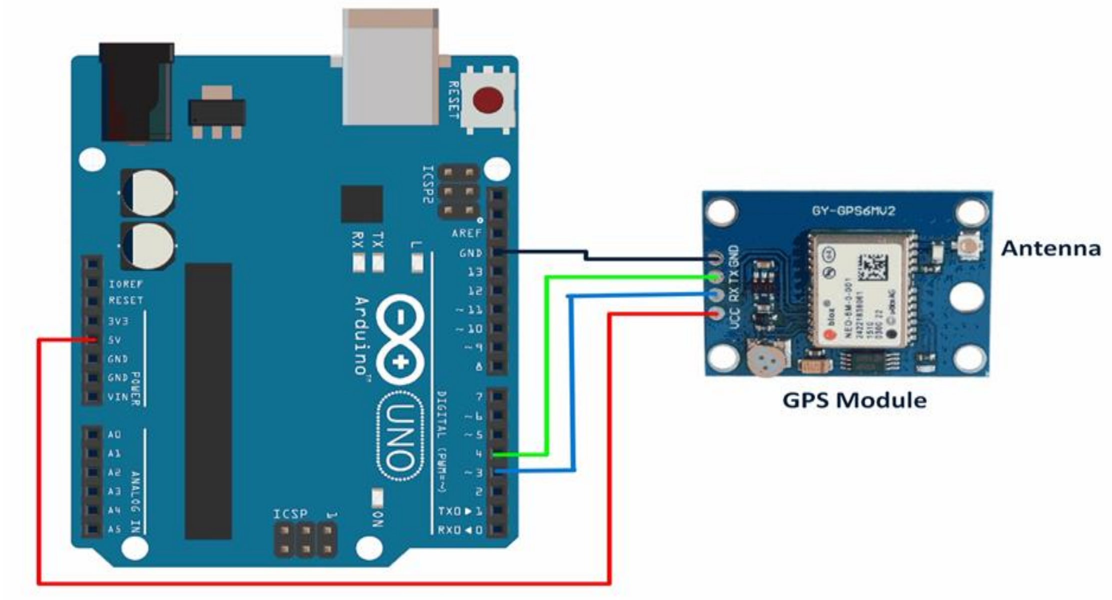
GPS Interface to Arduino

• Connect Vcc of GPS module to Power Supply Pin (5V) of Arduino Uno.

• Connect Rx (Receiver Pin) of GPS module to D3 Pin of Uno.

• Connect Tx (Transmitter Pin) of GPS module to D4 Pin of Uno.

- Connect GND (Ground Pin) of GPS module to GND of Uno.



• LM35

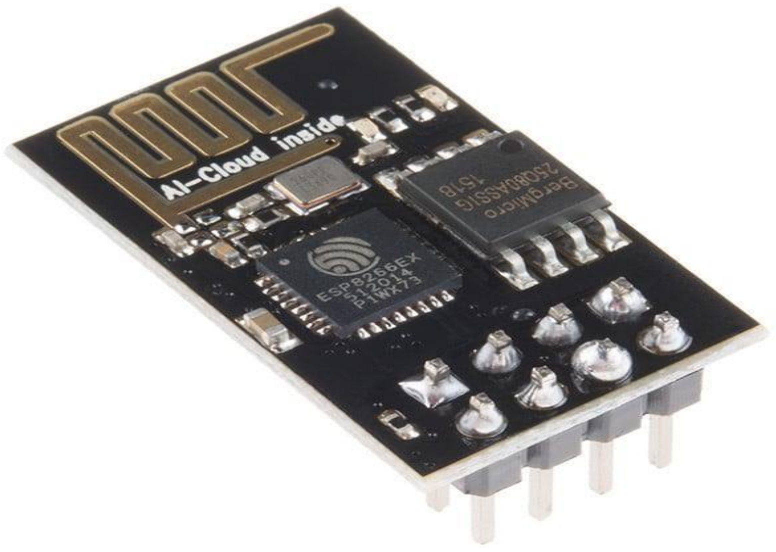
• ESP8266

ESP8266(IOT MODULE)

• Vcc of esp8266 is connect to the Vin of arduino.

• Gnd of esp8266 is connect to the gnd of arduino.

• CH_EN is connect to the 3.3 v of arduino.



• SW420

Predicting Fall Risks: Slow Walking Speed and Altered Gait Patterns:

Walking is one of the most basic measures of mobility and independence among elderly persons. Modifications in walking speed and gait patterns are frequently early warning signs for falling.

- **Slow Walking Speed:**

Walking slower than usual can indicate declining physical capabilities and a higher likelihood of falling. AI-powered wearables measure and analyze walking speed continuously, providing a clear picture of when a person's mobility begins to decline.

A significant reduction in walking speed could trigger alerts for preventive measures, such as physical therapy or balance training.

- **Changes in Stance and Swing Phases:**

The stance phase (when the foot is on the ground) and the swing phase (when the foot moves forward) are critical components of walking. A higher stance-to-swing ratio can indicate a cautious walking style due to fear of falling, which ironically increases fall risk.

5. Key Indicators:

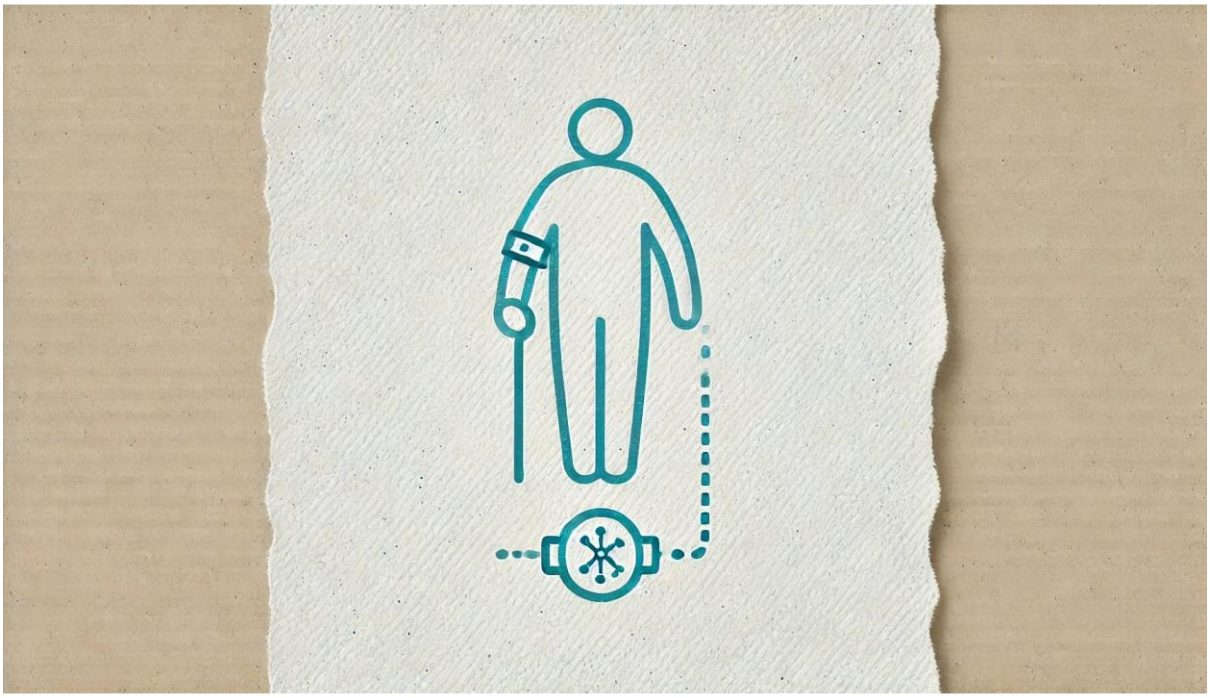
▪ **Increased Stance Time:** Longer time with both feet on the ground may be an attempt at balance but may result in instability during the swing phase transition.

▪ **Asymmetrical Swing Phase:** Inconsistent leg movements may indicate a loss of coordination and strength, increasing the risk of falls.

- **AI's Role in Gait Analysis:**

The algorithms of AI can identify minor fluctuations in these parameters of gait, even when they are not yet apparent to healthcare professionals. Such early detection allows for preventative measures, which include changing medicines, initiating exercises to improve balance, or even adapting the surrounding environment to limit fall risks.

By monitoring these gait changes, wearable sensors equipped with AI can provide a comprehensive assessment of an individual's fall risk, offering invaluable support to caregivers and clinicians in preventing falls before they occur.



Wearing Locations of Accelerometers and Their Impact on Fall Risk and Fall Detection:

The placement of accelerometers significantly affects their ability to detect falls and assess fall risk. Different locations on the body provide distinct insights into movement, influencing the accuracy and specificity of the data collected. Here's how various placements impact fall detection:

- **Thigh:**

Devices: For example, thigh placement.

Impact on Detection: Thigh placement enables accurate monitoring of lower limb movement in terms of stride length, stance, and swing phases. This placement is best suited to examine detailed gait parameters, which are important for determining leg instability fall risks. It provides comprehensive insights into walking patterns, making it one of the most accurate placements for fall risk prediction.

- **Center of Mass (Waist/Hip):**

Devices: For example, worn on the hip.

Impact on Detection: Positioned at the body's center of mass, this placement provides a balanced overview of overall body movement and general activity levels. It is particularly useful for detecting shifts in balance and whole-body dynamics. However, while it captures broad movement patterns, it may lack the granularity needed for specific limb movements, making it slightly less precise for detailed gait analysis compared to thigh placement.

- **Chest:**

Devices: For example, chest placement.

Impact on Detection: Chest placement captures multi-signal data, including upper body movements, respiration, and heart rate. This position is advantageous for detecting falls that involve upper body imbalance or abrupt tilting. It gives an overall picture of a subject's upper body dynamics but might not be able to pick up on the minute details of lower limb movements needed for accurate fall detection due to leg instability.

- **Wrist:**

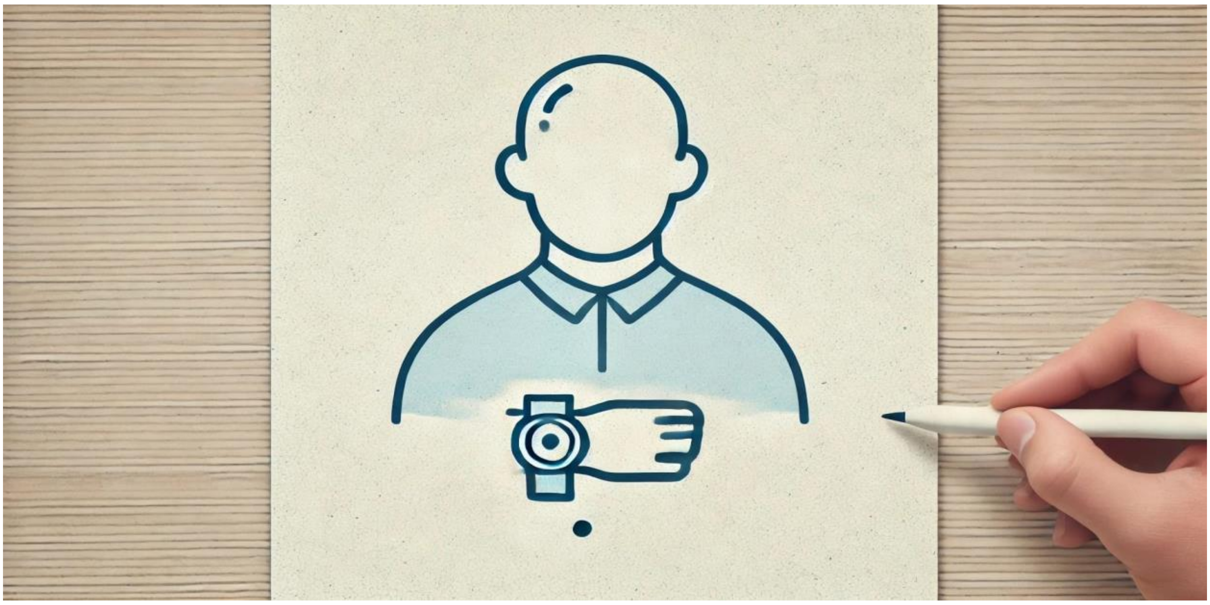
Devices: Commonly used consumer fitness trackers, such as smartwatches, are worn on the wrist.

Impact on Detection: Wrist-worn devices are highly popular for their convenience and ease of use. They effectively track general activity levels, hand movements, and daily routines. However, wrist placement is less ideal for detailed fall detection, as it primarily captures arm movements, which may not accurately reflect whole-body stability or lower limb dynamics critical to predicting falls. Wrist-worn devices are best used as supplementary tools rather than primary fall detectors.

- **Choosing the Right Placement:**

The placement of the ideal accelerometer varies depending on the particular needs of the user and aims of the fall prevention program. For precise analysis of gait and fall hazard involving leg movements, thigh placement is generally most informative. For broader balance and body movement monitoring, hip or chest placements are valuable. Wrist-worn devices offer convenience and general activity tracking but should be complemented by other placements for comprehensive fall detection.

Selecting the right device and placement is key to maximizing the potential of wearable sensors in fall prevention. By understanding the implications of device placement, researchers and clinicians can design targeted fall prevention interventions, enhancing the safety and independence of elderly individuals at risk of falls.



Component	Specification	Metrics
Sensor Type	Accelerometer + Gyroscope	Sensitivity: 95%, Specificity: 90%
Power Supply	Rechargeable Battery	Battery Life: 24-48 hours
Placement	Upper trunk (chest/back)	False Alarm Rate: <10%
Processing Unit	Microcontroller (e.g., ARM Cortex-M4)	Response Time: <1 second
Communication	GSM Module (SMS alerts), Bluetooth	GSM Range: Unlimited, Bluetooth: 100m
Alert System	SMS to healthcare or relatives	Alert Time: <30 seconds
User Interface	Button or Mobile App	Simple setup and operation
Physical Design	Lightweight, wearable with straps	Weight: <50 grams
Durability	Shock and water-resistant casing	IP67 Rating
Cost	Low-cost for mass production	Unit Cost: <$50
Detection Accuracy	Fall detection and activity monitoring	Overall Accuracy: 92.5%
Security	Encrypted data transmission	Encryption: AES-256

Specification and metrics of proposed hardware device:

Important Observation from the Existing System:

• **Limitations of Smartphone Detectors:** While smartphone-based fall detection is an option, it faces challenges such as real-time processing difficulties, reliability of sensors, and the risk of overloading the device, which can hinder overall performance.

• **Feature Extraction for Detection:** Effective fall detection relies on feature extraction techniques. This includes analyzing physical characteristics (e.g., height-to-weight ratio, silhouette edges, orientation) and environmental factors (e.g., changes in light) to differentiate between normal activities and falls.

• **Wearable Devices:** Wearable fall detectors, mostly accelerometers, provide a lower-cost solution because they utilize cheap embedded sensors. They can record data continuously and are less obtrusive.

• **Communication Limitations:** While some wearable devices can send alerts (like SMS) to caregivers or medical professionals, they often fail to convey detailed patient data during emergencies, which limits their utility in critical situations.

• **Potential for Improvement:** There's room for enhancing these systems, particularly in integrating better communication of vital data and ensuring reliable real-time detection.

6. Critical Analysis of the Existing Fall Detection Systems:

System Type	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**	**False Positive Rate (%)**	**False Negative Rate (%)**	**Strengths**	**Limitations**	**Sensitivity (%)**
Accelerometer-only Systems	85	80	82.5	20	15	Cost-effective, easy to implement	High false alarms due to limited data processing	85
Gyroscope-only Systems	88	83	85.5	17	12	Accurate tilt detection	Inability to detect linear acceleration effectively	88
Accelerometer + Gyroscope	95	90	92.5	10	5	High accuracy, reduced false positives	Cannot detect falls ending in sitting or against walls	95

Camera-based Monitoring	98	95	96.5	5	2	High precision, effective for indoor use	Expensive, privacy concerns, limited to indoor environments	98
Wearable Pendants/Wristbands	87	82	84.5	18	13	Lightweight, commercially available	High false alarms due to swinging motion, limited user comfort	87
AI-based Systems	96	92	94	8	4	Adaptive learning, handles diverse scenarios	Requires high computational resources, expensive	96

7. Advantages of AI-Integrated Wearables for Elderly Care:

AI-integrated wearables offer a range of benefits that go beyond traditional fall prevention methods, making them an invaluable tool in elderly care.

- **Continuous and Non-Intrusive Monitoring:** Wearable sensors provide around-the-clock monitoring without interfering with daily activities. Unlike periodic check-ins or manual assessments, these devices offer continuous data collection, ensuring that no significant changes in movement patterns are missed.

- **Actionable Insights and Personalized Care:** AI algorithms review the data gathered and give actionable feedback, which may be employed in the formulation of interventions for specific individual needs. For instance, if a wearable detects the drop in balance, it could recommend balance-promoting exercises or lifestyle changes in day-to-day life to decrease risks of falling.

- **Enhanced Data for Caregivers and Healthcare Providers:** The detailed information gathered through wearables assists caregivers and clinicians in making data-driven decisions regarding the care plan. The data-driven decision results in improved outcomes by facilitating intervention targeted to the identified movement patterns and risks.

- **Ease of Use and Comfort:** Modern wearables are designed with user comfort in mind. Devices like Fibion SENS and Fibion Vitals are lightweight, discreet, and easy to wear, ensuring that users do not feel burdened or inconvenienced by the technology. This user-friendliness is important in order to ensure compliance and achieve the maximum possible effectiveness of fall prevention measures.

AI-based wearables not only increase safety but also enable older adults to live independently by offering constant support that adjusts according to their evolving needs.

Findings and Trends:

Research by Choi et al. (2022) highlights the efficacy of a Modified Directed Acyclic Graph-Convolution Neural Network (DAG-CNN), achieving over 98% accuracy in classifying near-falls, underscoring the potential of advanced deep learning algorithms in enhancing detection capabilities.

The introduction of multi-modal datasets, such as the MUVIM dataset by Denkovski et al. (2022), has resulted in impressive performance metrics, with AUC ROC scores exceeding 0.94 for infrared and thermal imaging, demonstrating the advantages of integrating diverse sensing technologies.

Kamienski et al. (2023) created a reconfigurable walker based on Long Short-Term Memory (LSTM) networks that has a 97% success rate for fall prediction, pointing toward the direction of real-time, adaptive systems capable of preventing injury before it happens.

Piñeiro et al. (2024) emphasize the importance of user privacy in their low-cost LIDAR-based fall detection system, demonstrating a growing trend towards solutions that respect individual privacy while providing reliable monitoring and intervention.

Challenges and Gaps:

1. Many fall detection systems already in use, especially those that use cameras, cause serious privacy concerns for users, which discourages adoption. This emphasizes the requirement for technologies that guarantee efficient monitoring while protecting user privacy.

2. In certain situations, such as when someone falls against a wall or ends up seated, current systems have trouble reliably detecting falls. This disparity necessitates improvements in algorithms and sensor technologies to increase detection capabilities.

3. Wearable emergency transmitters can lead to desensitization of alarms because, with all the advancement, they often generate high false alarm rates due to normal user movements. An issue of particular difficulty is designing more user-friendly systems to discriminate between harmless motion and actual falls.

8. Gaps Identified:

1.**Limited Operation Scope:** The operation is restricted to areas where sensors have been deployed.

2.**Smartphone-Based Detectors:** Smartphones can be used as detectors but may face challenges in real-time operations.

3.**Challenges in Performance:**

1. Issues with the sensing architecture.
2. Stability problems with the accelerometer's sampling frequency.

4.**Resource Constraints:** Smartphones cannot handle continuous sensing tasks without compromising their performance.

Gaps in Research:

1. **Algorithm Improvements**: While many systems employ machine learning techniques, there is room for further exploration in supervised learning models and feature extraction methods. The integration of time-domain and frequency-domain analysis could enhance classification accuracy.

2. **Data Privacy Solutions**: Future research should focus on developing privacy-preserving algorithms that can effectively monitor without compromising user comfort. Methods like edge computing can assist in processing data locally, thereby minimizing the necessity for continuous monitoring.

3. **Comprehensive Testing:** Most systems in place are tested under lab conditions, which might not reflect actual situations. More thorough field studies are needed to confirm the reliability of these systems in a variety of environments.

Future Research Direction:

Supervised Learning: Develop models like decision trees or SVMs to classify fall vs. non-fall events using labeled data.

Deep Learning: Investigate neural networks (e.g., LSTM) for processing time-series data from sensors.

Time-Domain and Frequency-Domain Analysis: Extract useful characteristics from sensor information (e.g., acceleration, angular velocity) for better classification.

Sliding Window Technique: Implement algorithms that analyze data in real-time using a sliding window for immediate fall detection.

Event-Driven Processing: Create event-triggered algorithms that activate upon detecting sudden changes in motion.

9. Conclusion:

AI-powered wearable sensors are a revolutionary method for preventing falls in the elderly. With ongoing monitoring, early identification of risk of falling, and tailored interventions, such technologies provide a proactive answer to an affliction that reaches millions across the globe. With its ongoing development, the future only holds more promise for AI-powered wearables to enhance safety, autonomy, and quality of life in the elderly. Fostering the exploration and use of these new technologies is an important step toward a healthier and safer future for our aging population.

The several fall-feature parameters of 6-axes acceleration were firstly introduced and applied according to the algorithm. Possible falls were chosen through the simple threshold and then applied to the MPU to solve such problems as deviation of interpersonal falling behavioral patterns and similar fall actions. The test of the proposed device investigated along a different 350 case studies. The upper and lower bounds of acceleration and velocity parameters have been tuned to provide optimal fall detection with sensitivity, specificity, and accuracy greater than 95 %. The results confirm the minimization of the computing effort and resources compared to the original ones where all the events used were implemented. Then the suggested algorithms were quite rudimentary because it relies on a simple sensor (calculate the angle) and the software computes angular velocity and acceleration.

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