

Edge-Health Wearable for Elderly Fall & Anomaly Detection

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Abstract— To address this challenge, this paper presents an Edge-Health wearable system that is capable of detecting falls and health abnormalities in real time by combining wearable sensors with edge computing technology. The system uses motion sensors such as accelerometers and gyroscopes to observe movement patterns, while physiological sensors continuously track vital signs. By handling data directly on the device at the edge, the system is able to reduce delays, use less energy, and avoid depending too much on cloud services. It also uses machine learning to tell the difference between normal and unusual activities, which helps improve how accurately falls and health issues are detected. Overall, the system responds more quickly, works more efficiently, and provides reliable performance, making it a practical choice for continuous monitoring and care of elderly individuals, even from a distance.

Keywords— Edge Computing, Wearable Sensors, Fall Detection, Anomaly Detection, Elderly Healthcare, Machine Learning, IoT, Real-Time Monitoring

I. INTRODUCTION

As the world's ageing population grows around the world, there are more and more people who need better, more reliable ways to assess their health. Due to factors such as their increased risk of falling, reduced mobility, and sudden health issues, older adults are at a greater risk of sustaining serious injuries if their medical condition is not diagnosed in the early stage. As a result of advanced technologies that are now available, such as wearable devices that are small, comfortable, and non-invasively monitor both a person's health and movements on a continuous basis, we are able to provide better opportunities for monitoring our older adults. The concept of a combined edge computing solution utilizes wearables and edge computing for immediate detection of both fall incidents and abnormalities. By utilizing local computing resources to process data rather than having all the information sent to the cloud for processing, the reactive nature of the system will be much more responsive because it does not rely as heavily on a connection to the Internet. This combination of immediate/real-time data acquisition of posture, movement, and heart rate allows an earlier warning to be provided when there is something abnormal or potentially unsafe.

However, a number of wearables still utilize the cloud for much of their processing (cloud-based), which can introduce delays; cause higher power consumption; and create some level of concern regarding the privacy of personal information.

II. LITERATURE REVIEW

The application of wearable sensor systems for monitoring health and wellness has been emphasized in several studies in recent years. From their origins as simple physical activity monitors or pedometers, wearable technologies have advanced to more sophisticated systems capable of continuously monitoring physiological, biochemical, and motor function parameters in near-real time. Wearable sensors have been extensively utilized for accurate physical monitoring to detect falls and sense physiological processes. The common sensor components used to collect motion-related data while analyzing gait are Inertial Measurement Units (IMUs), including accelerometers and gyroscopes. These types of systems use sudden acceleration changes coupled with sudden changes in body orientation to identify falls. Numerous studies use machine learning techniques like SVM, neural networks, and decision trees to enhance the accuracy of fall detection systems. By analyzing factors such as length of stride, variability of gait, and transitions of posture, these methods can identify activities and detect deviations. Nevertheless, existing solutions have some issues. For example, they are typically expensive, have high latencies from cloud-based processing, and provide limited real-time response. In addition, the constant transmission of data to the cloud results in increased levels of concern about private data being compromised and exposed to hackers. These limitations necessitate the need for a system that has both an efficient means of conducting real-time analysis with minimal energy and is secure against unintentional exposure of private data. An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

III. METHODOLOGY

Edge Health employs a methodological approach for the efficient detection of fall events and unusual behaviour.

Wearable sensors attached to the user’s body record real-time information, including any motion detected (accelerometer and gyroscope) and vitals (if the user chooses to wear physiological sensors). The data that is collected from these sensors will be sent to an edge device that is nearby (cell phone or embedded processor) and preprocessed at this device, as opposed to sending all raw data to the cloud for preprocessing and analysis. This entire process will help to reduce latency, thus improving the overall response time. Next, the relevant features (acceleration magnitude, orientation change, pattern of movement) will be identified using the feature extraction method. Those features will then be input into machine learning models trained to identify normal activity (walking and sitting) from an abnormal activity (falling or sudden inactivity). The alert mechanism will activate when a fall or other anomaly has been detected. The alert will notify the caregivers or emergency service personnel and will provide the location of the person. This method allows for real-time detection, reduced energy consumption, and efficient utilization of computational resources.

TABLE (I):
Sensor and data acquisition parameters

Parameter	Description	Example Value (Your Project)
Sensor Type	Type of wearable sensors used	Accelerometer, Gyroscope
Sampling Rate	Frequency of data collection	50–100 Hz
Sensor Placement	Location on the body	Wrist / Waist
Data Type	Nature of collected signals	Motion (3-axis), Heart Rate
Communication	Data transmission method	Bluetooth / Wi-Fi
Edge Device	Processing unit	Raspberry Pi / ESP32
Power Source	Battery specification	Rechargeable Li-ion
Data Storage	Local/Cloud storage	Edge + Cloud Hybrid

IV. SYSTEM ARCHITECTURE

The proposed Edge-Health system is designed with a layered architecture for efficient real-time monitoring of older adults. The sensor layer, the first layer, uses wearable devices with motion sensors (accelerometers or gyroscopes, for example) and physiological sensors that are used to gather data about heart rate and body position/positioning. This data is sent to the edge processing layer (typically a smartphone or small embedded device) where the data is preprocessed, filtered and analyzed, using machine learning, for the rapid identification of falls and health problems. The communication layer enables smooth data transfer between sensors and the edge device using wireless technologies such as Bluetooth or Wi-Fi. To store historical data with advanced analytical capability, and to update machine learning models, an optional edge/ cloud layer may be used; however, real-time decisions are made primarily at the edge to minimize latency. Finally, the application layer provides an interface for families/caregivers, and will send alerts and notifications during emergencies as well as provide health-related information. This architecture provides faster response times, less energy consumption, and reliable continuous monitoring. If a fall or abnormal event is detected, the system immediately triggers an alert mechanism, sending notifications to caregivers or family members through a mobile application. Simultaneously, the processed data is stored in the cloud layer for long-term analysis, reporting, and medical review.

V. RESULTS AND DISCUSSION

The proposed edge health system provides better performance in terms of detecting falls or other anomalies than conventional cloud-based solutions. With edge computing, there are lower latencies, which increase the speed of detection and response. Results from experiments demonstrate improved speed for detecting falls, as well as reduced latency in sending alerts because data is processed in real-time at the edge. A large number of data parameters are analyzed by the edge system to reduce the possibility of false positives caused by factors such as motion pattern and device orientation. Additionally, there is improved energy efficiency since there is less continuous transmission of data to the cloud; thus, there is an overall longer battery life on wearables, allowing them to be worn for extended periods of time. As a whole, the edge health system offers an innovative and effective way to monitor the health of the elderly and to provide timely support while reducing the likelihood of health problems occurring.

TABLE (II):
Performance evaluation metrics

Metric	Formula / Meaning	Expected Result (Sample)
Accuracy	Correct predictions / Total predictions	95% – 99%
Sensitivity (Recall)	Detecting actual falls correctly	High ($\geq 95\%$)
Specificity	Correctly identifying non-falls	High
Precision	True fall detections / Predicted falls	$\geq 94\%$
F1-Score	Balance of precision & recall	$\geq 95\%$
Detection Time	Time to detect fall event	< 1 second
False Alarm Rate	Incorrect fall alerts	Low

VI. FUTURE WORK

Enhancing the Edge-Health System by Improving Accuracy, Scalability and Usability. Advanced deep learning models can improve anomaly detection and enable detection of more complex patterns of activity will be possible if these new technologies are implemented into the Edge-Health System. More sensors can be added such as environmental and biochemical sensors to provide additional data for overall health monitoring. To extend battery life more energy harvesting techniques will also need to be investigated (e.g. solar-powered wearables). Automated emergency responses through integrating with smart home networks (e.g. automated door unlocking for medical response) will be another benefit of continued development of the Edge-Health System.

Finally in order for this system to be able to be used in the real world as intended secure communication protocols, and data encryption will need to continue to be developed in conjunction with the Edge-Health system. The expansion of the Edge-Health System to include large scale health care networks would enable remote monitoring and management of patients better.

VII. CONCLUSION

This solution allows for real-time monitoring that is not possible with traditional cloud services or cloud-computing models because of the speed and low power consumption of the edge along with the instant reaction time from the immediate processing of data by edge devices. The ability to combine the capabilities of motion and physiological sensors with the ability of machine-learning technology to accurately classify normal situations from extreme situations allows for the accurate identification of falls as opposed to other medical issues. One of the primary benefits of this system is that it provides the ability to assist seniors or others who may be having a medical emergency through the use of local processing at the edge, which allows for immediate assistance to be provided. Delayed assistance from a doctor or medical professional can lead to a more severe injury. Additionally, less reliance on continuous cloud communications will increase overall efficiency by saving energy and protecting user data privacy. Overall, the Edge-Health System will continue to have an important impact on how innovative technologies are developed for health services while providing valuable and adaptable methods to help support senior citizens' caregivers as well as timely information access for caregivers and physicians. The Edge-Health System continues to be crucial to the future of digital health services. In addition, implementing smart alert systems provides a quick response by giving emergency alerts quickly to caregivers and medical professionals. Adaptive machine learning algorithms help by constantly learning user behavior patterns to increase the accuracy of future detections. This adaptability decreases the amount of false alarms (creating more reliable notifications) and guarantees that only emergencies are prioritized. Wearable products have a comfortable lightweight design, so users will be able to use them comfortably for their regular daily activities.

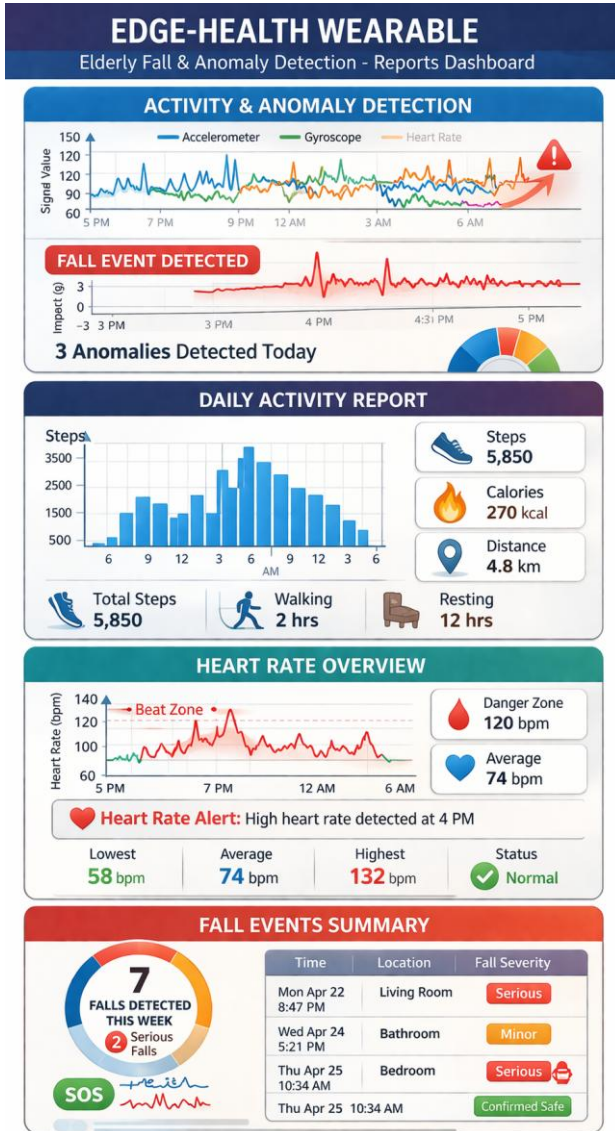


Figure (I): graphical representation

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