Low-Power Non-Invasive Fall Detection Device

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ABSTRACT
The Centers for Disease Control and Prevention (CDC) reports that annually, millions of individuals aged 65 and older experience falls. Notably, over 25% of the elderly population falls each year, yet fewer than half report these incidents to their healthcare providers. Significantly, a single fall incident doubles the likelihood of subsequent falls. The repercussions of falls among the elderly are profound and extend beyond physical harm; they also entail substantial healthcare costs. Statistically, 20% of fall incidents result in severe injuries such as fractures or head trauma, leading to approximately three million elderly individuals receiving emergency room treatment for fall-related injuries each year [1]. Project FAST is dedicated to addressing this critical issue by implementing proactive measures to mitigate the risks and consequences associated with elderly falls.

Keywords
Low Power, Non-Invasive Sensing, Fall Detection, Elderly Care, Embedded Systems, Real-Time Machine Learning, Wearable Devices

1. INTRODUCTION
Falls are a serious health concern for older adults, as they can result in injuries, disabilities, and even death. According to the CDC, more than one in four older adults report a fall each year, and falls are the leading cause of injury-related death for this age group. The cost of treating fall injuries is also staggering, estimated at $50 billion annually [1]. Therefore, there is a pressing need for effective and affordable fall prevention and detection solutions that can protect the lives and well-being of elderly people.

However, many older adults are reluctant to use existing fall prevention products, either because they are uncomfortable, intrusive, or compromise their privacy. For example, some products require the user to wear a pendant or a wristband that can be easily forgotten or lost, or that can cause skin irritation or allergic reactions. Other products rely on cameras or sensors that can invade the user's privacy or generate false alarms. Moreover, those products are expensive, complex, or require constant maintenance or charging.

FAST (Fall Assessment and Safety Tracking) consists of a wearable device that can attach to the core part of the body (Figure 1). The device uses artificial intelligence models and a low-power microcontroller to analyze the user's movements and identify falls. The device will send an emergency signal to a designated contact or a medical service when detecting a fall motion, and it is designed to be portable, low-cost, and power-efficient. Furthermore, our device respects user privacy and dignity by excluding external data harvesting devices and sensors while additionally offering complete data isolation and privacy in our system.

Figure 1. A close-up shot of FAST is placed at the waist of a person.

The target audience for this product is elderly people who are at risk of falling and want to feel safe and maintain their privacy without compromising their comfort or dignity. The product can also assist their caregivers, family members, and health professionals, who can monitor the user's status and intervene promptly in case of a fall. The product can be utilized in various settings, such as homes, hospitals, or nursing homes.

The main objective of this paper is to introduce the basic idea of FAST, the key motivation, the high-level background information, and the plans to describe in this paper. The rest of the paper is organized as follows: Section 2 provides a literature review of the existing fall prevention and detection products and their limitations. Section 3 describes the design and implementation of Project FAST, including the hardware, software, and communication components. Section 4 presents the evaluation and testing of FAST, including the performance, accuracy, usability, and user satisfaction metrics. Section 5 discusses the ethical, social, and economic implications of Project FAST, as well as the future work and challenges. Section 6 concludes the paper and summarizes the main contributions and findings.

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2. RELATED WORK

In prior research, the utilization of machine learning models in conjunction with accelerometer has been explored extensively, as noted in studies such as those by Butt, A. et al [2]. However, the unique aspect of our project lies in its emphasis on power efficiency. While previous work primarily concentrated on the intricacies of machine learning algorithms, our project shifted the focus toward optimizing the hardware aspect of the device.

The Apple Watch also has a feature to detect hard falls and includes emergency contact options. However, our product stands out as a low-cost and low-profile alternative. It provides precise monitoring, a long-lasting battery, and an ergonomic design, offering a cost-effective solution compared to the expensive and inconvenient Apple Watch.

Figure 2. Similar watch-style product on Amazon.

Commercially available products in this domain, typically in the form of watches and wristbands (Figure 2), have made their mark. Yet, these products often come with drawbacks, primarily their conspicuousness and the discomfort they pose when worn for extended periods. In contrast, our product has a compact form factor, enabling it to be discreetly attached to the skin near the waist area. This design not only ensures minimal visibility but also offers enhanced comfort, making it suitable for prolonged use. This approach marks a significant advancement in wearable technology, prioritizing user comfort while maintaining functionality.

Drawing inspiration from Butt et al. and incorporating an LSTM model, our fall detection device is designed for efficiency and precision [2]. Additionally, based on Qi Liu's findings on energy consumption, we have optimized our device by disabling the gyroscope, a decision rooted in the fact that gyroscopes are more energy-intensive than accelerometers [3]. This modification ensures our product remains power-efficient while still providing reliable fall detection. By leveraging the principles of energy-efficient, our product achieves a balance between accuracy and battery longevity. The accelerometer is carefully calibrated to detect falls with high precision. Our approach selectively processing critical data points, thus reducing unnecessary power usage. This strategy not only extends the battery life but also ensures our device remains lightweight and unobtrusive for the user. Our product stands out as a long-lasting, accurate, and user-friendly solution for fall detection, catering to the needs of those seeking a reliable yet cost-effective alternative to more traditional, power-intensive devices.

3. TECHNICAL DETAILS

3.1 Overview

The system is designed with embedded technology to facilitate the detection and seamless transmission of information across a network of interconnected devices (Figure 3).

At the core of the system lies an Inertial Measurement Unit (IMU) integrated into the FAST hardware platform. This unit is responsible for monitoring the acceleration experienced by the user who wears the device. The IMU captures dynamic movement data, including the x, y, and z acceleration vectors (Ax, Ay, Az), to accurately gauge motion.

After data acquisition, an onboard Microcontroller Unit (MCU) undertakes the initial data processing. This step involves filtering and normalizing the raw acceleration data to ensure reliability before further analysis. Should the processed acceleration data exceed a predetermined threshold, the system's Bluetooth module is activated. It then wirelessly transmits the pertinent data to a paired mobile device.

The mobile device serves as an intermediary, relaying the received data to a dedicated web server. Utilizing an advanced AI algorithm, the webserver evaluates the data to ascertain whether it corresponds to a fall event.

In the event of potential fall detection, the system initiates a grace period. During this interval, the user can dismiss the alert, thereby mitigating the occurrence of false positives. If the user fails to respond within the allotted time frame, the system escalates the situation and dispatches an emergency alert to pre-designated contacts. This mechanism ensures timely communication and prompt response in critical situations.

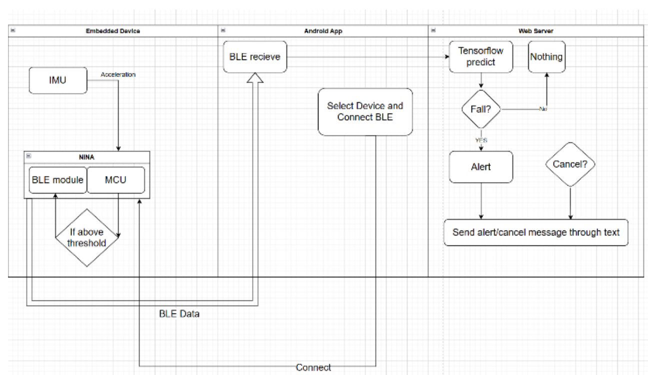


Figure 3. Block diagram of the entire system.

3.2 Theory of Operation

Our solution toward the fall detection system is separated into two parts: the lightweight wearable hardware on the user's body for collecting data and the web app on the portable devices to recognize falling motion then send the notifications to others.

3.3 Implementation Details

3.3.1 Hardware

The circuitry contains 3 parts: the MCU, IMU, and connectors. For the MCU, we picked the NINA-B306-00B, which is built on a nrf52840 chip from Nordic Semiconductors. We picked NINA-B306-00B because of its dedicated package for both the nrf52840, the antenna module, and the low power consumption feature of the nrf52 series. For the IMU, we picked the BMI270 module because it has an excellent balance of power consumption and data noise in transmission.

When designing the board, we needed to deal with two concerns: electromagnetic pulses (EMP) and board scale. For EMP, since we only use 2 layers of copper (1 oz.), we had limited layers for the ground plane. To solve this issue, we add vias all around the board boundary and the antenna to minimize the phase shift in the ground net (Figure 4). By applying this modification, we can lower the Bluetooth Low Energy (BLE) transmit power to -20 dB and have the same connectivity as the design without EMP optimization.

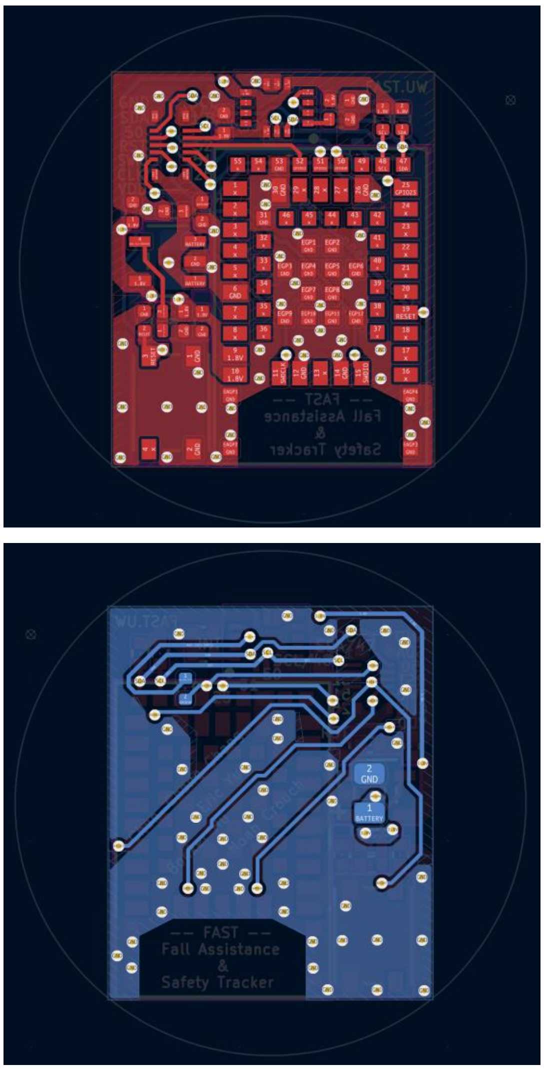


Figure 4. Up: The front side of the PCB
Down: The back side of the PCB

In our goal, the scale of the board needed to be smaller than the diameter of the battery we chose (LIR 2450). Thus, to decrease the board scale, we chose not to include the charging unit but to make a battery chassis for battery replacement. Also, we have included the General-Purpose Input/Output (GPIO), TWI interface, and power network in the on-board connector, which enables simple device repair and functional extensions for our device if needed (Figure 5, red wire connection part).

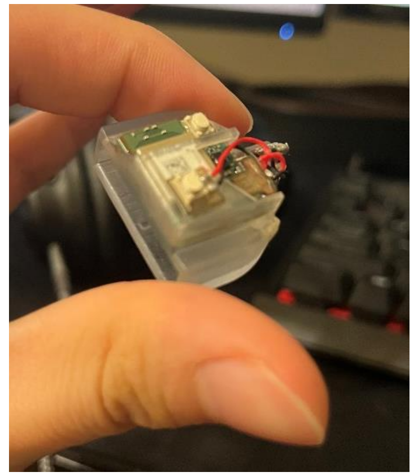


Figure 5. The photo of the device (without battery)

3.3.2 Software

In order to achieve a current consumption lower than 100 uA under 3.3V, we chose to use Zephyr's NRF connect SDK to give us full control of our device. There are three considerations for the current consumption: BLE, IMU, and data filtering. To lower the BLE current consumption, we changed several parameters for the BLE protocol, including changing PHY to a 2M channel, lowering the TX power consumption, extending the advertising and connection intervals, and maximizing the data transmission packet size to 243 bytes (limits for nrf52840).

For IMU and data filtering, we turn off all the sensors except the accelerometer and initialize it to low power mode through TWI protocol. In order to send most data in one BLE packet and reduce the notification frequency, we use a float array FIFO buffer to record 20 consecutive data points (device has a sampling rate about 20 Hz), which is approximately 1 second of data. When there is a set of data points (Ax, Ay, Az) has an intensity less than 0.75 G (G ~ 9.81 m/s^2), the program will send the entire buffer through BLE notifications and collect the next 1 second of data for the consecutive BLE notification packets. This means we will have a window of 2 seconds of data for the motion classification.

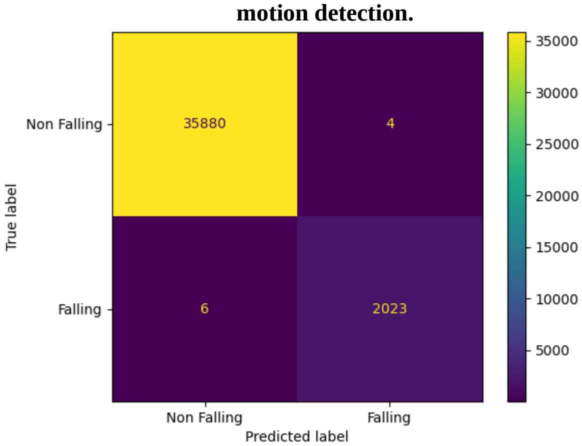
After being able to retrieve the data, we then moved on to the model training for fall detection. We evaluated a total of 3 model structures: Convolution Neural Network (CNN), Long Short-Term Memory (LSTM), and CNN+LSTM. The reason we picked these 3 models is that CNN is the simplest structure that contains signal processing essence; however, from the test results, the average accuracy of CNN model is 96% and CNN+LSTM is 99.4%, which do not fulfill our requirements. For LSTM, it has an extraordinary prediction accuracy on time-series data. Therefore, since our data is a consecutive time series data, we choose to utilize LSTM's benefits. The data we serve into each of the models is a 40 by 4 tensor, where there are 40 consecutive data in 2 second window and each data contain Ax, Ay, Az, and the intensity of these 3 values. For the prediction, we use 0.5 as the threshold that if the prediction is greater than 0.5 it will be recognized as the falling motion.

4. EVALUATION AND RESULTS

To Evaluate the fall detection AI model, a simple mannequin is constructed and attached FAST on the bottom part of the mannequin. Once the mannequin falls down the model should identify the fall and alert any interested party. Non-falling motion was conducted by taping FAST onto the waist area of an actual person, as shown in Figure 1. The participants performed various activities such as walking, sitting, standing, lying down, and falling. The device recorded the sensor data from its onboard accelerometer and transmitted it to a computer via Bluetooth. The computer ran machine learning algorithms to classify the activities as falls or non-falls. The result is compared and classified with the ground truth labels obtained in the methods. The accuracy, sensitivity, and specificity of the classification are calculated and evaluated.

The results of the experiments showed that the wearable device achieved an average accuracy of 99.97%, sensitivity of 99.80%, and specificity of 99.70% in detecting falls and non-falls. The confusion matrix of the classification is shown in Table 1. The device was able to distinguish between distinct types of falls such as forward, backward, sideways, and tripping, as well as distinct types of non-falls such as walking, sitting, standing, and lying down. The device also successfully triggered the alert system in case of a fall, sending a message to the caregiver or emergency service with the location and status of the user.

Table 1. The confusion matrix for the model we picked for motion detection.



After the evaluation of the LSTM model, we moved on to the power consumption test. Since the device will consistently work at 3.3V, we can use the current consumption as an indicator. After using the source meter, the device consumes 78 uA on average during extreme condition tests (turning off the on-device data filtering, which means the device will send 240 bytes of data through BLE notification every second). This result has reached our goal of current consumption lower than 100 uA.

5. DISCUSSION

5.1 Solution Evaluation

The solution, which combines the most advanced embedded technologies with a state-of-the-art machine learning algorithm, has demonstrated promising results in fall detection. The device was subjected to various vigorous scenarios from everyday activities such as standing, walking, and sitting, to more dynamic non-falling actions such as running, jumping, spinning, etc. The tests indicate that only four in 35880 non-falling activities trigger a false alarm, demonstrating a high specificity of the device. The device was also attached to a mannequin (Figure 6) to simulate fall events. Out of 2,000 tests conducted, only six occurrences where the system failed to detect the fall event were observed, indicating a high sensitivity of the device. Moreover, all the detected fall events were alerted on time, ensuring prompt communication and response.

Figure 6. "Mannequin" used for fall tests.

5.2 Additional Application

FAST is not limited to its intended application of fall detection but rather has the potential for wider applications in various domains, such as activity recognition, elder care management, and outdoor analytics. The onboard low-power IMU and MCU unit enables long-term motion monitoring, which can provide valuable insights into the user's behavior, health, and environment. The advancement of artificial intelligence models allows for more precise and accurate data interpretation in various contexts, enhancing the functionality and usability of FAST.

5.3 Future Works

FAST has the potential to be integrated into smart home systems, providing a more seamless and intuitive end-user experience. FAST could also be applied in senior care facilities for more professional analysis of high-risk individuals. The machine learning models could be trained on a larger and more diverse set of motion data, expanding FAST's applications. The data from FAST could be first sent to a Field Programmable Gate Array (FPGA) device, which could run multiple models concurrently, improving the prediction results [4].

Improving the stability of the software is one of the most important priorities. Aimimg to streamline the process by removing the webserver-based middleware intermediary software and are considering a direct implementation of machine learning algorithms on Android platforms.

Additionally, we plan to focus on improving the design aesthetics of our product. Presently, we utilize a 3D printed case and a glue gun for attaching the PCB and battery. However, for the purpose of scaling up to mass production, we will explore the use of injection-molded cases and more efficient adhesive techniques. This shift is essential to ensure that our product not only functions effectively but also have a professional and consumer-friendly appearance.

5.4 Key Insights

One of the interesting insights gained during the construction of the project is the importance of setting appropriate thresholds and categorizations for the fall detection algorithms. During the testing phase of the project, the AI model could return any values between 1 (fall) and 0 (non-fall). If the threshold were set at 0.5, there would be a 50% chance of a false positive rate of fall detection. The false positive rate was significantly reduced when the threshold was set above 0.9. However, the sensor was placed on different mannequins and would produce values ranging from 0.91 to 0.98. Therefore, the threshold for categorizing a fall would need to be adjusted based on the wearer's physical characteristics.

Another lesson learned was the difference between a computer and a mobile device when deploying the trained AI model. When the AI model was first trained on the computer, the sensor was connected directly to the computer for testing purposes. Although the model could easily run on a modern laptop, due to the different architecture between the laptop and a mobile device, additional translations would be required to accommodate the less computational-powered mobile devices.

The value of having a diverse team is crucial to our success. Our team includes members from both CSE and EE departments. This diversity ensures a well-rounded approach, as it balances the focus between software and hardware development. Moreover, it fosters an environment of mutual learning and collaboration. Having perspectives from different fields enriches our problem-solving strategies. Team members from the CSE department bring in-depth knowledge of software development and algorithm design, essential for the software stability and machine learning aspects of our project. On the other hand, colleagues from the EE department contribute their expertise in circuit design and hardware optimization, vital for making our device energy-efficient and user-friendly. This interdisciplinary collaboration not only enhances the technical aspects of our project but also promotes a broader understanding and appreciation of each other's disciplines. It encourages open-mindedness and adaptability, qualities that are indispensable in a rapidly evolving tech landscape. By leveraging our varied skills and knowledge, we are better equipped to innovate and create a product that is both technologically advanced and practical for everyday use.

5.5 Redesign and Improvements

The project development process faced several obstacles that could have been prevented or reduced with better planning and coordination. The project team focused too much on the hardware component, overlooking the challenges in software development. This led to setbacks and complications in the later stages, particularly in setting up the software environment and creating the mobile application. A more balanced allocation of resources and tasks between the hardware and software teams would have facilitated a smoother and more efficient development process. The software team initially created a mobile application for data collection, which involved a tedious procedure of exporting the data to a computer for processing and model training. This procedure wasted lots of time and effort, slowing down the progress of software development. It was only in the later stages that the hardware team developed a Python script to wirelessly collect data directly on computers, which greatly accelerated the data collection and processing. The script was later used as a mobile web application (Figure 7) as a backup option due to the application development difficulties. The earlier development and use of the script would have saved a lot of time and enabled the software team to concentrate more on testing and improving the final mobile application.

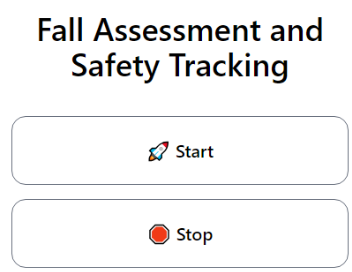


Figure 7. Python-based web application for alternative software system

One of the technical aspects that could be improved is the integration of an on-board charging unit. The current design depends on a pre-built rechargeable battery as a power source, which occupies a large fraction of the thickness of the entire unit. A custom-designed power source could be more suitable for the physical design of the entire unit, thus reducing a considerable amount of space. Furthermore, an on-board charging unit could also improve the functionality and usability of the device, as it would remove the need for openings for battery replacement as shown in Figure X.

6. RESEARCH POTENTIALS

6.1 Related Work

Recent research has highlighted the feasibility and efficacy of utilizing low-cost microprocessors in fall detection systems. Flora Amato, et al developed a compact wearable fall-detection system using an Arduino Nano BLE device. They employ an onboard acetometer, gyroscope, and microphone to collect daily motion data which is processed by the MCU unit [5]. Similarly, FAST incorporates the same MCU unit for data collection and preprocessing. However, FAST distinguishes itself by running its machine learning model on a web server, thereby conserving the device's power consumption.

This approach aligns with the methodology of Zabir Mohammad, et al. Their research leverages a wearable sensor suite, including accelerometers, gyroscopes, and magnetometers, to amass motion data. This data is subsequently transmitted to a remote deep learning model that classifies the data into distinct categories: non-fall, pre-fall, and fall, with an accuracy rate exceeding 95%. The model's predictive prowess allows it to foresee falls and dispatch alerts to caregivers or emergency services, thereby diminishing the fall's impact on elderly individuals. The model's efficacy is corroborated through rigorous testing involving over 10,000 simulated falls and activities, showcasing its superior accuracy and performance compared to other methodologies [6]. FAST employs a similar classification method, where the model scrutinizes a one-second moving window to discern non-fall and fall motions. This analysis results in FAST joining the pre-fall and fall events to activate a fall alert. However, unlike the study that utilizes the SisFall dataset, FAST opts not to use this dataset for model training. Instead, FAST's model training involves a proprietary dataset, allowing for enhanced customization and adaptability to the wearer's unique motion patterns.

The study by Lee et al. incorporates a preprocessing phase, which is a critical first step in their methodology. During this phase, the raw sensor data collected from the IMU is carefully converted into a sum of vector magnitudes [7]. FAST adopts a similar approach in its preprocessing routine as shown in equation 1. However, FAST places a particular emphasis on acceleration data, which is a strategic choice aimed at enhancing the system's power efficiency. The research by Lee et al. explores a variety of deep learning architectures, including 1D-CNN, 2D-CNN, LSTM, and Conv-LSTM, to predict falls from the processed IMU data. Their findings reveal that the Conv-LSTM model achieves an impressive accuracy of 97.6%, while the LSTM model boasts a specificity of 97.7% [7]. Inspired by these results, FAST adopts the LSTM model to classify and identify falls from the accelerometer's three axes and the computed magnitudes to ensure accurate and reliable fall detection.

$$|A| = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{1}$$

6.2 Future Research Direction

The current landscape of fall detection research, coupled with the performance outcomes of the FAST system, indicates substantial opportunities for further investigation. A critical challenge identified in the existing results is the limitation of data available for training artificial intelligence models. The FAST system has amassed a dataset comprising approximately 40,000 instances of fall and non-fall events. However, the non-fall data encompasses only a select range of motions, and all fall data were simulated using a mannequin. This approach may not accurately reflect the complex and varied fall patterns exhibited by humans in real-world scenarios.

Additionally, as highlighted in the study by Amato et al., the placement of the device significantly influenced the model's recognition rate [5]. Empirical evidence from FAST's testing indicates a substantial increase in false alarms of over 30% when the device is held in the hand and an even more pronounced rate of 60% when placed inside a pocket. Consequently, the FAST device has been optimized for attachment at the waist area to minimize false positives. Future research should focus on developing more specialized models that accommodate a broader range of body placements, thereby enhancing the versatility and user-friendliness of fall detection systems.

Further exploration is also warranted in the realm of data diversity and real-world applicability. Enriching the training dataset with a wider array of motion data, including authentic falls from human participants, could significantly improve the model's accuracy and generalizability. Additionally, investigating the impact of various environmental factors and personal attributes on fall detection efficacy could lead to more personalized and adaptive solutions.

In summary, advancing the field of fall detection requires a multifaceted approach that addresses data limitations, device placement optimization, and the incorporation of real-world variability into model training. These efforts will pave the way for more reliable, efficient, and accessible fall detection technologies.

7. CONCLUSION

In summary, our project FAST represents a significant breakthrough in elderly care, combining advanced machine learning with low-power technology in a non-invasive, wearable fall detection device. With a remarkable 99.97% accuracy in fall detection, this device stands out for its user-friendly design and efficiency. The successful collaboration of our interdisciplinary team was crucial in overcoming challenges in both hardware and software aspects. The interdisciplinary collaboration within our team was key in addressing the complexities of hardware and software development, enhancing our problem-solving strategies, and fostering innovation. Looking forward, we are excited about FAST's potential in diverse environments like homes and senior care facilities and see opportunities for advancements such as smart home integration and expanded machine learning capabilities, further advancing healthcare technology research and development. We are grateful for the support from our mentors and peers and are proud to contribute a meaningful solution to healthcare technology.

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