Wearable Fall Detection Device for Sustainable Communities

Pushkar R Kulkarni
Department of Electronics and Communication Engineering
RV College Of Engineering
Bangalore, Karnataka
pushkarrk.ec22@rvce.edu.in

Manjunath M
Department of Electronics and Communication Engineering
RV College Of Engineering
Bangalore, Karnataka
manjunathm.ec22@rvce.edu.in

Shubham R Kalghatgi
Department of Electronics and Instrumentation Engineering
RV College Of Engineering
Bangalore, Karnataka
shubhamrk.ei22@rvce.edu.in

Sreesha K R
Department of Electronics and Telecommunication Engineering
RV College Of Engineering
Bangalore, Karnataka
sreeshakr.et22@rvce.edu.in

Anand Jatti
Associate Professor
Department of Electronics and Instrumentation Engineering RV College Of Engineering
Bangalore, Karnataka
anandjatti@rvce.edu.in

Abstract - **Falls are a significant concern for elderly individuals and those with mobility challenges, often resulting in severe injuries and loss of independence. Conventional fall detection systems face challenges such as bulkiness, limited battery life, and high false alarm rates, making them unsuitable for widespread use in resource-constrained communities. Compact and efficient wearable solutions, powered by advancements in microcontroller technology and machine learning, present a promising alternative. This paper proposes a wearable fall detection device built around the Arduino Nano RP2040 Connect microcontroller, which classifies various movements using a decision tree algorithm. The system achieves compaction and portability by utilizing a lightweight LiPo battery to power the device. Experimental analysis demonstrates the effectiveness of this design in achieving high accuracy in fall detection while maintaining energy efficiency and compactness. This innovation highlights the potential of cost-effective wearable devices to enhance safety and promote sustainable living in vulnerable populations.**

Keywords—Fall Detection, Wearable Technology, Decision Tree Algorithm, Energy Efficiency, Sustainable Communities, Inertial Measurement Unit, Variance of Sum Vectored Acceleration, Internet of Things.

I. Introduction

Falls are a leading cause of injury among the elderly and those with mobility challenges, posing significant risks to their health and independence. With the global aging population rising, the demand for reliable fall detection systems has grown exponentially. Many existing devices are bulky, energy-intensive, and prone to false alarms, limiting their effectiveness in real-world scenarios. This challenge is particularly pressing in resource-constrained communities where affordability and efficiency are critical. Wearable devices not only ensure continuous monitoring but also offer portability and user-friendliness. Recent advancements in wearable technology offer promising solutions, enabling accurate real-time detection with minimal power consumption. By incorporating optimal hardware and advanced algorithms, these devices are transforming safety measures for at-risk individuals. This paper introduces a compact, energy-efficient wearable fall detection device that uses advanced sensors and machine learning algorithms. Its enhanced accuracy makes it an ideal choice for promoting safety and independence in vulnerable populations.

The proposed device leverages cutting-edge technologies, including accelerometers and gyroscopes, to capture motion data, which is then processed using machine learning algorithms to distinguish between normal activities and fall events. The system is designed to minimize false positives by employing techniques such as sensor fusion and advanced feature extraction, ensuring reliability even in dynamic environments. Additionally, the device integrates wireless communication modules to send real-time alerts to caregivers or emergency services, providing timely assistance when a fall occurs.

To address energy efficiency, the wearable employs optimized hardware design and low-power operational modes, extending battery life and reducing maintenance needs. The compact form factor ensures user comfort, encouraging consistent usage, especially among older adults who may be resistant to bulky or intrusive devices.

In resource-constrained settings, affordability remains a critical factor. This system is designed with cost-effective components and scalable production methods, making it accessible to a wider population. Future iterations of the device aim to incorporate predictive analytics to identify fall risks before they occur, further enhancing preventive care.

The introduction of this wearable device marks a significant advancement in fall detection technology, bridging the gap between affordability, efficiency, and accuracy. By combining state-of-the-art sensors, machine learning algorithms, and a user-centric design approach, it offers a comprehensive solution to a growing global challenge. This device not only empowers individuals by promoting their safety and independence but also alleviates the burden on caregivers and healthcare systems by enabling early intervention and timely assistance. Furthermore, its adaptability for various environments, such as homes, care facilities, and outdoor settings, makes it a versatile tool for ensuring safety across diverse scenarios. By addressing the needs of resource-constrained communities and prioritizing accessibility, this innovation has the potential to make fall detection technology widely available, ultimately improving the quality of life for vulnerable populations worldwide

II. LITERATURE REVIEW

Previous research has explored various technologies to address fall detection, with the aim of developing devices that leverage sensors and implement IoT-based frameworks to notify caregivers or emergency services. Many studies have been focused on advanced computer vision algorithms for fall detection devices. Ionescu et al,used a threshold-based algorithm that uses k Nearest Neighbor (kNN) classifier in order to improve the recognition accuracy to 97.53% sensitivity and 94.89% specificity. The accelerometer sampling is made at 50Hz and a set of 14 features is extracted that are used by a kNN classifier to distinguish between a fall and normal activity. One improvement proposed by this paper is that the sampling frequency is reduced when the sensor movement level is slow [1].

Next to improve efficiency, T.Xu et al, proposed a fall detection method combining a threshold-based approach (TBM) on a wearable device and Support Vector Machine (SVM) on a server. TBM identifies potential falls using features like weightlessness, impact, and stationary phases, minimizing data transmission by uploading only suspected falls. The server further processes these events using 13 features and GridSearchCV-optimized SVM for final classification. Experimental results demonstrated high accuracy (97.96%), sensitivity (98.56%), and specificity (97.76%), while reducing power consumption and improving detection efficiency compared to existing methods[2].

Falls were successfully detected; however, significant improvements were required in accurately classifying different types of falls. A.Ibrahim et al, proposed an algorithm which was based on a simple threshold method and used three different features: Acceleration, angular velocity and body angle changes. The algorithm was able to detect falls with high sensitivity (93.3%) and specificity (100%). However, the challenge was in identifying the optimal thresholds. In fact, any low threshold selection may increase the detection of false positives during Activities of Daily Living (ADL) which may result in decreasing the specificity. Alternatively, any high threshold selection would lead to increase in the false negatives and decrease in the system sensitivity[3].

The Limitation of this study was that the thresholds were determined using data collected from young subjects simulating falls onto cushioned mats. In the real case, falling on the floor would generate a higher peak for accelerations and angular velocities. With the advent of Artificial Intelligence & Machine Learning in all fields a lot of AI models were proposed for fall detection where models were trained on images & videos, which acted as objects for the model to train on S. Mobsite et al, used a dynamic video classification system which proposed to detect falls using a single surveillance camera. The framework involved two steps: extracting human body silhouettes from video frames using Mask R-CNN, and employing a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) to learn long-term dependencies between successive frames. The system achieved its best results using 10 frames per video, with 100% accuracy, precision, recall, and F1-score[4].

Furthermore, developing a model based on patients for better specificity in treatment of individuals transpired into a model presented by C. Rougier et al, proposed detecting falls in elderly individuals by combining motion analysis and changes in human shape to assess activities. The system demonstrated robustness on realistic image sequences of simulated falls and daily activities. It assumed the person remained on the ground with minimal motion post-fall, though rapid movement due to injury could occur. Enhancing robustness could involve integrating 3D information to verify if the head is near the floor or using audio data from a webcam microphone. A speech recognition algorithm might also detect distress cries. These improvements could enhance the system's reliability and effectiveness[5].

To improve on personal attention to each patient W. Saadeh et al, proposed a system which distinguishes between ADL and fall events using two modes: Fast Mode for Fall Prediction (FMFP) and Slow Mode for Fall Detection (SMFD). FMFP predicts falls 300-700 milliseconds before they occur using a nonlinear support vector machine (NLSVM) classifier with seven pre-fall features, achieving 97.8% sensitivity and 99.1% specificity. SMFD detects falls 1 second after occurrence using a three-cascaded, 1-second sliding frames classification with linear regression-based training for patient-specific thresholds, achieving 98.6% sensitivity and 99.3% specificity. Validated with the MobiFall Dataset, the system alerts patients and healthcare providers, ensuring timely interventions[6].

This not only reduced latency but also addressed privacy concerns associated with video-based monitoring, making these systems more acceptable for users. These developments pointed to a future where fall detection systems were not only more precise but also seamlessly integrated into the daily lives of individuals, ensuring their safety without compromising their comfort or privacy.

III. METHODOLOGY

In the initial stage of the methodology, the smart wearable fall detection system was conceptualized and designed with a focus on leveraging the capabilities of the Arduino Nano RP2040 Connect. The device incorporates inbuilt sensors, including an accelerometer and gyroscope, and an onboard ML core to classify various movements. The architectural framework was formulated to ensure compactness, user comfort, and unobtrusiveness for seamless daily wear.

The second stage involved data acquisition. The onboard accelerometer and gyroscope were used to record real-time motion data, specifically capturing the x, y, and z components of acceleration (ax, ay, az) and angular velocity (gx, gy, gz). This data was extracted in the form of a text file for preprocessing. The recorded dataset provided a comprehensive representation of various movements, including falls and non-fall activities.

To refine the feature selection process, the net acceleration and net angular velocity were calculated using the acquired data. These parameters were further analyzed for statistical significance. Two critical graphs were plotted: one depicting the variance of net acceleration across different movement types and another showing the variance of net angular velocity. These graphs highlighted distinct separability between falls and other movements, providing a strong rationale for selecting variance as the key feature for model training.

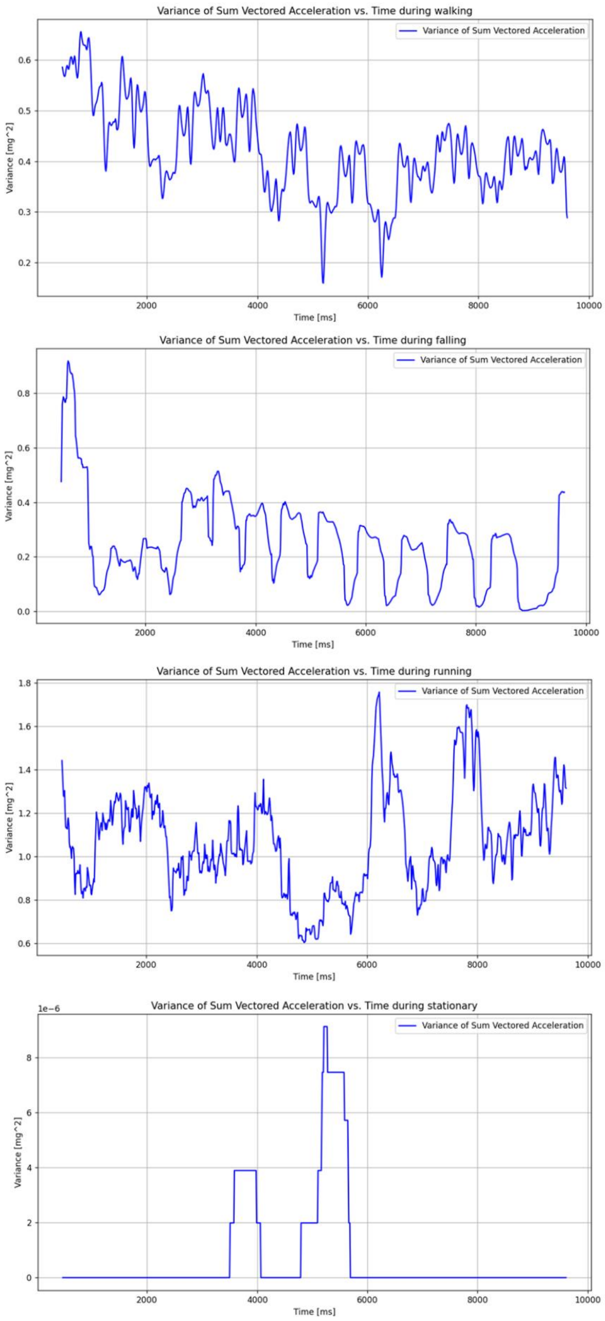

Fig. 1. Variance of sum vectored net acceleration during stationary, walking, running and fall movements respectively.

In the next phase, a machine learning model was trained using the UNICO GUI. A decision tree algorithm was implemented, leveraging the variance of net acceleration and net angular velocity as input features. This approach ensured a lightweight yet effective model suitable for deployment on edge devices. Once the model was trained and validated, a Universal Configuration File (UCF) was generated using the UNICO GUI. This UCF file encapsulated the decision tree model for direct integration with the Arduino Nano RP2040 Connect.

Subsequently, the UCF file was used to generate a header file, which was incorporated into the final Arduino code. The Arduino Nano was programmed to process real-time sensor data, compute the variance of net acceleration and angular velocity, and classify movements using the embedded ML model. Upon detecting a fall, the system was configured to trigger immediate alerts via the device's communication interfaces, such as Wi-Fi or Bluetooth, ensuring timely notifications to caregivers or emergency services.

In the final stage, the system underwent rigorous testing and validation. Controlled experiments and real-world scenarios were conducted to evaluate the model's accuracy, false positive rate, and responsiveness. The results were analyzed, and user feedback was incorporated to optimize the system for reliability and usability. This comprehensive methodology culminated in a robust, energy-efficient fall detection system tailored to meet the needs of at-risk populations while ensuring user comfort and real-time responsiveness.

Flowchart:

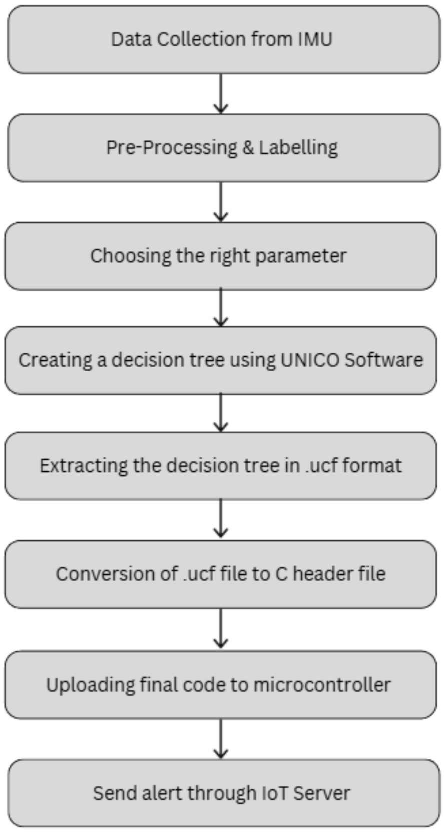

Fig. 2.Flowchart of the proposed model

Integration with IOT

The wearable fall detection system integrates with IoT through the use of the Blynk server platform. When a fall is detected, an alert is sent to the Blynk server, notifying the user or caregiver in real time. The customizable Blynk dashboard allows users to monitor fall detection data and device status, enhancing user experience and ensuring prompt action in case of emergencies. This integration ensures continuous connectivity and improves safety by enabling remote monitoring through mobile devices.

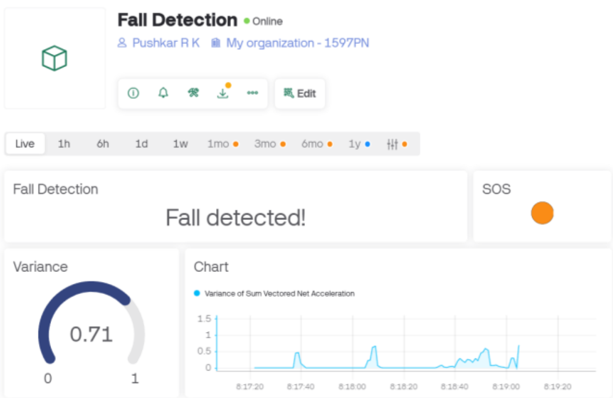

Fig. 2. IoT Dashboard

IV. Hardware Details

The presented design includes LIPo rechargeable battery, Arduino Nano RP2040 connect, 5V DC-DC power converter and charging module. The complete connection diagram of the presented model is illustrated in Figure 3.

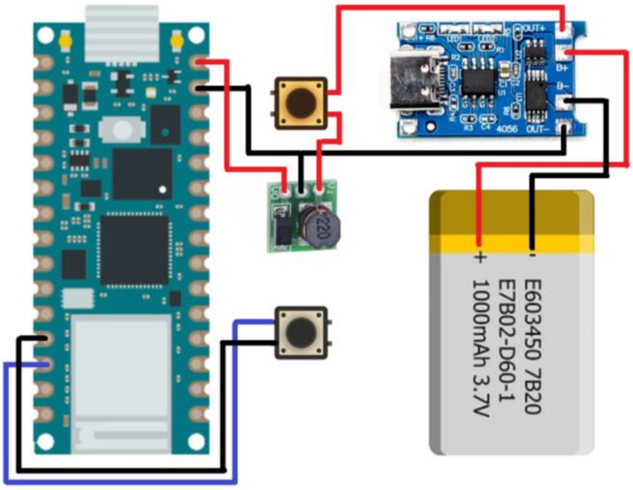

Fig. 3. Schematic of proposed model

A. Arduino Nano RP2040 Connect

The Arduino Nano RP2040 Connect serves as the central microcontroller for the Raspberry Pi RP2040 chip and the system. It is powered byd includes inbuilt Wi-Fi Bluetooth and IMU capabilities, making it suitable for IoT applications like real-time fall detection and alert systems.

B. LiPo Rechargeable Battery

The system is powered by a LiPo (Lithium Polymer) rechargeable battery, offering a compact and efficient energy source. Its lightweight nature and ability to deliver high energy density make it ideal for wearable applications, providing long operational life with a single charge.

C. Charging Module

The charging module is responsible for safely recharging a LiPo battery. It manages the charging process, protecting the battery from overcharging and ensuring long-term reliability by maintaining proper voltage and current levels during the recharge cycle.

D. 5V DC-DC Power Converter

A 5V DC-DC power converter is used to regulate the power supply, ensuring that the Arduino Nano RP2040 and other components receive a stable 5V output. This converter efficiently steps down or steps up the input voltage to maintain optimal performance without excess power loss.

E. Switch Buttons

Two switches are employed to manage the device's operational states, ensuring user control over the device's functionality. One of them is the main power button and the other is an SOS Button.

V. Working

The wearable fall detection system operates by continuously monitoring the user’s movements using the inbuilt IMU module of the Arduino Nano RP2040 Connect. The accelerometer and gyroscope data are processed using the microcontroller on board machine learning core, which classifies daily activities and fall events. A decision tree model, trained using variance in net acceleration, helps distinguish normal movements from falls. When a fall is detected, the system triggers an alert via the Blynk IoT platform, notifying the user or caregiver in real time. Power is supplied through a rechargeable LiPo battery, regulated by a 5V DC-DC converter and managed by a charging module. Two switches allow user control over system functions, ensuring efficient operation and power management.

VI. Conclusion

In summary, this research has successfully developed a tailored smart wearable fall detection device for the elderly, meeting a critical need in healthcare. By integrating IoT technology and advanced sensor arrays, our device aims to transform fall detection, prioritizing precision, user comfort, and real-time response. The iterative design process, informed by insights from the literature review, led to the creation of a seamlessly integrated wearable device for continuous and non-intrusive monitoring in daily life. The methodology involved meticulous sensor selection and calibration, IoT framework integration, algorithm development, and rigorous testing. The algorithms exhibited commendable accuracy in distinguishing genuine falls from routine activities, and user acceptance studies validated the device's usability. Integration into broader healthcare IoT ecosystems positions the device to significantly contribute to personalized healthcare interventions and timely assistance.

The research goes beyond technological innovation, offering potential enhancements in well-being, safety, and the overall quality of life for the elderly. Serving as a proactive and preventative solution, our smart wearable device addresses the limitations of existing fall detection systems, aligning with the evolving landscape of healthcare technology. Moving forward, continuous refinements, user feedback, and deeper integration with healthcare systems will play a pivotal role in realizing the full potential of this technology, positively impacting the lives of elderly individuals susceptible to fall-related incidents.

VII. References

[1] V. M. Ionescu and F. M. Enescu, “Using smart devices for fall detection: algorithms, systems and applications,” 2022 14th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), pp. 1–6, Jun. 2022, doi: https://doi.org/10.1109/ecai54874.2022.9847475.

[2] T. Xu, J. Liu, and M. Geng, “Fall Detection Method Based on TBM and SVM,” 2022 41st Chinese Control Conference (CCC), pp. 2984–2989, Jul. 2022, doi:

https://doi.org/10.23919/ccc55666.2022.9901974.

[3] A. Ibrahim, K. Chaccour, G. Badr, and Amir, "Fall Detection Algorithm using Body Angle for Accurate Classification of Falls and ADLs," 2021 International Conference on e-Health and Bioengineering (EHB), pp. 1–4, Nov. 2021, doi: https://doi.org/10.1109/ehb52898.2021.9657540.

[4] S. Mobsite, N. Alaoui, and M. Boulmalf, "A framework for elders fall detection using deep learning," IEEE Xplore, Jun. 01, 2020.[Online].'doi: https://ieeexplore.ieee.org/document/9357184

[5] C. Rougier, J. Meunier, A. St-Arnaud, and J. Rousseau, "Fall Detection from Human Shape and Motion History Using Video Surveillance," 21st International Conference on Advanced Information Networking and Applications Workshops (AINAW'07), 2007, doi: https://doi.org/10.1109/ainaw.2007.181.

[6] W. Saadeh, S. A. Butt, and M. A. B. Altaf, "A Patient-Specific Single Sensor IoT-Based Wearable Fall Prediction and Detection System," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 5, pp. 995–1003, May 2019, doi: https://doi.org/10.1109/tnsre.2019.2911602.

[7] M. Bundele, H. Sharma, M. Gupta, and P. S. Sisodia, "An Elderly Fall Detection System using Depth Images," IEEE Xplore, Dec. 01, 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9358330.

[8] A. Kitkamchon, K. Dissorn, and D. Bunnjaweht, "A Wearable Fall Detection Device: From Research Advances and Public Datasets to a Senior Design Project," IEEE Xplore, Nov. 01, 2021. Available: https://ieeexplore.ieee.org/document/9745209

[10] "A Flexible Fall Detection Framework Based on Object Detection and Motion Analysis," typeset.io, Feb. 2023, doi: https://doi.org/10.1109/icaiic57133.2023.10066990

[5] C. Rougier, J. Meunier, A. St-Arnaud, and J. Rousseau, "Fall Detection from Human Shape and Motion History Using Video Surveillance," 21st International Conference on Advanced Information Networking and Applications Workshops (AINAW'07), 2007, doi: https://doi.org/10.1109/ainaw.2007.181.

[12] G. Mastorakis and D. Makris, "Fall detection system using Kinect's infrared sensor," Journal of Real-Time Image Processing, vol. 9, no. 4, pp. 635–646, Mar. 2012, doi: https://doi.org/10.1007/s11554-012-0246-9.

[14] J. Dai, X. Bai, Z. Yang, Z. Shen, and D. Xuan, "PerFallD: A pervasive fall detection system using mobile phones," IEEE International Conference on Pervasive Computing and Communications,May2010,doi:https://doi.org/10.1109/percomw.2010.5470652.

[15] A. M. Khan, Y.-K. Lee, S. Y. Lee, and T.-S. Kim, "A Triaxial Accelerometer-Based Physical-Activity Recognition via Augmented-Signal Features and a Hierarchical Recognizer," IEEE Transactions on Information Technology in Biomedicine, vol. 14, no.5,pp.1166-1172,Sep.2010doi:https://doi.org/10.1109/titb.2010.2051955