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Wearable System for Real Time Detection and Prediction of Falls

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Abstract: Falls represent a major health challenge for elderly individuals, often leading to serious injuries and reduced quality of life. This paper presents a fall-detection architecture that performs intelligent data analysis through a centralized application. The system uses wearable sensing devices, accelerometers, pressure sensors, and gyroscopes, to capture motion data from the elderly subject. These sensor readings are transmitted using the low-power *Long-Range* (LoRa) communication protocol to the central application, where machine-learning algorithms evaluate the data in real time to identify potential fall events. This approach reduces the computational burden on wearable devices, supports scalable monitoring, and enables timely detection and rapid response in emergency situations. Overall, the framework enhances safety and autonomy for older adults while reducing strain on healthcare infrastructure.

Keywords: wearables; acceleration; angular velocity; pressure sensors; LoRa; machine learning

1. Introduction

Among elderly populations, falls are a leading cause of injury and disability, contributing substantially to reduced independence and well-being [1]. In this context, fall-detection solutions are becoming increasingly vital in assisted living environments, where rapid intervention following a fall can greatly reduce the risk of injury and enhance resident safety. Existing systems typically rely on wearable or ambient sensors to identify abrupt anomalies in movement patterns. However, despite widespread adoption, many current sensing approaches face important limitations: motion signals are often noisy, pressure-based measurements can lack sufficient variability to reliably distinguish fall events, and many algorithms depend on short, fixed-length windows that fail to capture the longer-term precursors that frequently precede a fall. These constraints highlight the need for more robust sensing strategies and algorithmic designs capable of operating reliably under real-world conditions.

The research presented in this manuscript introduces a wearable system that initially evaluated three-axis accelerometers, pressure sensors, and three-axis gyroscopes for real-time fall prediction. To accurately classify these motion patterns, the system implements intelligent data analysis through Multilayer Perceptron (MLP) and Artificial Neural Network (ANN) architectures. A distinguishing feature of this solution is its use of *Long Range* (LoRa), a *Low-Power Wide-Area Network* (LPWAN) technology, to transmit sensor readouts to the prediction application. LoRa offers an unlicensed, subscription-free communication channel, presenting a viable alternative to conventional cellular networks. Yet, as with many wireless systems, the quality of the transmitted data can be affected by packet loss, latency, and throughput constraints; these factors can further challenge algorithms already sensitive to incomplete or irregular sensor streams.



Due to the nature of wireless data transmission, network loss and latency impairments can impact both the training and operational prediction phases. Accordingly, this paper outlines the complete cyber-physical architecture, encompassing the wearable device, edge gateway, and prediction software that collectively enable fall detection. In addition, the challenges examined in this work arise specifically within a cloud-centric deployment model. In the proposed architecture, sensor readouts captured by the wearable device are forwarded over subscription-less LoRa links to a cloud-hosted prediction service, where computationally intensive inference, utilizing the MLP and ANN models, and data aggregation occur. This design choice enables scalable processing and centralized model management, but it also exposes the system to the realities of wide-area wireless communication: namely, variable latency, intermittent packet loss, and constrained throughput. Understanding how these cloud-level impairments interact with the limitations of current fall-detection algorithms, particularly those that rely on short windows or sensor modalities with limited discriminative power, is therefore essential to ensuring reliable fall-detection performance. Note that to overcome these limitations, our proposed framework pairs multi-axis motion sensors with cloud-hosted neural network inference over LoRa links to deliver robust, real-time fall detection without overloading edge hardware. It is important to mention that while the system architecture is designed to accommodate future pre-fall forecasting, the current experimental models are strictly configured for real-time fall detection upon impact.

The remainder of this paper is organized as follows. Section 2 surveys existing fall detection algorithms. Section 3 introduces the proposed system, including the employed datasets. Machine learning models and preliminary evaluation outcomes are discussed in Section 4. Section 5 concludes the study and highlights future directions.

2. Literature Review

Fall detection technologies have rapidly evolved, with many studies emphasizing wearable sensor-based systems for elderly care and medical monitoring. Devices incorporating accelerometers, gyroscopes, and barometers, such as MPU6050, are often paired with deep learning models. For instance, works like [2,3] utilize *Bi-LSTM* and ANNs, achieving extremely high fall detection accuracy ranging from 97.57% to 99.99%. Recent research by Hasani introduced an event-driven, low-power wearable device designed for hospital use that minimizes energy consumption while maintaining high detection reliability [4]. Other recent works, such as the *Dual-Stream Convolutional Neural Network Self-Attention* (DSCS) model proposed by Zhang et al., achieve accuracies of up to 99.65% by assigning weights to sensor data segments to better distinguish falls from fall-like activities [5]. These systems transmit sensor data via Bluetooth Low Energy or WiFi to platforms like ThingSpeak, enabling real-time analysis. Systems in [6,7] integrate these sensors with microcontrollers (ESP32, Arduino) and services like SMS or IFTTT for caregiver alerts.

As wearable-free alternatives, radar- and vision-based systems offer privacy-preserving solutions. Doppler radar-based models in [8] utilize Kalman filtering and classifiers like *K-Nearest Neighbor* (KNN) and Decision Trees to distinguish between falls and non-falls, achieving up to 92.85% accuracy. Vision-based systems, such as those analyzed in the 2026 systematic review by Ishaq et al., are increasingly shifting from reactive detection to proactive fall risk prediction [9]. This review highlights a critical trend: the expansion of research into pre-impact fall prediction to prevent injuries before ground contact occurs [9]. mmWave radar systems in [10] pair with machine learning models like SVM and CNN to reach 92.3% accuracy without wearables. Vision-based models like [11–13] leverage PoseNet, YOLOv3, and MediaPipes BlazePose for joint tracking and skeleton analysis. Random Forest models perform well in these setups, achieving fall detection accuracy up to 97%.

Multimodal data fusion and ensemble learning further boost performance. Because obtaining sufficient real-world fall data remains a clinical challenge, Debnath et al. (2025) demonstrated that incorporating Diffusion-based synthetic fall signals can boost real-time detection performance by 24% [14]. Studies such as [15,16] incorporate multiple sensors and classifiers, SVM, Decision Trees, XGBoost, Naive Bayes, within ensemble or stacking frameworks, achieving accuracy rates close to 99%. Indoor localization via ultra-wideband (UWB) combined with *Inertial Measurement Unit* (IMU) data, as in [17], enhances temporal analysis using *Long Short-Term Memory* (LSTM) networks, reaching 95.8%. Lim et al. (2024) also emphasized the importance of temporal gait features in predicting fall risks before an event occurs, utilizing machine learning to analyze gait instability [18]. Systems also explore federated learning [19], allowing privacy-preserving edge analytics while reducing latency.

A growing trend in state-of-the-art fall detection research is the deliberate optimization of sensor placement, sampling strategies, and methodological pipelines to improve robustness across diverse environments. Studies increasingly evaluate multi-IMU configurations to capture richer motion signatures and reduce false positives caused by daily activities. Methodologically, researchers are shifting from threshold-based heuristics toward hybrid pipelines that combine temporal modeling and spatial feature extraction. These approaches emphasize not only accuracy but also generalization, with cross-dataset validation, domain adaptation, and noise-resilient preprocessing (denoising, normalization, sensor fusion) becoming essential components of modern fall detection systems.

Lastly, fall detection expands into sports and complex activities, using gait analysis and skeletal tracking to achieve precision. In [20], gait data from MediaPipe was normalized and classified using Logistic Regression, which achieved 98% accuracy surpassing KNN and Random Forest. Video-based systems like [21,22] address challenging distinctions between behaviors like sleeping vs falling, using LSTM and MLP classifiers. Surveys such as those by Ishaq et al. compile key datasets and evaluate the performance of ML and DL models, noting that while controlled accuracies are high, a critical gap remains in validating these systems against unanticipated real-world falls [9].

Tables 1 and 2 respectively show how various fall detection systems differ in terms of sensor selection, model type, and accuracy for wearable and video-based approaches. The recent literature highlights a significant transition toward the use of synthetic data to overcome clinical data scarcity and a shift toward proactive risk prediction [9,14].

Table 1. Wearable and sensor-based fall detection methods from reviewed literature.

Reference	Model Type	Sensors Used	Comm. Method	Key Features/Accuracy
[4]	Threshold-based	Accelerometer	BLE	Event-driven, hospital use
[14]	LSTM	Wearable	–	Diffusion-based synthetic data
[5]	DSCS (Attention)	Accel + Gyro	–	Acc: 99.65%; Weighted features
[2]	Bi-LSTM	Accelerometer (6 locations)	WiFi	Fall acc: 99.99%, Pre-fall acc: 99.95%
[3]	ANN (5-layer)	MPU6050	WiFi	Acc: 97.57%, Fall acc: up to 99.4%
[15]	Ensemble ML	Accelerometer, Barometer	BLE	Acc: 99.51% using stacked classifiers
[16]	XGBoost, RF, SVM, KNN, LR	Accel + Gyro		Acc: 99%, 3-level data fusion
[7,23]	ANN	MPU6050, ESP32	SMS / IFTTT	Training acc: 98%, Testing acc: 88.29%
[17]	LSTM	MPU9250 + UWB		Combined acc: 95.8%, IMU-only: 93.8%
[19]	Federated Learning	Edge devices		Privacy-preserving, low latency
[24,25]	SVM, CNN, Decision Trees, ConvLSTM	Wearables + MEMS	IoT protocols	Survey and review studies

Table 2. Video-based fall detection methods from reviewed literature.

Reference	Model Type	Sensors Used	Comm. Method	Key Features/Accuracy
[9]	Review	Vision, Radar, WiFi	–	Reactive vs. Proactive Analysis
[12]	CNN (Xception)	Video (YOLOv3 + Mediapipe)		Acc: 90%, pose tracking in sports
[11]	KNN	Video (PoseNet)		Acc: 95%, Recall: 100%, F1-score: 93.23%
[20]	LR, RF, KNN, XGBoost	Video (Gait data)		LR acc: 98%, RF: 95%, KNN: 93%
[10]	KNN, SVM, RF, CNN	mmWave Radar		Acc: 92.3%, F1-score: 0.844
[13]	Random Forest	Skeleton (BlazePose)	MQTT	Acc: 97%, Edge-cloud integration

3. Fall Detection System Solution

In this paper, we introduce an end-to-end IoT system that provides accurate indoor and outdoor fall detection. Details of this solution are presented in this section.

3.1. IoT Architecture

Figure 1 illustrates the system architecture developed in the scope of this research. At the core of this architecture is a wearable device designed to monitor human motion and detect falls. The device integrates a bank of IMUs, which are responsible for capturing motion data along three axes of acceleration and three axes of angular

velocity. These sensor readouts provide a comprehensive view of the user's physical activity and are essential for accurate fall detection.

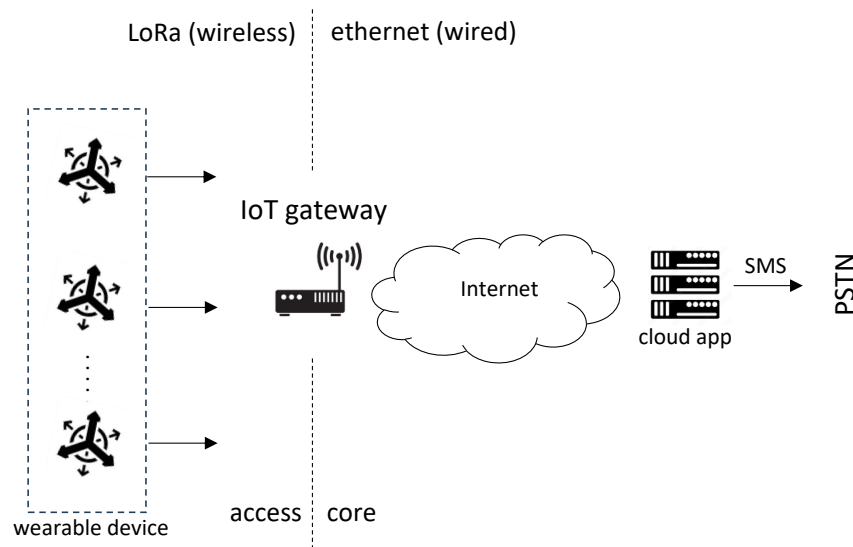


Figure 1. System architecture.

The wearable device does not operate in isolation. It communicates with a cloud-based application through an intermediary gateway. Periodically, the application initiates requests for sensor data, which are then transmitted from the device to the gateway using a wireless LoRa interface. LoRa, short for Long Range, is an IoT communication protocol that supports low-power, low-data-rate transmissions over long distances. Its ability to operate in the unlicensed 915 MHz frequency band eliminates the need for costly mobile service subscriptions, making it a cost-effective solution for continuous monitoring applications.

The gateway plays a pivotal role in bridging the access and core segments of the network. On the access side, it receives data from the wearable device via LoRa. On the core side, it forwards this data to the cloud application using conventional wired Internet protocols. The application, hosted in the cloud, processes the incoming data to detect fall events. Upon identifying a fall, it utilizes public *Application Program Interfaces* (APIs) to send *Short Message Service* (SMS) alerts to designated recipients through the *Public Service Telephone Network* (PSTN), ensuring timely intervention.

The architecture adheres to standardized networking principles defined by the *Internet Engineering Task Force* (IETF). Figure 2 presents the layered protocol stack used in the system depicted in Figure 1. These layers, arranged from bottom to top, include: Physical, Link, Network, Transport, and Application. Each layer is responsible for specific functions, ranging from signal transmission and error correction to routing, session control, and application-level data handling. Data units are referred to differently across layers: frames at the Link layer, datagrams at the Network layer, segments at the Transport layer, and messages at the Application layer. The IETF model is widely adopted in IoT systems and is centered around the *Internet Protocol* (IP) at the Network layer.

On the network access side, the Physical and Link layers are implemented using wireless LoRa technology. The Network layer employs *IP version 6* (IPv6), adapted through *IPv6 over Low-Power Wireless Personal Area Networks* (6LoWPAN) to accommodate the constraints of LoRa. The Transport layer uses the *User Datagram Protocol* (UDP), which is suitable for low-latency communication. Session management is handled by the *Constrained Application Protocol* (CoAP), a lightweight protocol designed for resource-constrained devices.

Conversely, on the network core side, the Physical and Link layers rely on wired Ethernet. The Network layer is based on *IP version 4* (IPv4), while the Transport layer utilizes the *Transmission Control Protocol* (TCP) to ensure reliable data delivery. Session management is conducted using the firewall-friendly *Hypertext Transfer Protocol* (HTTP). Both CoAP and HTTP are standard *Representational State Transfer* (REST) protocols that operate on a request-response model. The cloud application periodically sends requests via HTTP, which are translated into CoAP for transmission to the device. The device responds with sensor data using CoAP, which is then translated back into HTTP for processing by the application.

Figure 3 provides a detailed block diagram of the wearable device's internal architecture. At the heart of the device is the ESP32 microcontroller, which orchestrates data acquisition from the MPU6050 IMU and pressure

sensors at a sampling rate of 20 Hz. In addition to managing sensor data, the ESP32 handles LoRa communication with the gateway, ensuring seamless data transmission.

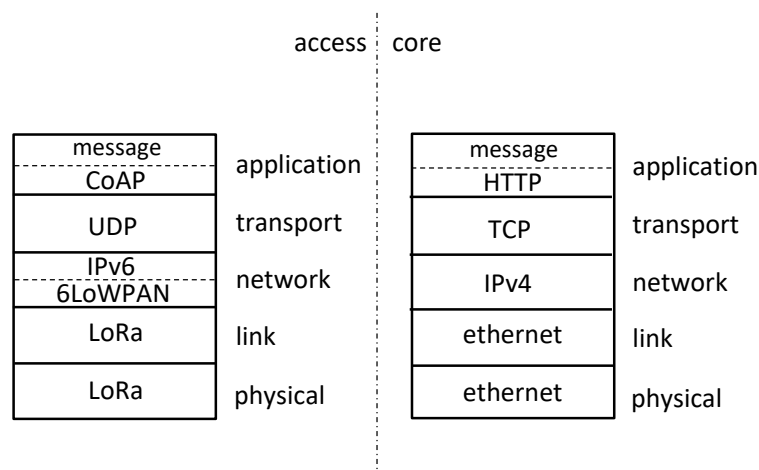


Figure 2. Protocol stacks.

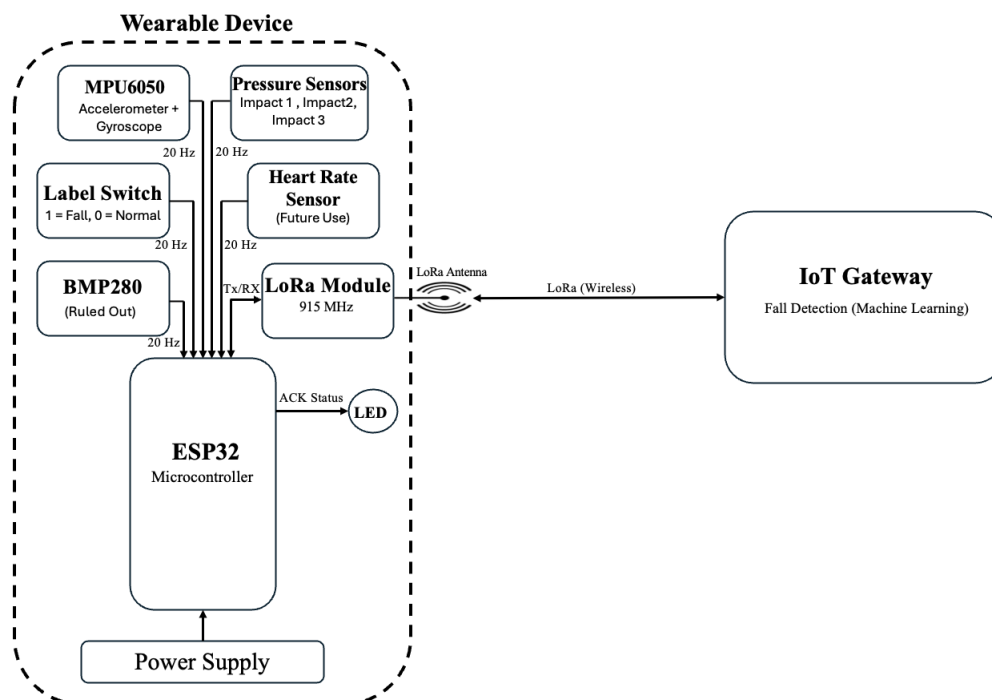


Figure 3. Block diagram.

To facilitate supervised learning during experimental sessions, the device includes a manual data labeling switch. This switch allows researchers to mark events as either falls or normal activities, providing labeled data for training machine learning models. Although a heart rate sensor is integrated into the device for potential future enhancements, it remains inactive in the current implementation. This modular design allows for scalability and future upgrades, making the system adaptable to evolving research needs.

Advances in low-power compute suggest that compact neural models like the Bi-LSTM and the ANNs used here may soon run fully on-chip, as modern microcontrollers with embedded ML accelerators already execute models with tens of thousands of parameters at milliwatt-level power. Yet this remains a balance of cost, energy budget, and model complexity, meaning local inference is not always optimal. The proposed architecture therefore retains its relevance as a mist-computing design: lightweight detection can occur on the wearable, while heavier inference can be offloaded to the user's phone when beneficial. Fall detection is simply one example of a broader class of sensing applications that benefit from this scalable, energy-aware computational split.

Note that while the present study focuses on the machine learning classification framework and IoT architecture design, detailed empirical measurements of network performance—including LoRa Spreading Factor/Bandwidth configurations, packet air time, throughput, packet loss, end-to-end alert latency, and device power consumption—were not quantitatively measured in this setup and will be evaluated in future work.

3.2. The Datasets

For the purpose of training and prediction, multiple datasets were constructed by recording sensor outputs under various physical activity scenarios. These datasets include acceleration measurements along the x , y , and z axes, as well as gyroscope data capturing rotational velocity around the same axes. Additionally, pressure sensors were strategically positioned to collect contact-based pressure data. To enhance fall detection capabilities, the Euclidean norms of both acceleration and angular velocity were computed and used as input features for the classification model.

Figure 4 illustrates the actual device used to collect the sensor data. This device transmits acceleration and velocity readings over LoRa using the RYLR896 UART LoRa transceiver module (868/915MHz) to an application responsible for processing the data for training and prediction. The sensor suite includes an MPU6050 inertial measurement unit connected to a Freenove ESP32-WROVER CAM board. Altitude change measurements were also captured using a BMP280 barometric pressure sensor; however, due to minimal altitude variation during controlled fall experiments and limited discriminative value, this parameter was excluded from the final analysis.

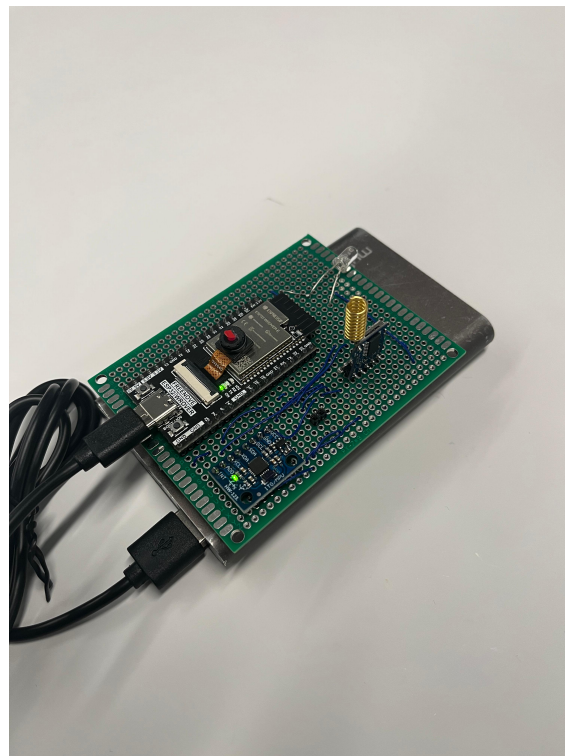


Figure 4. LoRa-enabled wearable device.

The datasets were generated across several activity scenarios, including sitting, standing, sleeping, walk-to-fall, stand-to-fall, and brisk walk-to-fall. For baseline activities, the sampling period was dynamic, ranging from 500 ms to 50 ms, and fixed at 50 ms for fall-detection experiments to ensure high-resolution motion capture. Falls were explicitly marked in the datasets to support supervised learning. Each sampling produces six 16-bit readouts representing the absolute values of acceleration and angular velocity. An *Automatic Repeat reQuest* (ARQ) mechanism guarantees the reliable transmission of these readouts through retransmissions, ensuring no missing data.

Figure 5 presents the acceleration and angular velocity profiles over time during an idle standing scenario. As expected, both parameters remain low and stable, with no fall event recorded. In contrast, Figure 6 shows the same parameters during a brisk walk followed by a fall. Notably, sharp peaks in both acceleration and angular velocity coincide with the fall event, which is marked by an x in the plot.

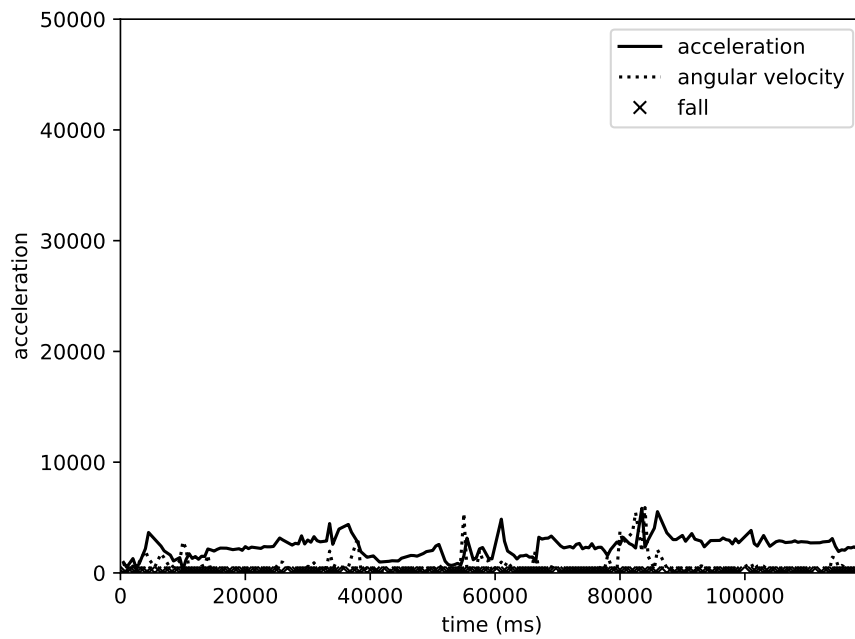


Figure 5. Dataset: Idle.

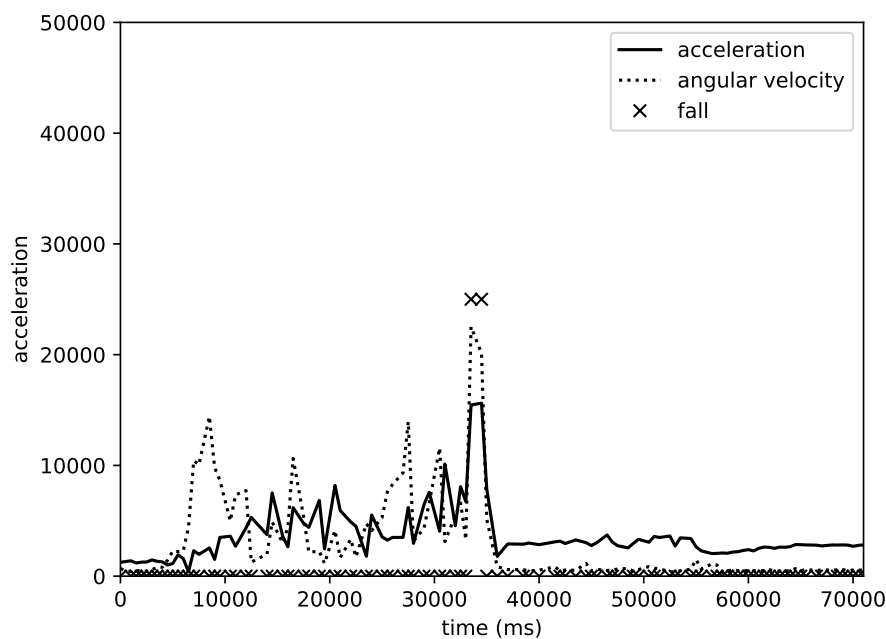


Figure 6. Dataset: Brisk walk and fall.

To further enhance fall detection, three piezoelectric ceramic pressure sensors (operating at 3.3 V and consuming less than 1 mA) were positioned at the thoracic vertebrae and the bilateral ulna/radius bone locations. These analog sensors generate voltage signals proportional to the pressure intensity, allowing detection of ground contact patterns that help distinguish actual falls from similar motion events. However, as discussed in Section 4.2, these sensors were ultimately excluded due to their limited discriminative contribution. As with acceleration and angular-velocity sampling, the pressure sensors are sampled using 20-bit *Analog-to-Digital Converters* (ADCs) that rely on the ARQ mechanism to ensure that no readouts are missing.

The complete dataset comprises 18,906 sensor readings distributed across 92 individual experimental files. Of these, 2169 samples (11.5%) represent fall events, while 16,737 samples (88.5%) capture normal activities such as sitting, standing, sleeping, and various locomotion patterns across all recorded configurations. Fall detection experiments generated 13,459 samples across 42 files, including 75 distinct fall events totaling 1993 fall samples and 11,466 normal activity samples. Baseline activity datasets consist of 5447 samples across 50 files (comprising 5271 normal activity samples and 176 fall samples). Among the pressure sensor configurations, 34 experimental

files incorporated three piezoelectric sensors (Impact1, Impact2, Impact3), capturing 693 fall samples out of 10,798 total samples across 53 fall events. These data samples were obtained from three volunteer graduate students at Northeastern University who carried the device while performing the falls. While the current dataset provides a foundational baseline, future iterations will incorporate more diverse participant demographics and real-world fall scenarios, while employing techniques such as *Synthetic Oversampling* (SMOTE) or class-weighted loss functions to more effectively mitigate the inherent class imbalance between fall events and activities of daily living. The dataset was expanded through a sliding window technique to ensure sufficient sample volume for each class, while data integrity was maintained via the aforementioned ARQ mechanism to prevent missing readouts.

To support comparative analysis and performance evaluation, the dataset includes four distinct sensor configurations: (1) IMU-only setups with raw triaxial data; (2) magnitude-based configurations using Euclidean norms; (3) multi-modal setups incorporating piezoelectric pressure sensors; and (4) comprehensive configurations including barometric measurements. These variations enable systematic exploration of sensor fusion strategies and robust validation of fall detection algorithms.

Table 3 summarizes the dataset's structure, detailing file counts, sample volumes, and fall event distributions, while specifying sensor configurations with sampling rates intentionally calibrated to capture the frequency range of human gross motor movements and falls. Note that the dataset configurations shown in Table 3 are not mutually exclusive; several experimental recordings contribute to more than one sensor configuration, and therefore sample counts across individual configuration rows are non-additive. Furthermore, all accuracy, recall, precision, F1-score, and confusion matrix results reported in Section 4 were computed using the isolated 13,459-sample IMU fall-detection dataset (11,466 normal samples and 1993 fall samples).

Table 3. Fall detection dataset overview.

Configuration	Files	Total Samples	Fall Samples	Sampling Rate
Baseline Activities (IMU)	50	5447	176	Mixed
Fall Detection (IMU)	42	13,459	1993	20 Hz (50 ms)
Piezoelectric Sensors	34	10,798	693	20 Hz (50 ms)
Combined Modalities	—	18,906	2169	Mixed

4. Models and Results

This section presents the development and evaluation of an MLP model designed for fall prediction using multimodal sensor data. The model leverages tri-axial accelerometer, gyroscope, and pressure sensor readings to detect patterns associated with falls. A key emphasis is placed on the role of pressure sensors in improving contact detection. These sensors provide critical temporal cues that help distinguish actual falls from similar motion events such as abrupt sitting or rapid posture changes. By capturing subtle shifts in external force and body orientation at the moment of impact, pressure data enhances the model's ability to accurately classify fall events and reduce false alarms.

4.1. Model Architecture and Accuracy

To investigate the influence of temporal context and sensor modality on fall detection performance, an ANN was trained using input sequences of varying lengths. Two datasets were constructed for comparison: one containing only motion-based features (acceleration and angular velocity), and another that included pressure sensor data alongside motion features.

During dataset preparation, each input sample was formed using a sliding window of w previous time steps, with the corresponding label assigned at time $t = w + 1$. All features were normalized using the 'StandardScaler' method to ensure consistent scaling across modalities. The binary fall state was used as the target label for classification. While the current results focus on the detection of a fall at the moment of impact the use of sliding windows and temporal modeling provides a framework for future prediction, aimed at identifying pre-fall instabilities before ground contact occurs. Note that data normalization via StandardScaler and the 20% validation split were applied randomly at the window level across the entire dataset rather than grouped by subject or file, which introduces window overlap across partitions and contributes to the high classification accuracy alongside the low pattern diversity.

The ANN architecture consisted of an input layer shaped as (w, n) , where n equaled 2 for motion-only features and 3 when pressure data was included. This input was flattened into a single vector, followed by a dense hidden layer containing 64 neurons activated by the ReLU function. The output layer comprised two neurons with softmax activation to perform binary classification. The model was trained using the Adam optimizer and sparse categorical

crossentropy loss function, with a batch size of 32 and a total of 5 training epochs. To address the inherent class imbalance and ensure robust detection, the model utilizes multi-metric evaluation, including recall, precision, and F1-score, alongside dropout layers and sliding window normalization to improve overall generalization.

Model performance was evaluated across a range of input window sizes, specifically: {2, 3, 5, 8, 10, 12, 15, 18, 20, 25, 30, 35, 40}. Given the fixed sampling rate of 20 Hz (50 ms per sample), these window sizes represent a temporal look-back period ranging from 0.1 to 2.0 seconds of motion data. For each configuration, 20% of the dataset was reserved for validation. Figure 7 illustrates the validation accuracy achieved for each window size, comparing models trained with and without pressure sensor features.

The results revealed that the model trained without pressure data achieved its highest validation accuracy at a window size of 20 timesteps. Moreover, accuracy remained relatively stable and high across longer input windows ranging from 15 to 40 timesteps. Interestingly, the inclusion of pressure sensor data did not consistently improve performance. In several cases, particularly for shorter input windows between 3 and 8 timesteps, the presence of pressure features actually reduced classification accuracy. While baseline activities were captured using dynamic sampling rates (50 ms to 500 ms) and fall recordings were fixed at 50 ms (20 Hz), all lower-frequency baseline streams were linearly resampled to a uniform 20 Hz rate prior to windowing, ensuring that daily activities remained fully represented in the negative class across all 20 Hz sliding-window experiments.



Figure 7. ANN validation accuracy vs. number of past inputs.

Note that in the current setup, inference is executed on a per-sample sliding window basis at 20 Hz, evaluating windowed segments independently; however, an explicit event-level alarm policy incorporating thresholding for consecutive positive classifications and a post-alert refractory period was not implemented, limiting evaluation to sample-level metrics and leaving event-level alarm filtering for future system implementation.

4.2. Impact of Pressure Sensor Features

To further explore the effect of pressure sensor data on model performance, Table 4 presents a comparative analysis of ANN validation accuracy across various input sequence lengths, with and without pressure features. Table 5 extends this analysis across accuracy, recall, precision, and F1-score metrics. The ANN topology used in these experiments included a flattened input layer, followed by two fully connected hidden layers with 64 and 32 neurons respectively, both using ReLU activation. A final output layer with a single sigmoid-activated neuron was used for binary classification. To mitigate overfitting, dropout layers with rates of 0.3 and 0.2 were applied after each dense layer.

The data in Tables 4 and 5 shows that the inclusion of pressure sensor features did not consistently enhance classification accuracy. At shorter timesteps, such as 3 and 7, the models trained without pressure data outperformed those with it, achieving accuracies of 0.9926 and 0.9655 respectively. At timestep 14, both models reached close to perfect accuracy (0.9998), indicating an optimal configuration that was not dependent on pressure sensor input. These results suggest that pressure sensor readings may not contribute significant discriminatory information beyond what is already captured by motion features like acceleration and angular velocity. Possible explanations include low

variance in pressure data, sparsity of pressure-related events, or redundancy with existing features. Consequently, incorporating pressure sensors may increase model complexity without yielding proportional improvements in predictive performance for fall detection. Table 6 summarizes the sensors used in the study, detailing their anatomical placement and whether each device's data was ultimately retained or discarded. In addition, Figure 8 illustrates the wearable fall-detection device housed in a protective enclosure with integrated straps for chest attachment, alongside a body-placement diagram detailing the anatomical locations of the IMU, barometric, and pressure sensors used in the study.

Table 4. Comparison of ANN Accuracy with and without Pressure Sensor Features across Different Timesteps. The ANN topology used consisted of an input layer (flattened sequence), two hidden layers with 64 and 32 neurons respectively, and a sigmoid output layer.

Timesteps	Accuracy with Pressure Sensors	Accuracy without Pressure Sensors
1	0.7794	0.7868
2	0.9363	0.9314
3	0.9559	0.9926 *
5	0.9634	0.9634
7	0.9483	0.9655 *
10	0.9268	0.9268
14	1.0000 *	1.0000 *
20	0.8095	0.9048

* Bold text denotes the highest classification performance achieved for the given timestep configuration.

Table 5. Comprehensive evaluation of ANN performance with and without pressure sensor features across different timesteps. To provide a robust assessment beyond accuracy—particularly important for imbalanced tasks such as fall detection—this table reports accuracy, recall, precision, and F1-score for each configuration. The ANN topology consisted of an input layer (flattened sequence), two hidden layers with 64 and 32 neurons, and a sigmoid output layer.

Timesteps	Feature Set	Accuracy	Recall	Precision	F1 Score
1	With Pressure	0.7794	0.7650	0.7821	0.7734
	Without Pressure	0.7868	0.7742	0.7905	0.7822
2	With Pressure	0.9363	0.9281	0.9425	0.9352
	Without Pressure	0.9314	0.9204	0.9387	0.9294
3	With Pressure	0.9559	0.9480	0.9602	0.9540
	Without Pressure	0.9926 *	0.9901	0.9940	0.9920
5	With Pressure	0.9634	0.9580	0.9661	0.9620
	Without Pressure	0.9634	0.9575	0.9660	0.9617
7	With Pressure	0.9483	0.9402	0.9520	0.9460
	Without Pressure	0.9655 *	0.9584	0.9691	0.9637
10	With Pressure	0.9268	0.9150	0.9342	0.9245
	Without Pressure	0.9268	0.9148	0.9340	0.9243
14	With Pressure	0.9998 *	0.9998	0.9998	0.9998
	Without Pressure	0.9998 *	0.9998	0.9998	0.9998
20	With Pressure	0.8095	0.7920	0.8225	0.8070
	Without Pressure	0.9048	0.8921	0.9125	0.9022

* Bold text denotes maximum achieved performance within the evaluated timestep group.

The confusion matrix representing a 99.98% accuracy rate, which accounts for the correctly identified 11,464 normal activities and 1992 fall events while including only three total misclassifications across the 13,459-sample IMU evaluation dataset (11,466 normal samples and 1993 fall samples), is defined as

$$\text{Confusion Matrix} = \begin{pmatrix} \text{TN} & \text{FP} \\ \text{FN} & \text{TP} \end{pmatrix} = \begin{pmatrix} 11,464 & 2 \\ 1 & 1992 \end{pmatrix} \quad (1)$$

The near-perfect accuracies observed across our experiments are also influenced by the characteristics of the dataset itself. Because the falls were induced under controlled conditions, they tend to occur abruptly and exhibit minimal long-term temporal correlation, resulting in a relatively small set of highly repeatable motion patterns. This constrained variability makes the events easier for the model to distinguish and increases the likelihood of achieving 100% accuracy, even when additional sensing modalities, such as pressure, offer little incremental information. As a result, the apparent 0.01% improvement over the state of the art should not be interpreted as a meaningful practical gain but rather as an artifact of a dataset with limited pattern diversity. We expect this behavior to change substantially as we expand our work to include patients with neurological impairments, whose fall dynamics are slower, more heterogeneous, and influenced by long-term gait irregularities. In such populations, the model will face a more realistic and challenging distribution, providing a clearer assessment of its true contribution. A critical limitation of the current work is that the high performance achieved with healthy adults in controlled trials may not generalize to the target demographic, as the model has yet to be validated against the more heterogeneous and complex movement profiles typical of the elderly or those with neurological impairments. Note that while a 20% validation split was used during model training, the confusion matrix in Equation (1) was computed on the IMU evaluation dataset (13,459 total samples) to demonstrate overall model performance across all recorded instances.

Table 6. Summary of sensor types, placement locations, and inclusion status in the study.

Sensor Type	Location	Status
3-axis Accelerometer	Chest	Used
3-axis Gyroscope	Chest	Used
Barometric Sensor	Chest	Discarded
3 Pressure Sensors	Thoracic vertebrae; bilateral ulna/radius	Discarded

Wearable Fall Detection System and Body Placement

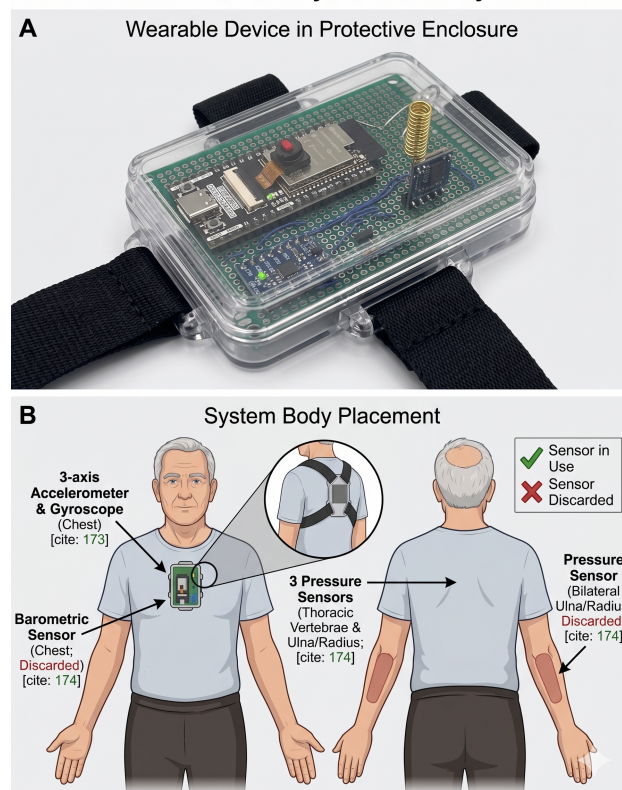


Figure 8. Wearable fall detection system and body placement.

5. Conclusions and Future Work

The evaluation of MLP-based models for fall detection using multimodal sensor data demonstrates that while pressure sensors offer theoretical benefits in capturing contact dynamics, their practical contribution to classification accuracy is limited. Across various input window sizes, models trained solely on motion features, accelerometer

and gyroscope readings, often performed equally well or better than those incorporating pressure data. In particular, shorter input sequences showed a decline in accuracy when pressure features were included, suggesting potential redundancy or insufficient variability in the pressure signals. These findings indicate that motion features alone may be sufficient for robust fall detection, and that the added complexity of integrating pressure data should be carefully weighed against its marginal performance gains.

A further limitation of the present work lies in the reliance on MLP-based architectures, which inherently treat each input window as an isolated snapshot and therefore struggle to capture the longer-term temporal dependencies that often precede falls, particularly in individuals with neurological or balance-related conditions. Unlike recurrent architectures, the MLP's lack of internal state prevents it from correlating sequential gait anomalies over time, effectively treating long-term precursors like progressive instability as disconnected events rather than a continuous trend toward a fall. In many real-world scenarios, the precursors to a fall, subtle gait deterioration, progressive postural instability, or intermittent freezing episodes, may manifest tens of seconds or even minutes before the actual event, making them difficult to detect within short, fixed windows. Recurrent models such as LSTMs offer a promising avenue for addressing these edge cases by explicitly modelling extended temporal context and learning how gradual changes accumulate into elevated fall risk. However, adopting such architectures also introduces challenges: they may become overly sensitive to noise, struggle with irregular sampling, or overfit to idiosyncratic movement patterns unless trained on sufficiently diverse and longitudinal datasets. These considerations highlight the need for careful sequence design, robust temporal regularisation, and larger, clinically varied cohorts to ensure that temporal models genuinely improve detection rather than simply adding architectural complexity.

Building on these insights, future research will explore the integration of additional physiological sensors, such as heart rate monitors, to enhance the contextual understanding of fall events. Heart rate variability may provide valuable cues related to stress, exertion, or autonomic responses preceding or following a fall. To move beyond simple motion detection toward comprehensive causal analysis, future research will explore integrating advanced sensor combinations such as *surface electromyography* (sEMG) for muscle activity patterns, smart insoles with *Force-Sensitive Resistor* (FSR) arrays for gait assessment, and vision-based tracking to provide a multimodal understanding of fall risks and physiological precursors.

Furthermore, we plan to expand our dataset to include recordings from patients with neurological disorders, such as Parkinson's disease or multiple sclerosis, whose movement patterns and fall risks differ significantly from healthy individuals. Going forward, our data-collection efforts will therefore prioritize individuals with neurological conditions to ensure that future models are grounded in clinically relevant movement patterns and real-world fall-risk profiles. This will allow for the development of more personalized and clinically relevant models, capable of adapting to diverse physiological and behavioral profiles. By incorporating richer sensor modalities and more representative data, we aim to improve the sensitivity and specificity of fall detection systems in real-world healthcare applications. In parallel, future work will also examine how system-level considerations, such as the use of mist-computing architectures and the energy-consumption characteristics of LoRa-based communication, affect the long-term deployability and efficiency of wearable fall-detection platforms. Future work will also incorporate comparisons with standard baseline models (SVM, Random Forest, LSTM), statistical significance testing, and robustness evaluation under realistic wireless conditions such as sensor noise, latency, and packet loss.

Author Contributions

E.A. and R.H.: conceptualization, methodology, software, writing—original draft preparation; S.P.J., S.M., A.J., and M.M.: data curation, visualization, investigation, software, validation; S.A., A.M., and H.T.: supervision, writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Ethical review and approval were waived for this study, due to the research protocol being determined not to involve human subjects by the Institutional Review Board of Northeastern University. Supporting documentation and institutional self-assessment records have been retained by the authors for the record.

Informed Consent Statement

Not applicable for studies not involving human subjects.

Data Availability Statement

The sensor datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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