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A Balanced big dataset for Sensor-Based Fall Detection: Enhancing Model Accuracy and Robustness

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ABSTRACT Falls represent a critical challenge in healthcare, particularly for the elderly and those with limited mobility. They can cause severe injuries or deaths if not detected and addressed. Existing fall-detection systems often struggle with lacking large, diverse, and balanced datasets; this limitation hinders the development of accurate and generalizable machine-learning (ML) solutions. This paper introduces a complete big dataset designed explicitly for video- and sensor-based fall detection, featuring 8,953 recorded activities, including 2,791 falls and 6,162 activities of daily living (ADL), collected from 29 diverse subjects. The dataset encompasses various fall scenarios—left, right, front, back, and complex cases such as attempting to sit on a chair or falling from elevated positions—along with ADL tasks such as walking, running, standing up from the ground, and driving. Each activity is recorded for 8 s at 100 Hz, yielding 800 data points per file. Including barometer-derived altitude-delta data significantly improves the performance of transformer-based models, raising accuracy from 97–98 % to more than 99.5 %. All 3,000 fall recordings were individually processed and non-matching patterns removed to confirm data quality, producing a clean and consistent corpus. Comparative experiments with existing datasets demonstrate superior detection accuracy and reduced false-positive rates, underscoring the robustness and reliability of our contribution. Overall, the proposed dataset provides the research community with a vital resource for advancing fall-detection systems and promotes the development of robust, deployable ML solutions for real-world healthcare applications.

KEYWORDS fall detection; big dataset; sensor-based fall detection; Activities of Daily Living; machine learning; dataset balancing; healthcare; elderly care; multi-modal data

I. INTRODUCTION

FALL detection is a vital area of research in healthcare due to the increasing incidence of falls, particularly among the elderly population [1]. Falls are one of the leading causes of fatal and non-fatal injuries, often leading to serious health consequences such as fractures, head injuries, and long-term disabilities [2]. According to the World Health Organization (WHO), around 684,000 individuals die from falls annually, making it the second leading cause of unintentional injury deaths worldwide [3]. The elderly population is particularly vulnerable, with approximately 30% of people 65 years and older experiencing a fall each year [4]. The aging population and the growing number of people living alone have further amplified the need for automated fall detection systems. These systems are crucial to ensure timely medical intervention [5]. A delay in identifying falls can lead to severe health complications, such as dehydration, pressure ulcers, and even death, due to the prolonged period spent on the ground without assistance [6].

The increasing prevalence of chronic conditions such as osteoporosis and diabetes also exacerbates the severity of fall-related injuries [7] [8]. These conditions reduce bone density, muscle strength, and balance, making individuals more prone to falls and complicating recovery [9]. Traditional fall detection systems, such as wearable sensors and alert buttons, rely on user or active monitoring, which may not be feasible in all circumstances [10]. Therefore, advances in video and sensor-based fall detection systems are important [5]. These systems can monitor individuals in real time, allowing for continuous, unobtrusive tracking of movements and immediate detection of falls [11]. Creating and curating big datasets that combine video and sensor data for fall detection is essential in this context. These datasets provide a foundation for developing robust machine learning models. They allow researchers to train, test, and refine their algorithms to improve fall detection accuracy, reduce false alarms, and contribute to life-saving interventions.

In tasks such as fall detection, the availability of large and well-balanced datasets is crucial for developing accurate and reliable ML. A large dataset confirms that the model is exposed to different scenarios, covering various types of falls, daily activities, and conditions. This is essential because fall events are rare compared to normal activities, making it challenging for models to differentiate between falls and non-fall activities [12]. A well-collected large dataset helps to improve the generalization capabilities of ML, allowing them to identify fall events more accurately in real-world settings [13]. In addition, datasets that include video and sensor data offer a multi-modal approach to fall detection, providing the model with richer information for analysis. For example, while a sensor may detect rapid movement, video data can provide visual context, helping the model determine whether the movement is a fall or just a regular activity [14].

However, the balance of the dataset is equally essential. Unbalanced datasets, where fall events are significantly lower than non-fall activities, can lead to biased models [15]. In such cases, models tend to favor the majority class (non-fall activities) and may not correctly identify falls, increasing false negatives [16]. This is particularly dangerous in detecting falls, as a missed fall could delay medical intervention, exacerbate injuries, or even lead to fatalities [17]. Moreover, unbalanced datasets can also result in high false positive rates, where everyday activities are misclassified as falls. This causes alarm fatigue for users and reduces trust in the system's reliability. Therefore, ensuring that the datasets used for fall detection are both large and balanced is vital to improving the performance and robustness of ML. Techniques such as data augmentation, resampling, or using cost-sensitive algorithms can address the issue of unbalanced datasets, enhancing the model's ability to detect falls while minimizing false alarms [18].

Several publicly available solutions have been proposed to address the issue of unbalanced datasets in falling detection. Standard techniques include under-sampling, where a portion of the majority class is removed to create a balanced dataset, and over-sampling, where the minority class (fall events) is duplicated or synthesized to match the size of the majority class [19]. More advanced methods involve using Generative Adversarial Networks (GANs) to generate synthetic fall data, enriching the minority class without duplicating existing samples [20]. Although these techniques can help balance the dataset, they have significant drawbacks. Undersampling can lead to the loss of valuable information from the majority class, weakening the model's ability to recognize non-fall activities [21]. Oversampling, mainly through duplication, can cause overfitting, where the model performs well in the training data but does not generalize to unseen data [22]. Synthetic GAN-based data generation, while promising, can introduce unrealistic or non-representative samples that may not accurately reflect real-world fall events, further complicating model performance [23]. These limitations highlight the need for alternative solutions that do not compromise data quality or model robustness.

Given the shortcomings of existing methods, there is a pressing need for big, balanced datasets designed explicitly for fall detection tasks. Such datasets must accurately represent the diversity of fall events and non-fall daily activities to ensure that models can effectively differentiate between them. A balanced dataset improves the model's ability to detect rare fall events and reduces the occurrence of false positives, which can be a significant issue in real-world applications. By providing a large volume of well-balanced and high-quality data, researchers can develop models that are more robust, reliable, and capable of generalizing to different environments and populations. In addition, the availability of a complete dataset with both video and sensor data can significantly improve the accuracy of multi-modal models, allowing them to make more informed decisions by combining different information streams.

This research aims to create a large, balanced dataset for sensor-based fall detection that can be used to train, test, and validate ML. This dataset will address the current limitations of unbalanced datasets and provide a solid foundation for developing more accurate fall detection systems, ultimately improving the safety and quality of life of vulnerable populations. The research objectives are as follows:

- To curate and compile a complete fall and non-fall activity dataset using video and sensor data.
- To ensure that the dataset is balanced, employ advanced techniques that maintain the quality and diversity of the data without introducing biases.
- To evaluate the performance of ML trained on the balanced dataset and compare it with models trained on traditional imbalanced datasets.

The proposed dataset consists of data from 29 subjects, encompassing a diverse range of falls and ADL. Fall-related activities include scenarios such as falling to the left, right, front, or back, as well as sliding, stumbling, and custom falls, where subjects decide independently how to fall. Scenarios have also been carefully recorded, such as falling while trying to sit in a chair or from a higher place. ADL activities span walking, running, standing up from the ground, and driving, along with specific actions such as reaching, waving, climbing, and descending. Each file contains 8 seconds of data recorded at a 100 Hz, resulting in 800 records per file. The structure of the dataset mirrors the real-world constraints of detecting falls directly on devices, demonstrating consistency in the data representation.

This dataset incorporates barometer data (altitude delta), significantly improving the accuracy of transformer-based fall detection models (from 97-98% to over 99.5%). The altitude delta is calculated by subtracting the initial altitude from each subsequent record, enhancing the dataset's ability to provide actionable insights. Furthermore, every one of the 3,000 recorded falls was individually processed, with charts drawn to identify and remove non-matching fall patterns, demonstrating data consistency and reliability.

To validate the robustness of the dataset, its performance was compared to baseline fall detection methods. The results show that including different fall and ADL scenarios improves detection accuracy and confirms a better generalization between varying environments and subject behaviors. This balanced and high-quality dataset is an essential resource for advancing fall detection research, allowing the development of ML that can reliably differentiate between falls and routine daily activities.

A. RESEARCH CONTRIBUTIONS

- We collected a large and balanced dataset of 8,953 recorded activities, including 2,791 falls and 6,162 ADLs, showing diversity and real-world applicability. Each file contains 8 seconds of data sampled at a 100Hz frequency, producing 800 records per file.
- Processed all 3,000 fall recordings individually by generating charts and removing non-matching patterns to confirm the consistency and reliability of data for training ML.
- The introduced barometer (altitude delta) data, calculated using the initial altitude, significantly increases the accuracy of transformer models from 97-98% to over 99.5%.
- Complex and realistic fall scenarios captured, including falls while trying to sit on a chair or from elevated positions, alongside various ADLs such as driving, standing up from the ground, and climbing.
- Validated the dataset performance against baseline fall detection methods, demonstrating improvements in accuracy and generalizability across different environmental and behavioral conditions.
- Combined sensor data and barometer readings to create a dataset optimized for advanced machine learning algorithms, enabling better differentiation between fall events and everyday activities.
- Provided the research community with a valuable resource to advance fall detection systems, promoting the development of robust and reliable models for healthcare applications.

II. LITERATURE REVIEW

Fall detection is a vital area of research in healthcare, especially for older people and people with mobility challenges, where timely detection of falls can significantly reduce health risks. Advancements in technology, body-worn sensors, and video-based fall detection systems have contributed to developing different datasets to increase machine learning-based fall detection methods. This review covers all the significant datasets, their contributions, and the ML applied to fall detection tasks. In addition to sensor-based datasets, video-based fall detection datasets illustrate the broader scope of research in this domain.

A. EXISTING FALL DETECTION DATASETS

Publicly available datasets for fall detection vary according to the types of sensors used, the number of subjects, and the activities recorded. These datasets serve as vital resources for developing and testing machine learning algorithms, particularly to benchmark their performance in detecting falls.

The MobiFall dataset [24] consists of data collected from smartphone accelerometers and gyroscopes that are worn in the pocket of the pants. The dataset includes 24 subjects aged between 22 and 47 years who performed four types of falls (fall forward, backward, sideways, and impact on the knees) and 10 ADL, such as walking, running, and sitting. Studies using the MobiFall dataset have applied threshold-based models and SVMs, achieving a high accuracy of 99.12% in fall detection. However, the placement of the sensor in the trouser pocket limits its generalization to other sensor placements.

The SisFall dataset [25] is one of the most complete datasets, containing 4505 activities (2701 ADLs and 1804 falls) of 38 subjects. It uses two accelerometers and a waist gyroscope to record different types of falls, including forward, backward, lateral, and seated falls. ML such as Random Forest (RF) and Convolutional Neural Networks (CNN) have been used on this dataset, achieving up to 95. 4% fall detection precision in young adults and 88.1% in elderly subjects. The SisFall dataset highlights the potential for significant model improvements when addressing the discrepancy in performance between age groups.

The FARSEEING dataset [26] offers a unique perspective by capturing real-world fall events with body-worn inertial sensors. This dataset includes more than 300 real-world falls recorded between 2012 and 2015, with more than 208 verified falls available for analysis. Real-world fall data offer insight into how falls occur in uncontrolled environments, and models trained on this dataset have achieved promising results. For example, a ConvLSTM model achieved a sensitivity of 93. 33% and a specificity of 73. 33%, showcasing real-world data's potential to increase fall detection accuracy. However, the small number of falls in this dataset remains a limitation.

The UP-Fall dataset [27] includes data collected from 17 young participants using a combination of sensors (IMU, EEG) and vision-based devices (cameras, infrared). The dataset covers 11 activities and fall types, collected from more than 850 GB of motion data. ML such as RFs and Support Vector Machines (SVMs) have been evaluated on this dataset, with results reaching 95. 58% accuracy and 99. Specificity 5% for different sensor modalities. The use of multi-modal data makes this dataset particularly valuable for researchers interested in exploring the integration of sensor and video data for fall detection.

The KFall dataset [28] was developed to address the need for pre-impact fall detection using body-worn inertial sensors. It includes 21 types of ADL and 15 types of falls collected from 32 Korean participants. One key feature of this dataset is the inclusion of temporal labels for fall events, allowing researchers to focus on detecting fall before impact. When benchmarked with SVMs, threshold-based models, and Deep Learning (DL) models, the dataset achieved excellent performance, with SVMs reaching a sensitivity of 99. 77% and a specificity of 94. 87%. This dataset is essential for exploring proactive fall detection and prevention.

The NTU-RGB+D dataset [29] consists of 276 fall samples and 55,724 ADL samples from 40 subjects performing 60 activities. The TST Fall Detection dataset [30] contains 132 fall samples from 11 subjects. These datasets primarily use RGB-D cameras for fall detection and rely on skeleton joints and accelerometer data to detect falls. Spatial-temporal graph convolutional networks (ST-GCN) applied to these datasets achieved remarkable precision 100% in detecting falls. Although effective, these datasets are primarily vision-based and may not generalize well to scenarios without video surveillance.

The UMAFall dataset [31] provides a complete set of movement traces using wearable sensors at five different locations in the body: ankle, wrist, waist, chest, and thigh. The dataset includes 17 subjects who performed a combination of ADLs and falls. The focus on sensor placement is vital in this dataset, as it allows researchers to study the effect of sensor positioning on fall detection accuracy. Experiments using this dataset have demonstrated the importance of optimal sensor placement, with models achieving a sensitivity of 95% and a specificity of 97%.

The Charfi dataset [32] includes falls recorded using one Kinect camera. The dataset contains data for falls in different directions, along with different ADLs such as walking, sitting, and house cleaning. The fall detection performance of this dataset using 3D-based SVM models achieved an accuracy of 99.6%, making it a valuable resource for vision-based fall detection research.

The EDF dataset [33] contains falls and ADLs recorded using two Kinect cameras from 10 subjects performing 8 types of falls in different directions. Similarly, the OCCU dataset records falls and ADLs using two Kinect cameras, including occluded falls. These datasets have been used to test CNN and SVM models, achieving accuracies between 81% and 94%. However, their reliance on visual data may limit their generalizability to non-visual fall detection scenarios.

Auvinet et al. [34] includes fall recordings captured by eight cameras placed in different positions around the subject. The dataset focuses on recording both forward and backward falls and ADLs such as sitting and standing. Using multiple camera viewpoints allows for robust detection of fall events in different directions, with models achieving an accuracy of 95.7%. However, the complexity of the setup may limit its real-world applicability.

The Dovgan dataset [35] uses six infrared cameras and wearable sensors to record different types of falls and ADLs. Integrating multi-modal data enables the development of more accurate fall detection systems. A combination of SVM and C4.5 algorithms applied to this dataset achieved a fall detection accuracy of 95 7%, making it one of the most effective datasets for multimodal fall detection research.

B. MODEL PERFORMANCE ON FALL DETECTION DATASETS

Different ML models have been applied to these datasets, producing a wide range of results. Below is a summary of some key algorithms and their performance in different datasets:

1) Threshold-Based Models

Threshold-based models are simple and easy to implement, but often have low specificity. For example, on the KFall dataset, threshold-based models achieved a sensitivity of 95.50% but a low specificity of 83.43%, resulting in a high number of false positives.

2) Support Vector Machines

SVM models have shown strong performance in fall detection. For example, on the MobiFall dataset, SVM achieved an accuracy of 99.12%, while on the KFall dataset it achieved a sensitivity of 99. 77% and a specificity of 94. 87%. SVMs require careful tuning and may not always generalize well across all datasets.

3) Convolutional Neural Networks

CNNs have been widely used in vision-based datasets such as Charfi et al. and NTU RGB+D, where they achieved accuracies above 95%. CNNs are particularly effective in capturing complex visual patterns associated with falls, but require large datasets and computational power.

4) Convolutional LSTM (ConvLSTM)

ConvLSTM models have been successfully applied to multimodal datasets such as FARSEEING and UP-Fall. In the FARSEEING dataset, ConvLSTM achieved a sensitivity of 93. 33% and a specificity of 73. 33%. These models are beneficial for handling temporal data and can be applied in real-time fall detection scenarios.

C. RESEARCH GAP

Although fall detection systems have advanced significantly, several challenges remain. First, many datasets remain unbalanced, with far more ADL samples than fall samples,

Table 1. Summary of Sensor-Based Fall Detection datasets

dataset	Year	Subjects	ADLs	Fall	Sensor Type	Accuracy (%)	Model Used
MobiFall	2014	24	10	4	Accelerometer, Gyroscope	99.12%	SVM
SisFall	2015	38	19	15	Accelerometer, Gyroscope	95.4%	RF, CNN
FARSEEING	2015	different	-	-	Inertial Sensors	93.33%	ConvLSTM
UP-Fall	2018	17	11	11	IMU, EEG, Infrared	95.58%	RF, SVM
KFall	2019	32	21	15	Inertial Sensors	99.32%	SVM, DL
NTU-RGB+D	2016	40	60	276	RGB-D Cameras	100%	ST-GCN
TST Fall	2015	11	5	132	Accelerometer	97.33%	CNN, SVM
UMAFall	2016	17	8	9	Wearable Sensors	95.4%	RF

which can bias ML. Techniques like data augmentation and GAN-based synthetic data generation are promising but have limitations, including overfitting and generating non-representative data. Second, video-based datasets offer high accuracy but are only practical in some environments, especially when continuous monitoring is impossible.

In addition, the placement of the sensor plays a vital role in the accuracy of fall detection. As seen in datasets such as UMAFall and SisFall, the position of sensors on the body can lead to vastly different results. Finally, despite the success of models such as SVM, CNN, and ConvLSTM, there is still room for improvement in real-time performance, energy efficiency, and robustness in uncontrolled environments.

Given the limitations of existing datasets, a large, balanced dataset is needed that incorporates sensor and video data across diverse fall types and ADLs. Such a dataset would enable the development of more robust, generalizable models for real-world fall detection. Furthermore, combining multi-modal data from wearable sensors, RGB cameras, and depth cameras would allow researchers to build more accurate, reliable, and applicable models in different environments.

III. DATA ACQUISITION

The dataset for fall detection was collected using a combination of sensors and cameras to confirm the complete capture of motion and visual information. The primary sensor used is the custom SoC, a versatile inertial measurement unit (IMU) capable of capturing acceleration, angular velocity, and orientation. Additionally, a Samsung Galaxy A33 5G smartphone camera was used to record videos of falls and ADL in different environments. The total size of the dataset is approximately 20 GB. Data acquisition occurred over 4 months, starting on June 3rd, 2024. Due to the nature of the environment and equipment, the data frequently captured noise, which required multiple reshoots of several actions to confirm high-quality recordings. The dual-modality approach, which uses sensor-based and video-based data, provides rich multimodal data to increase the robustness and accuracy of fall detection algorithms. Figure 1 provides the sensor interface.

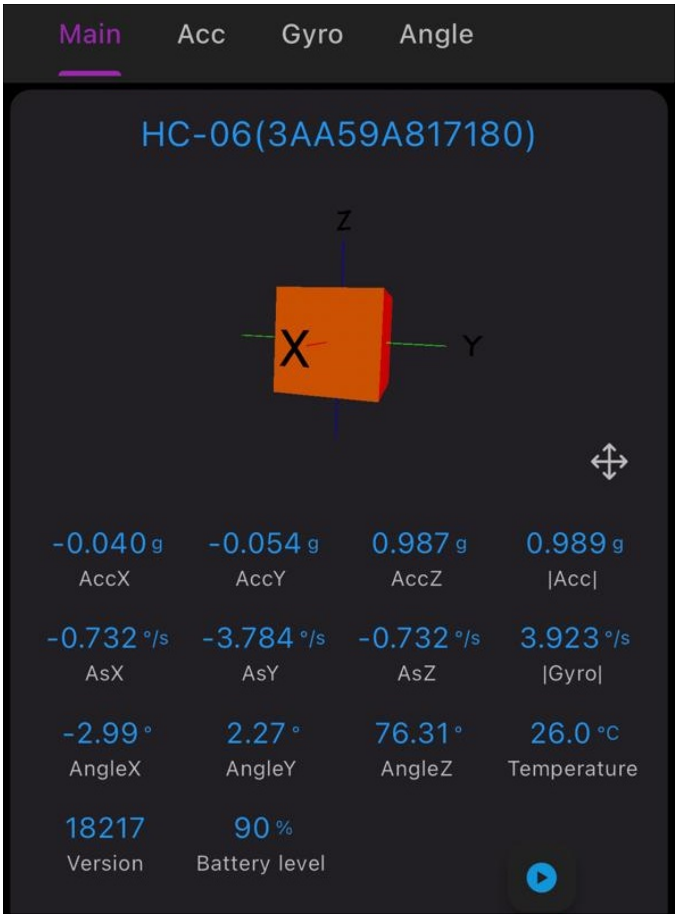

Figure 1. The Interface of Senor on the connected Mobile device

A. PARTICIPANTS

The dataset comprises 29 subjects, including male and female participants between 19 and 42 years of age. The table below outlines vital participant details, such as subject code, weight, height, age, consent, and number of falls and ADL performed. All subjects consented to participate in the study, and their falls and ADLs were carefully recorded.

B. ACTIVITIES

The dataset recorded a total of 8,953 activities, including 2,791 falls and 6,162 ADLs. Fall-related activities include common scenarios such as falling to the left, right, front, or back, as well as scenarios such as sliding, stumbling, and falling from a higher place. ADLs include walking, running, standing up from the ground, driving, and other routine activities. Each file contains 8 seconds of data sampled at a

Table 2. Overview of Participant Characteristics: Includes subject code, weight, height, age, and the number of falls and ADLs recorded per participant.

Code	Weight (kg)	Height (cm)	Age	Total Falls	Total ADLs
SBJ01	96	178	32	43	0
SBJ02	90	175	30	37	0
SBJ03	83	180	32	32	41
SBJ04	85	176	19	43	60
SBJ05	73	176	19	50	15
SBJ06	90	173	22	50	65
SBJ07	70	178	27	51	52
SBJ08	68	174	24	50	52
SBJ09	65	N/A	N/A	52	52
SBJ10	67	183	30	49	53
SBJ11	78	180	30	52	0
SBJ12	95	176	22	49	0
SBJ13	60	172	20	52	28
SBJ14	60	180	20	50	48
SBJ15	71	178	32	50	0
SBJ16	87	176	29	49	0
SBJ17	100	179	29	52	0
SBJ18	91	183	29	52	0
SBJ19	66	176	34	0	53
SBJ20	63	173	32	49	43
SBJ21	88	180	30	52	0
SBJ22	57	160	31	52	0
SBJ23	72	182	31	0	49
SBJ24	63	173	31	0	52
SBJ25	80	184	32	0	52
SBJ26	50.5	162	25	0	47
SBJ27	100	180	42	0	44
SBJ28	85	179	31	0	52
SBJ29	70	177	26	0	52

100Hz frequency, resulting in 800 records per file.

Table 3. Summary of Recorded Activities: Includes the total number of falls and ADLs performed, categorized by activity type and code.

Activity Type	Code	Type	Total
Fall on the left	ACT1	Fall	290
Fall on the right	ACT2	Fall	300
Fall on the front	ACT3	Fall	310
Fall on the back	ACT4	Fall	320
Slide	ACT5	Fall	250
Fall on knees	ACT6	Fall	300
Stumble upon	ACT7	Fall	250
Try to sit on a chair and fall	ACT8	Fall	143
Walking	ACT9	ADL	2,839
Running	ACT10	ADL	1,141
Stand up from ground	ACT11	ADL	2,009
Driving (car/bus)	ACT12	ADL	174

C. LOCATIONS

Data collection was carried out in five different environments to capture diverse scenarios and test the system's robustness under different conditions. The locations included:

- **Basement (LOC1)**
- **Acrobatic Gym (LOC2)**
- **White Room (LOC3)**
- **Backyard (LOC4)**
- **Office (LOC5)**

D. DATA QUALITY

Each video recording contains details about the subject, the action, the position (left, right, front, back), and the location of the activity. Although most recordings are of high quality, some sensor data exhibited noise or unexpected spikes due to environmental factors or sensor malfunctions. These imperfections in the data are noted and should be considered during pre-processing and model training.

The dataset offers a complete overview of different types of falls and ADL in multiple environments, providing a rich data source to test machine learning-based fall detection systems. The sensor and video data combination offers multi-modal insights, contributing to more accurate and reliable fall detection models.

IV. DATA CLEANING AND PREPROCESSING

The raw dataset, collected using the custom Soc sensor, contained significant noise due to different environmental factors, motion artifacts, and sensor limitations. Complete data cleaning and pre-processing steps were applied to confirm the fall detection system's accuracy. A Butterworth low-pass filter was employed to eliminate high-frequency noise and improve signal quality.

The noisy accelerometer data from the sensor's X, Y, and Z axes were smoothed using a fifth-order Butterworth low-pass filter. This filter was applied to each axis individually, showing that motion signals were retained while noise was significantly reduced. The result was a cleaner, more accurate dataset, essential for training reliable ML for fall detection. These figures demonstrate the effectiveness of the filtering process. Noise reduction was crucial in eliminating motion artifacts and smoothing out irregularities, enhancing the dataset's quality.

However, due to the noise levels in some sessions, reshoots were often required, which extended the data acquisition period to four months, starting from June 3, 2024. Despite these challenges, the cleaned data provide a robust foundation for further analysis and model development. The following algorithm outlines the process for cleaning and filtering noisy accelerometer data.

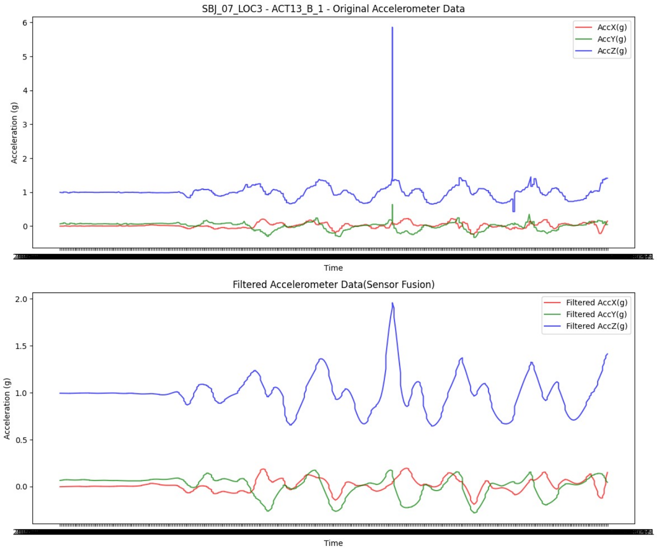

Figure 2. Comparison of noisy vs. filtered accelerometer data for an Activity of ADL.

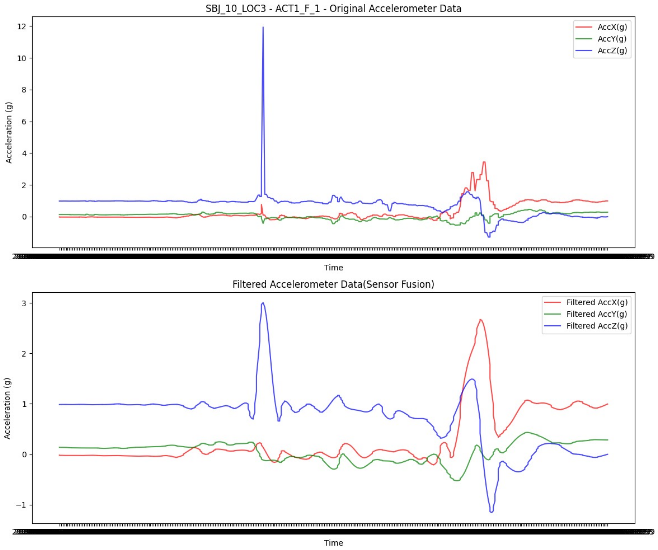

Figure 3. Comparison of noisy vs. filtered accelerometer data for a fall activity.

Algorithm 1 Data Cleaning and Filtering Algorithm

Input: Raw accelerometer data ($AccX$, $AccY$, $AccZ$)
Output: Filtered accelerometer data ($AccX\_filtered$, $AccY\_filtered$, $AccZ\_filtered$)
Step 1: Load data
Load the raw accelerometer data from TSV files for each subject and activity.
Step 2: Define Butterworth low-pass filter
Define a 5th-order Butterworth filter with a cutoff frequency of 1 Hz and a sample rate of 15 Hz.
Step 3: Apply filter
Apply the low-pass filter to the accelerometer data on each axis ($AccX$, $AccY$, $AccZ$).
Step 4: Visual comparison
Generate graphs to compare each axis's noisy vs. filtered data.
Step 5: Save filtered data
Save the filtered accelerometer data for further analysis and model training.

The above algorithm was applied consistently across all subjects and activities, showing a uniformly cleaned and processed dataset. This step was essential for the accurate detection of falls and the classification of Activities of Daily Living. Figures were generated to compare the original noisy accelerometer data with the filtered data:

V. EXPLORATORY DATA ANALYSIS

Exploratory Data Analysis (EDA) was performed to uncover the rich and diverse characteristics of the dataset. Using insightful figs, we demonstrate this dataset's unique strengths and potential for activity recognition and fall detection tasks. Each figure highlights vital aspects that highlight the versatility and usability of the data.

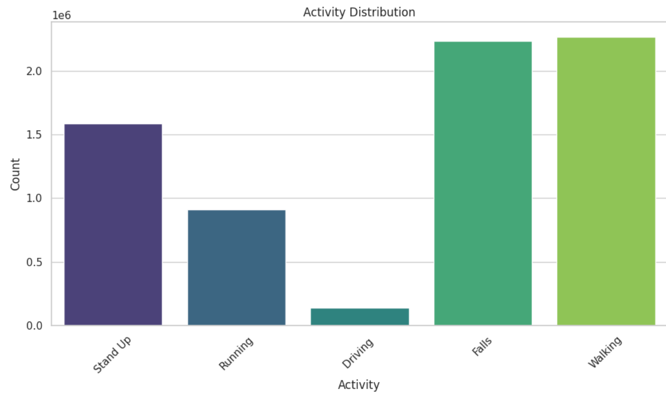

Figure 4. Activity Distribution Bar Chart

Figure 4 illustrates the distribution of activities within the dataset. This chart highlights the dataset's complete nature, covering a wide variety of activities such as Walking, Running, Standing Up, Driving, and Falls. This diversity confirms that the dataset can support multiple research applications, ranging from general activity recognition to specific fall detection tasks. The well-documented class definitions further increase its usability for different machine learning tasks.

The density plot of Acceleration in the x-direction ($AccX$), shown in Figure 5, captures the distinctive movement patterns associated with each activity. The dataset's detailed recording of sensor data allows for observations, making it particularly suitable for applications requiring precision and robustness, such as fall detection and health monitoring systems.

Figure 6 further demonstrates the ability of the dataset to differentiate between activities based on the y-direction acceleration ($AccY$). These plots emphasize the dataset's

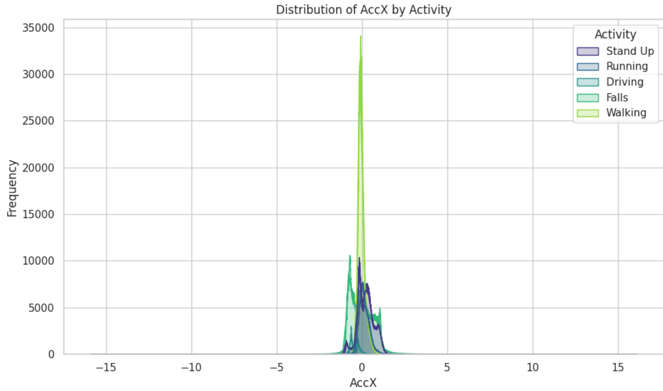

Figure 5. Density Plot of AccX by Activity

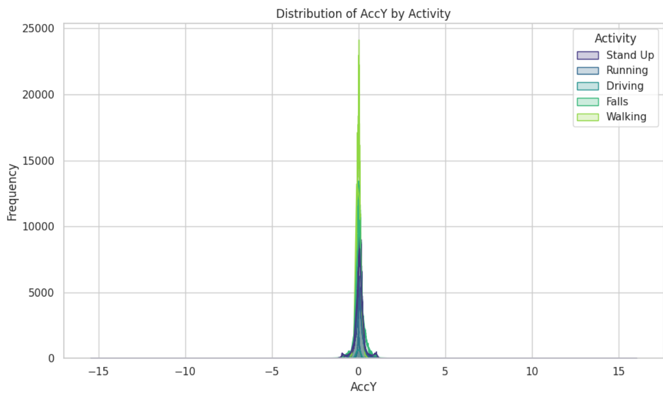

Figure 6. Density Plot of AccY by Activity

capability to identify patterns that can be used in multi-class classification problems.

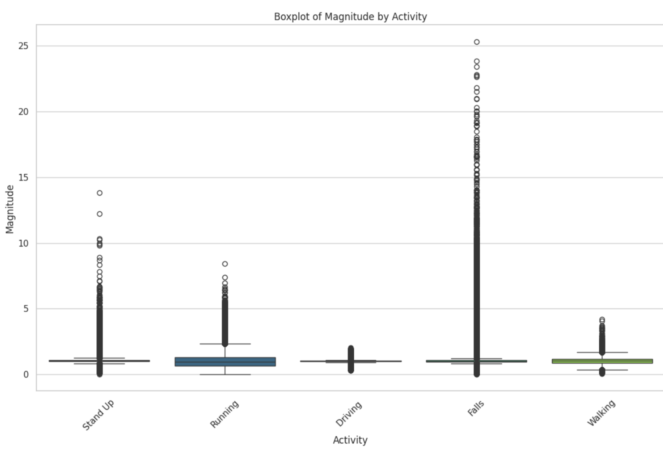

Figure 7. Boxplot of Magnitude by Activity

The box plot of the magnitude of the movement (Figure 7) provides information on the activity intensities. The dataset includes precise magnitude calculations derived from accelerometer readings, which are essential to detect abrupt changes in movement, such as those that occur during falls. This feature confirms its suitability for real-world applications such as elderly monitoring and fitness tracking.

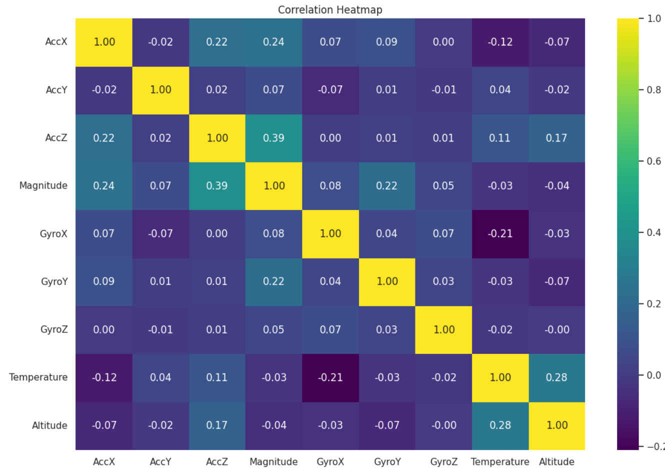

Figure 8. Correlation Heatmap of Features

The correlation heat map in Figure 8 demonstrates the interrelationships among features. This figure shows the completeness of the dataset, capturing both independent and correlated sensor measurements. This richness supports advanced feature engineering techniques, improving the adaptability of the dataset for different machine learning algorithms.

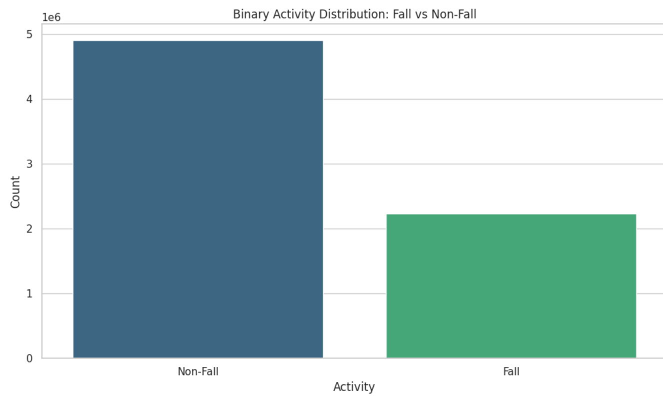

Figure 9. Binary Activity Distribution: Fall vs Non-Fall

For binary classification tasks (fall vs. nonfall), the dataset's structure remains robust and detailed, as shown in Figure 9. By aggregating non-fall activities into a single category, this distribution demonstrates the dataset's flexibility for use in targeted applications like fall detection systems. Inclusion of realistic fall scenarios provides a valuable resource for developing and testing safety-critical systems.

The density plot for *AccX* in binary classification tasks (Figure 10) highlights the ability of the dataset to distinguish falls based on sensor readings. The clear differences in the distributions between falls and non-falls underscore the potential of the dataset to improve fall detection algorithms.

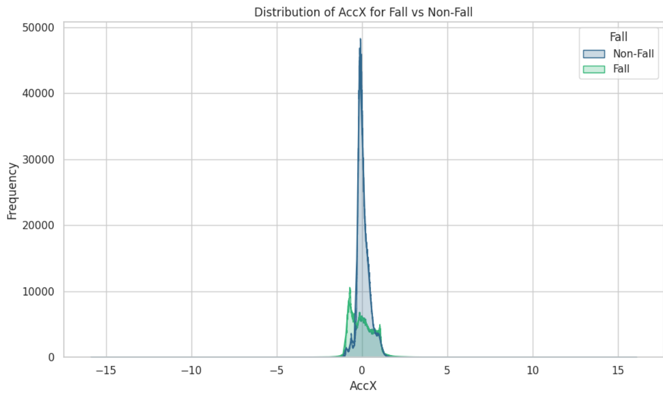

Figure 10. Density Plot of AccX for Fall vs Non-Fall

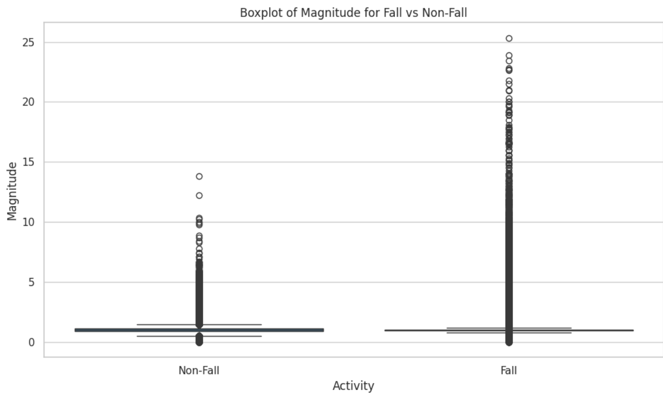

Figure 11. Boxplot of Magnitude for Fall vs Non-Fall

Figure 11 illustrates the box plot of the magnitude of the movement for fall and non-fall activities. The higher magnitude values associated with falls reflect the ability of the dataset to capture abrupt impacts accurately. This makes the dataset a valuable tool for designing reliable fall detection systems.

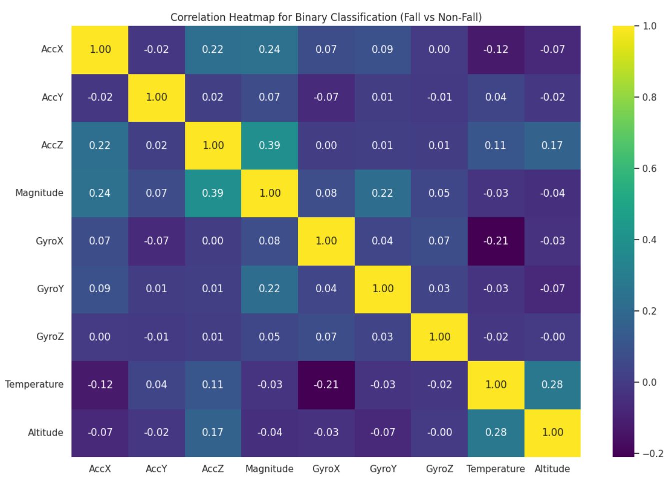

Figure 12. Correlation Heatmap for Binary Classification (Fall vs Non-Fall)

Finally, the correlation heatmap for binary classification (Figure 12) demonstrates the relationships between features, specifically in fall and non-fall scenarios. The dataset captures vital patterns that can be used to develop high accuracy and reliability models to distinguish falls.

These analyses highlight the versatility, detail, and potential of the dataset for diverse applications, from activity recognition to safety-vital systems, such as fall detection. The careful design and rich feature set make this dataset valuable for advancing research and development in wearable sensor-based activity monitoring.

VI. SIGNAL QUALITY AND STATISTICAL ANALYSIS

The statistical and spectral properties of the dataset were analyzed to assess its quality, reliability, and representativeness. Summary statistics, variability measures, and spectral characteristics of key sensor channels, such as acceleration, gyroscope, altitude, and magnitude, are presented. Additionally, correlation matrices were computed to evaluate inter-channel relationships.

The statistical distribution of the dataset provides insight into its signal quality. For example, each channel's mean, median, standard deviation, skewness, and kurtosis were computed. Acceleration on the x-axis (AccX) exhibited a mean of 0.0479, a median of -0.0187, and a standard deviation of 0.5133. The skewness and kurtosis values of 1.0304 and 17.0458, respectively, suggest a significant right skew and the presence of outliers.

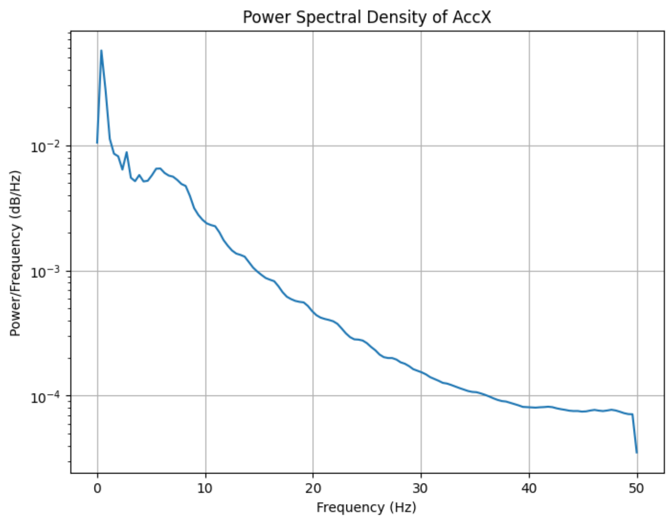

Figure 13. Power Spectral Density of AccX. The plot highlights dominant low-frequency components, reflecting gradual and steady movements.

Similarly, AccY had a mean of 0.0193, a median of 0.0108, and a standard deviation of 0.2595, with a skewness of 1.0368 and kurtosis of 49.5291, indicating pronounced deviations from normality.

AccZ displayed a mean of 0.7271, a median of 0.9041, and a standard deviation of 0.6309, with a slightly negative

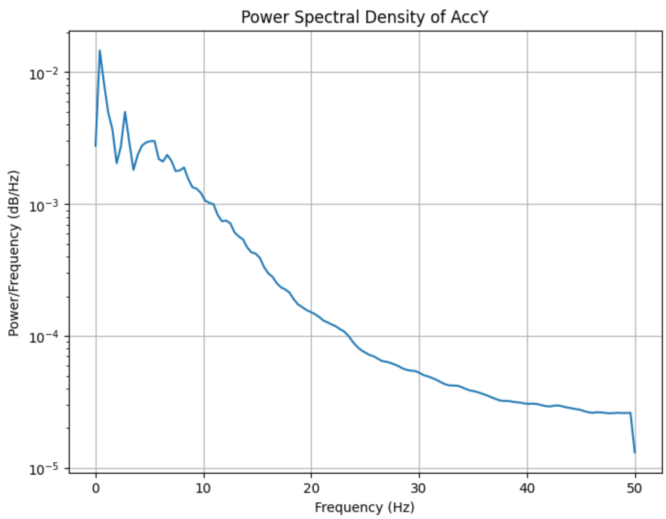

Figure 14. Power Spectral Density of AccY. The distribution confirms similar trends to AccX, emphasizing low-frequency dominance.

skewness of -0.6464 and a kurtosis of 4.8846, highlighting more symmetric but peaked data.

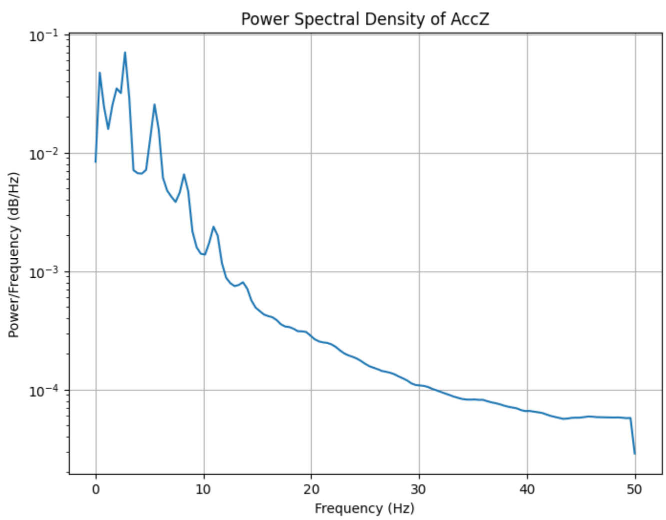

Figure 15. Power Spectral Density of AccZ. The plot reflects a relatively consistent frequency pattern, aligning with steady motion changes.

The signal-to-noise ratio (SNR) estimates reveal the clarity of the sensor signals. AccX had an SNR of 0.0377 dB, indicating some noise presence, while AccZ achieved a higher SNR of 3.6700 dB, suggesting better signal quality. Altitude signals demonstrated the highest clarity with an SNR of 9.9573 dB, affirming its reliability for activity detection tasks. Magnitude, a composite measure, exhibited an SNR of 9.1001 dB, reflecting its consistency in aggregating multi-dimensional data. Spectral characteristics were analyzed using power spectral density (PSD) plots, highlighting frequency domain properties. The PSD of AccX revealed dominant low-frequency components, reflecting gradual changes in motion. Similar trends were observed for AccY and AccZ.

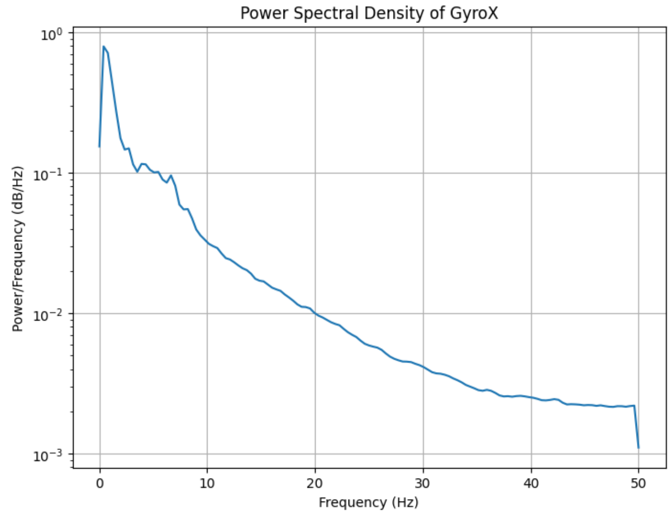

Figure 16. Power Spectral Density of GyroX. The broader frequency range indicates rapid rotational movements typical of dynamic activities.

Gyroscopic signals exhibited broader frequency distributions due to faster rotational movements. The altitude channel's PSD showed a steep decline, reflecting its stable and consistent signal nature, which is particularly important for distinguishing between activities involving significant elevation changes.

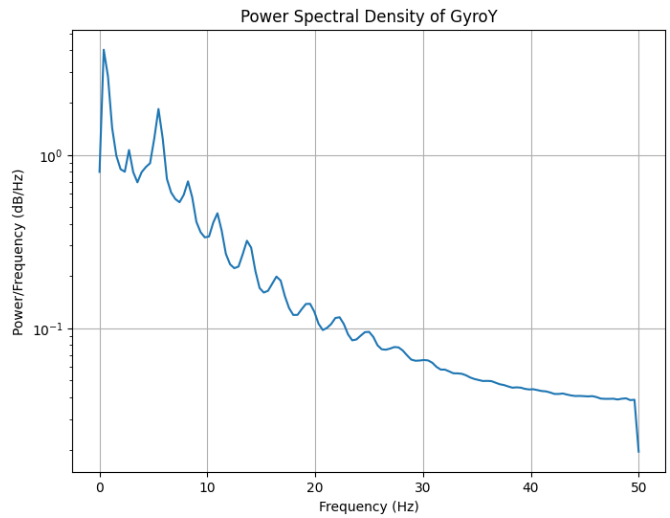

Figure 17. Power Spectral Density of Altitude. The steep decline highlights its stable signal characteristics, which are essential for identifying elevation-related activities.

Correlation analysis further evaluated inter-channel relationships. Pearson and Spearman correlation matrices revealed notable relationships between certain channels. AccX and AccZ showed moderate positive correlations (0.22), indicating linked movements along these axes. The magnitude channel was strongly correlated with AccZ (0.39), which confirms its composite nature as an aggregate of acceleration components. The altitude correlations were minimal, reflecting its distinct signal characteristics and independence from other channels.

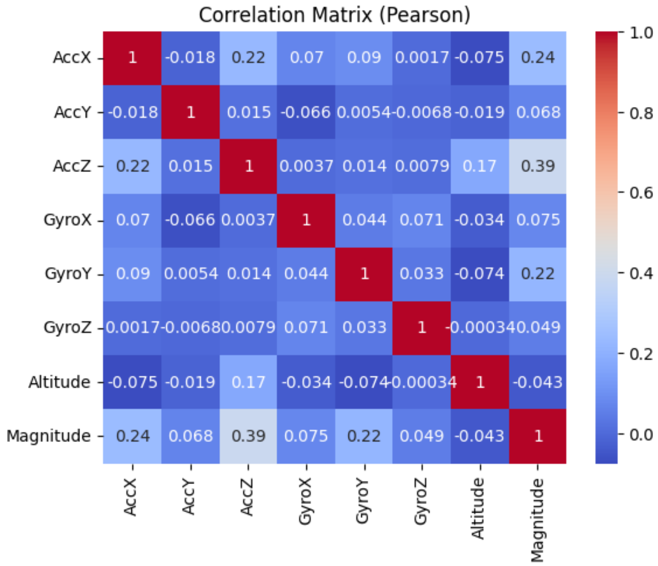

Figure 18. Pearson Correlation Matrix of Sensor Channels. The matrix highlights the relationships between different channels, showing stronger correlations among acceleration components.

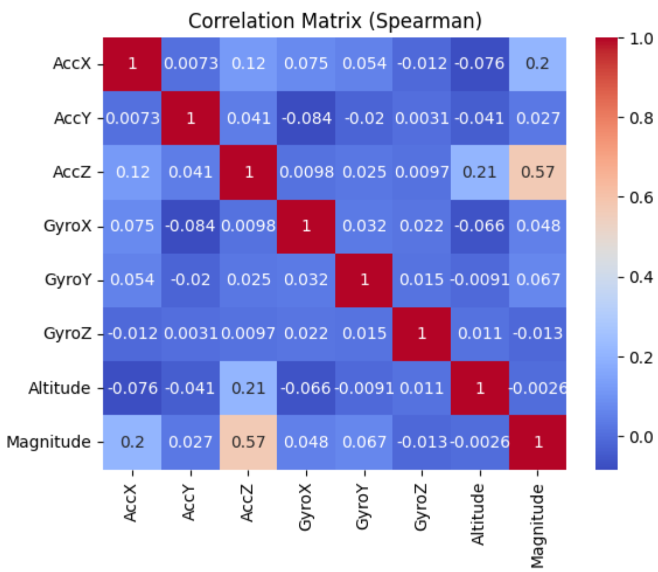

Figure 19. Spearman Correlation Matrix of Sensor Channels. The non-parametric correlation emphasizes similar trends as Pearson, with slight variations in strength.

VII. EXPERIMENTS AND RESULTS

The experiments conducted on this dataset aimed to evaluate its suitability for both multiclass and binary activity classification tasks using standard ML. The results demonstrate the dataset's exceptional quality and utility, as evidenced by the high classification performance across multiple models.

For multi-class classification, models including XGBoost, RF, Decision Tree (DT), and Logistic Regression were evaluated. Table 4 summarizes the performance metrics for each model. XGBoost achieved an overall accuracy of 99%, with a macroaverage precision, recall, and F1 score of 99%. RF performed exceptionally well, achieving near-perfect metrics across all classes, reflecting its robustness and ability to handle the dataset's complexity. DT also performed well with 99% accuracy, but slightly lower precision and recall for minority classes. Logistic regression, however, struggled with multiclass classification, particularly for less frequent activities, yielding an overall accuracy of 60%.

Table 4. Multi-Class Classification Results

Model	Precision	Recall	F1-Score	Accuracy
XGBoost	0.99	0.99	0.99	99%
RF	99.53	99.51	99.56	100%
DT	0.99	0.99	0.99	99%
Logistic Regression	0.58	0.60	0.58	60%

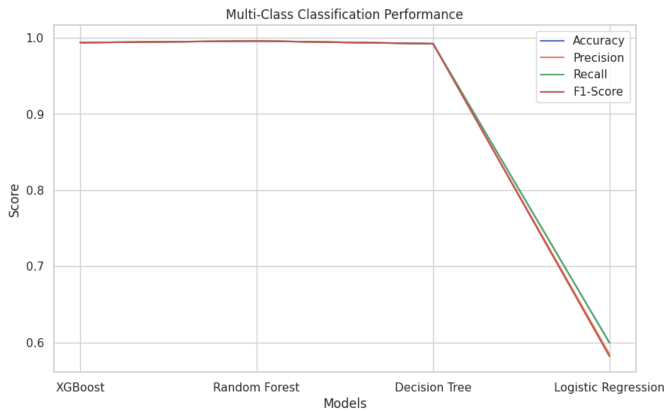

Figure 20. Comparison of Model Performance for Multi-Class Classification

In binary classification, the dataset was analyzed for its ability to differentiate between fall and non-fall activities. RF and DT both achieved perfect accuracy, precision, recall, and F1-scores, showcasing the dataset's ability to provide clear distinctions between these two categories. Logistic Regression, while slightly less effective, still achieved an accuracy of 79%, with notable disparities in recall for the fall class.

These results highlight the strengths of the dataset, including its low noise levels, diverse activity coverage, and well-defined patterns between classes. Compared to other datasets in the literature, this dataset offers unparalleled performance in fall detection and activity recognition tasks. For example,

Table 5. Binary Classification Results

Model	Precision	Recall	F1-Score	Accuracy
RF	99.52	99.52	99.52	100%
DT	99.57	99.56	99.54	100%
Logistic Regression	0.77	0.71	0.73	79%

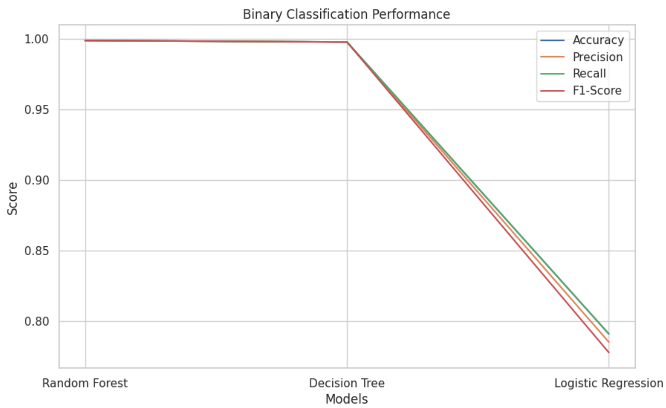

Figure 21. Comparison of Model Performance for Binary Classification

Table 6 compares the dataset with existing benchmarks such as MobiFall, SisFall, and UMAFall. The proposed dataset consistently outperforms the others in terms of precision and reliability.

Table 6. Comparison with public fall-detection corpora.

Dataset	Yr	Subj	ADL	Fall	Acc. %	Model	Limitation
MobiFall	14	24	10	4	99.1	SVM	Pocket-only sensor, young cohort
SisFall	15	38	19	15	95.4	RF,CNN	Age-gap performance deficit
FARSEEING	15	45†	–	real	93.3	C-LSTM	Few falls; uncontrolled noise
UP-Fall	18	17	11	11	95.6	RF,SVM	Vision gear needed; small cohort
KFall	19	32	21	15	99.3	SVM,DL	Belt IMU only; no video
UMAFall	16	17	8	9	95.4	RF	Five fixed sensor spots
Ours	25	29	25	9	99.5–100	RF,XGB,DT	Balanced; altitude; 5 venues

† Count taken from FARSEEING metadata.

The proposed dataset stands out for its complete coverage of activities, large subject pool, and high reliability. Unlike many existing datasets, it addresses limitations such as limited activity diversity and small subject pools. With more than 3,000 fall events and more than 25 ADLs, it provides a rich dataset to train robust models. Including altimeter data adds a unique dimension, improving classification accuracy and reliability. The results achieved, as shown in Tables 4 and 5, further validate their quality and utility for fall detection and activity recognition tasks.

VIII. CONCLUSION

This paper presents a novel contribution to the field of fall detection and human activity analysis by introducing a complete, big dataset. By capturing 8,953 activities, including 2,791 falls and 6,162 ADL activities, the dataset addresses the vital need for diverse, high-quality data in developing accurate and generalizable ML. The inclusion of barometer-derived altitude delta data, recorded at 100Hz, demonstrates a substantial improvement in the performance of the transformer-based model, increasing the accuracy from 97 to 98% to over 99. 5%. The detailed pre-processing of 3,000 fall recordings to remove inconsistencies further confirms the reliability and robustness of the dataset.

The innovations introduced in this work are complemented by the challenges encountered during the data collection process. The self-built device, designed for scalability, showcases its potential to revolutionize fall detection research globally. However, practical challenges, such as sweating-induced malfunctions, SD card oxidation, and wire detachments during intense activities, highlighted areas for improvement. These challenges have driven the development of a PCB design that increases device stability and ensures consistent data collection. Ethical considerations were rigorously upheld throughout the study. Participants provided their informed consent and no personal data were recorded, demonstrating privacy and compliance with ethical research standards. This ethical approach supports the integrity of the dataset and its utility for the broader research community.

In the future, the scope of the dataset will expand with the integration of EKG sensor data in future iterations. This increase in the applicability of the dataset will further enrich the applicability, opening doors for new research opportunities, and solidifying its value as a benchmark for fall detection and human activity analysis. This work not only provides a robust resource for advancing fall detection systems but also addresses vital gaps in existing datasets, setting a new standard for quality and scalability in human activity recognition research. By overcoming challenges and paving the way for future increasements, this dataset has the potential to drive significant advancements in healthcare technologies and beyond.

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