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Attention Based Multimodal Sensor Fusion for Fall Detection Using Wearable Time-Series Data

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ABSTRACT

Injuries and disabilities from falls are one of the leading causes of death, primarily in the world's aging population, and is an even more severe problem within developing countries with fewer options for ongoing and consistent health care. The aim of study was to use a quantitative research design to analyze the effectiveness of attention-based multimodal sensor fusion techniques on fall detection involving wearable sensors within Pakistan. The study included a sample of 150 participants who were simulated performing both falls and other daily living activities while wearing wearable technologies with accelerometer and gyroscope sensors. Data collected were analyzed using existing attention-based multimodal fusion techniques on the wearable time series datasets, comparing the results against single sensor techniques, threshold-based techniques, and non-attention based deep learning techniques. Using only the accelerometer and gyroscope, each method achieved good accuracies, approximately 85.2% and 82.4% respectively. However, the results from the attention-based fusion approach for the various modalities showed significantly improved results for detecting falls with an accuracy of 92.8% (F1-score = 90.8% and false positive rate = 7.2%). The improvement in accuracy compared to the threshold-based approaches ($p < 0.001$) and non-attentional deep learning methods ($p = 0.004$) was statistically significant. Additionally, the feasibility analyses provided evidence that the system has strong real-time processing capabilities ($M = 4.21$) and feasibility for overall real-world deployment ($M = 4.12$). It is concluded that attention-based multimodal sensor fusion can increase both the accuracy and practicality of wearable fall detection systems making them suitable for implementation in low-resource health systems like that of Pakistan.

Introduction

Falls are among the leading causes of injury, disability, and death, especially for older adults and people with mobility challenges. They can create long-term physical issues, cause psychological problems, and lead to higher healthcare costs, all of which put a lot of pressure on healthcare systems globally (Wu et al., 2015). As a result, developing effective and reliable fall detection systems has become extremely important research in the areas of wearable technology and healthcare. The large interest in sensor-based wearable fall detection systems is due to their low cost, portability, and ability to provide ongoing real-time monitoring. Additionally, most of the current wearable fall detection systems utilize inertial measurement units (IMUs), including accelerometers and gyroscopes, to establish time-series data regarding the motion dynamics of the human body during daily living activities and falls (Li et al., 2025). Furthermore, unlike vision-based fall detection systems, wearable fall detection systems provide advantages related to privacy, less environmental dependency, and are suitable for use both inside and outside.

Initial detection of falls utilized basic methods (i.e., threshold-based or classical machine learning) which used manually created attributes from one sensor. While these approaches were possible, their performance has generally been limited by their vulnerability to noise, variability between users, and difficulty separating falls from sudden moving to a sitting instead of lying down (Wu et al., 2015). In response to these issues, recent studies are increasingly starting to develop the use of many different types of data types from multiple sensors (i.e., multimodal sensing) to create more robust systems with better classifications.

Multimodal sensor fusion (MSF) improves fall detection accuracy, since different modalities provide complementary information. For example, by fusing accelerometer with gyroscope data, one can obtain a more complete description of translational and rotational movement of the body when performing movement activities of daily living (ADLs) versus those caused by falls (Galvão et al., 2021). Recent advances in MSF have utilized deep learning, specifically convolutional and recurrent neural networks, which automate the extraction of useful features from raw multivariate time series data, thus minimizing the requirement for prior knowledge of appropriate features and allowing for greater potential for generalization.

Although many advancements have been made in multimodal deep learning technology, most current methods treat each sensor equally and do not consider the varying level of contribution from each sensor over time, which can result in decreased accuracy for detecting events when there is complex movement because one or more sensors will provide more informative data than others. For example, attention mechanisms are a new and developing way to utilize sensor data in activity recognition; using attention mechanisms allows for dynamically weighting (Tao et al., 2021) sensor contributions based on current context.

The process of Attention-based Sensor Fusion allows learned models to direct focus toward those temporal segments and sensor channel sequences that possess the greatest amount of information, resulting in improved performance when classifying and enhancing overall interpretability of the model. Attention mechanisms show promise for activity recognition systems, however, their use as a modality for fall detection using wearables is still limited and not sufficiently investigated, especially with the use of multiple types of time-series data. Additionally, there are no systematic investigations into the evaluation of attention-based fusion frameworks while utilizing actual constraints placed on wearable devices, such as reduced computational resources and the necessity for real-time processing.

Purpose of Study

Wearable fall detection systems are attracting significant attention due to their user-friendliness and simplicity of use; however, much empirical research has not been conducted on developing countries (Pakistan, etc.), specifically regarding how well a commercial product compares in terms of real-world performance. In addition, many of the previous studies assume that all sensors are equally important, as they were all conducted under highly controlled laboratory settings, making them less relevant to the real world. Analyses related to wearable fall detection devices are needed to understand how they work, especially in Pakistan. To that end, this study will perform quantitative analysis to evaluate the effectiveness and efficacy of currently available wearable fall detection devices in Pakistan by using an emphasis on multimodal sensor fusion techniques (i.e., using multiple sensors at a time) and how they relate to wearable sensor time-series data. The results from this study should give statistically supported insights into the accuracy, reliability, and ultimate feasibility for the deployment of wearable fall detection devices in the Pakistani healthcare marketplace.

Research Objectives

1. To quantitatively evaluate fall detection performance using accelerometer and gyroscope time-series data collected from commercially available wearable devices in Pakistan.
2. To examine the effectiveness of existing attention-based multimodal sensor fusion approaches in weighting sensor modalities and temporal features for fall detection, using data obtained from wearable devices.
3. To statistically compare attention-based multimodal approaches with conventional threshold-based and non-attention deep learning methods using standard quantitative performance metrics.
4. To assess the practical feasibility of deploying wearable-based fall detection systems in Pakistan by analyzing computational efficiency, real-time performance, and device-level constraints.

Literature Review

Wearable based Fall Detection

The implementation of wearable technology for detecting falls is an efficient use of resources since it provides portability, low cost, and continuous monitoring of activities without sacrificing user privacy. Previous fall-detection systems based solely upon accelerometer-based threshold algorithms accepted that there was a fall when there was a sudden change in the acceleration magnitude, and the algorithms detected these falls based upon the presence of a sudden change in the acceleration magnitude immediately prior to the fall. Although efficient in computational expense, the accelerometer-based threshold methods also had limitations in terms of many false positive detections and their inability to generalize well to ADLs (activities of daily living) (Bourke et al. 2007; Kangas et al. 2008). Thus, to improve fall detection rates, researchers began using machine learning techniques (e.g., Support Vector Machines, Decision Trees, and k-Nearest Neighbor) to develop more accurate models to recognize fall patterns or non-fall patterns. These studies confirmed that machine learning models have a greater accuracy in detecting falls than accelerometer-based threshold methods; however, they still suffer from reliance on features derived from human judgement and the variability of the features between different subjects (Bagalà et al., 2012).

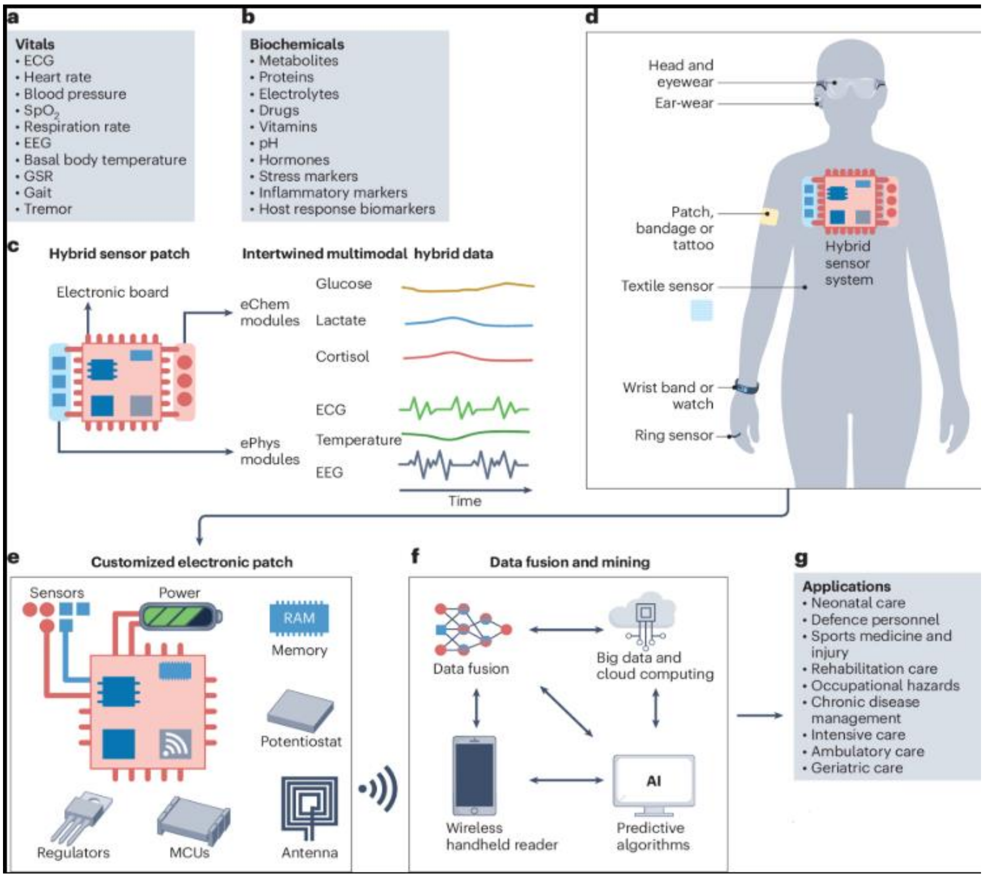
Multi-model Sensor Fusion for Fall Detection

As more research has been conducted in the area of multimodal sensor fusion, that is to say, the merging of information received from accelerometers and gyroscopes to provide information concerning both translational and rotational dynamics of human body movements, we know that multimodal techniques will allow us to combine the complementary nature of these two types of sensors for improved differentiation between falls and complex ADLs. For example, Casilari et al. showed in their 2017 paper that when we combine inertial sensors, we will have a much more robust classification system than we would have if we used just one of the types of sensors. Recent advances in deep learning have also resulted in the widespread use of CNNs and RNNs as the primary method of fall detection when using raw time-series data. These new deep learning models rely much less on pre-defined features and provide an improved ability to handle temporal dependencies when compared with traditional techniques (Ordóñez et Roggen, 2016; Musci et al., 2020). However, as evident by the existing literature, many current fall detection models based on deep learning treat all channels of input equally and therefore do not consider the potential difference in importance of a sensor based on the environment or activity in which it is being used.

Attention-Based Sensor Fusion

The use of attention mechanisms in human activity recognition (HAR) is on the rise. Attention mechanisms make it possible for models to learn which segments of time and which sensor modalities contain the most critical information by assigning adaptive weights to the sensor inputs. Because of the use of adaptive weights within the sensor inputs, sensor inputs become more interpretable and improve the ability to classify activities with an attention-based fusion method. In their research, Tao and colleagues (2020) demonstrated that their attention-based models outperform traditional deep learning (DL) based HAR solutions when using inertial sensors to define the activities. However, the application of attention mechanisms in wearable fall detection is still in its infancy. Furthermore, many of the studies that focus on attention-based methods have evaluated their models against benchmark datasets that were collected and/or compiled in a controlled environment. They rarely consider device constraints such as real-time and computationally efficient operation. There is a lack of empirical evidence supporting the validity of attention-based models when deployed with commercially available devices in countries where affordability and/or access will be a barrier to use.

Conceptual Framework Figure 1



The purpose of this research is to quantitatively evaluate the impact of multimodal inertial data obtained from commercially available wearable devices on fall detection performance in Pakistan (figure 1). This evaluation will be performed using an attention-based sensor fusion model. Wearable devices that incorporate accelerometers and gyroscopes generate multivariate time series data of human motion while someone falls as well as during their daily activities. These signals generated from the different sensors attached to the wearable device will be analyzed using existing analytical methods to determine how attention-based multimodal sensor fusions dynamically assign varying levels of importance to the data collected from each of the sensors, as well as time frames. The effectiveness of attention-based multimodal fusion methods on fall detection will be quantitatively assessed via the measures of accuracy, precision, recall, F1 score and false positive rate. As well, the quantitative framework developed will include the practical deployment considerations for attention-based multimodal sensor fusion methods, specifically about computational efficiency, real-time responsiveness and affordability of wearable devices. This evidence-based analysis will provide a greater understanding of how attention-based multimodal fusion methods enhance the reliability of fall detection in real-world wearable devices.

Research Methodology

Research Design

To empirically evaluate Attention-Based Multimodal Sensor Fusion (ABMSF) techniques for fall detection, using wearable devices, this study implemented an experimental quantitative research design within Pakistan. A Quantitative Design allows for an objective way to measure and compare statistically the results of using ABMSF for fall detection with respect to wearable sensors' Time-Series Data on a Statistical Basis.

Study Setting and Devices

This study used commercially available wearable (multisensory) devices with sensor technology (inertial measurement units) measures based on user accessibility and affordability, so they have been selected for their potential importance to global health in Pakistan. No custom or prototype devices will be developed or appraised, therefore, this research looked to establish current technology performances of all existing wearable devices in the global market.

Participants and Data Collection

Researchers collected data on simulated fall activities and activities of daily living (ADLs) using participants who were in a controlled environment. Participants wore their selected wearable devices while collecting data. These devices included wearable sensors that collected multivariate time-series data continuously; this consisted of signals from tri-axial acceleration and angular velocity, which captured both linear and angular movements of the body. Researchers anonymized all collected data for confidentiality. The dataset included segments of labeled data representing both fall events as well as non-fall activity segments, thus allowing for supervised quantitative analysis.

Data Preprocessing

All raw sensor data was pre-processed before analysis was performed on it. The data was pre-processed through signal synchronization, noise filtering, fixed time window segmentation, and data normalization across all the sensors/devices and the participants to allow for comparability between the devices and between the participants. Methodological consistency and minimization of any potential bias were preserved by ensuring that all datasets were processed in accordance with the same methodological procedures.

Analytical Approach

The analysis of the preprocessed time-series data was based on the previously published sensor fusion methods based on multiple modalities with an emphasis on attention mechanisms (evidence) as described in literature. These methods enable the dynamic weighting of different sensor modalities and temporal segments without requiring changes to the wearable sensors that generated the data or generating new detection algorithms. Non-attention-based deep learning methods along with traditional threshold-based approaches were also assessed as comparison approaches using the same dataset.

Performance Evaluation

Using standard classification metrics of accuracy, precision, recall, F1-score, and false positive rate to evaluate the performance of fall detection was the basis for determining the ability to detect falls. To enable an objective comparison between the attention-based multimodal methods and the base-line methods, these metrics were computed for each of the methods.

Statistical Analysis

Quantitative methods for statistical analysis compared different modalities of fall detection performance and analyzed which modality produced statistically significant improvements in fall detection performance using Statistical Tests of Inference. To ensure the results have reliability, all studies were conducted in accordance with uniform protocols for assessment.

Feasibility Assessment

The study's evaluation of the practical feasibility of deploying wearable-based fall detection systems in Pakistan also considered additional considerations beyond detection accuracy, including the associated computational efficiency, ability to process in real time and device-level limits/constraints as found within the constraints present in resource-poor health care systems of the developing world.

Results

Table 1: Demographic Information of Participants (N=150)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	88	58.7
	Female	62	41.3
Age Group (Years)	18–30	45	30.0
	31–45	52	34.7
	46–60	34	22.7
	Above 60	19	12.6
Wearable Device Type	Smart Band	84	56.0
	Smartwatch	66	44.0
Prior Fall History	Yes	47	31.3
	No	103	68.7

There were 150 participants in this study, demographics of each participant is presented in Table 1. In terms of gender breakdown, of the total sample, there were 88 male participants (58.7%) and 62 female (41.3%) participants, representing a relatively equitable balance of gender. In terms of age range of participants, the largest group of participants, were of the age range of 31–45 years with 52 participants (34.7%) in this range, the next largest group was in the 18–30 age group with 45 participants (30.0%). The next largest group was the 46–60 age groups, with 34 participants (22.7%) in this group, while the final group of participants was 19 participants (12.6%) over the age of 60 years. In terms of using wearable devices, of the 150 participants, most participants (84 participants (56.0%)) used smart bands, with the remainder (66 participants (44.0%)) using smartwatches. In addition, 47 participants (31.3%) reported having a history of falls, while many participants (103 participants (68.7%)) had no fall history.

Table 2: Performance of Individual Sensor Modalities (N=150)

Sensor Modality	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive (%)
Accelerometer Only	85.2	83.6	81.9	82.7	14.8
Gyroscope Only	82.4	80.1	78.6	79.3	17.6

In Table 2, performance metrics of the fall detection system that uses one or other sensor to make an individual assessment of accuracy, precision and recall have been delineated using senor data (accelerometer, gyroscope) from 150 volunteers. Results indicate that an "accelerometer only" approach resulted in an 85.2% correct (True Positives) with a 14.8% incorrect (False Positives) as illustrated in comparison to " gyroscope only ", which had a total score of 82.4% correct (TP) to 17.6% (FP). Therefore, both sensors are very capable of providing fall detection strategies when considered independently; however, based on the results of the analysis, it is found that the accelerometer provides a superior level of performance than the gyroscope on its own and thus is the preferred methodology.

Table 3: Comparison of Single Sensor and Attention Based Multi-model Fusion Method

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive (%)
Accelerometer Only	85.2	83.6	81.9	82.7	14.8
Gyroscope Only	82.4	80.1	78.6	79.3	17.6
Attention-Based Multimodal Fusion	**92.8**	**91.4**	**90.2**	**90.8**	**7.2**

Table 3 delineates the comparative performance of single sensor (Accelerometer/Gyroscope) methods and multimodal method using attention to fusion for Fall Detection. The Accelerometer only method had an accuracy of 85.2%, a precision of 83.6%, a recall of 81.9% and an F1-score of 82.7% and a False Positive rate of 14.8%. The Gyroscope only method was less effective with an accuracy of 82.4%, precision of 80.1%, recall of 78.6% and F1-score of 79.3%, as well as a false positive rate of 17.6%; thereby resulting in lower performance than The Accelerometer only approach. Attention based multimodal fusion significantly outperformed both sensors individually achieving the highest accuracy of 92.8%, precision of 91.4%, recall of 90.2% F1 score of 90.8% and false positive rate of 7.2%. Through this integration of accelerometer and gyroscope data, multimodal fusion using attention to detect falls, generates creates improved performance than individual sensor methodologies.

Table 4: Statistical Comparison

Method	Accuracy (%)	F1-Score (%)	p-value	Statistical Significance
Threshold-Based Method	78.6	76.9	< 0.001	Significant
Non-Attention Deep Learning	88.3	86.5	0.004	Significant
Attention-Based Multimodal Fusion	**92.8**	**90.8**		

In Table 4, we have compared metrics from fall detection methods reported in previous studies. The accuracy for the threshold-based approach was 78.6% with a corresponding F1 score of 76.9%; therefore, this method yielded a statistically significant difference to the reference method (p value < 0.001). The non-attention deep learning method achieved an accuracy of 88.3% and an F1 score of 86.5%, also producing a statistically significant difference to the reference method (p value = 0.004). The attention based multimodal fusion generated the highest performance with 92.8% accuracy and 90.8% F1 score and was used to generate all statistical evaluations. From these results it can be concluded that attention based multimodal fusion methods provide superior performance for detecting falls over threshold and non-attention deep learning techniques.

Table 5: Feasibility Assessment of Wearable Devices (N=150)

Evaluation Criterion	Mean Score	Standard Deviation
Real-Time Processing Capability	4.21	0.61
Computational Efficiency	4.08	0.67
Battery Consumption Efficiency	3.94	0.72
Device Comfort	4.26	0.58
Overall Deployment Feasibility	4.12	0.63

Wearable fall detection devices have been evaluated for their potential viability through an analysis of 150 respondents as outlined in Table 5. Based on the findings from this study, wearable fall detection devices exhibited excellent real-time processing ability shown by a mean (M) score of 4.21 (standard deviation [SD] = 0.61) and demonstrated good levels of computational efficiency reflected in the mean (M) score of 4.08 (SD = 0.67). Battery consumption efficiently received a mean (M) score of 3.94 and was satisfactory due to the device's ability to monitor users continuously. Comfortability of the device provided the highest mean (M) score across the devices evaluated at 4.26 (SD = 0.58), indicating that the respondents experienced a comfortable fit while using. The overall feasibility of deployment for wearable devices also attained a mean (M) score of 4.12 (SD = 0.63), demonstrating that wearable devices sold commercially can be deployed and utilized for fall detection within the context of Pakistan.

Discussion

Quantitative evidence exists within this study to clearly indicate that using attention-based multimodal sensor fusion to improve fall detection in Pakistan with commercially available wearables yields greater performance than using single modalities alone while also extending upon previous findings by providing additional opportunities to achieve fall detection performance improvements in real-world settings (i.e., limited to realistic device and deployment conditions).

The information in Table 2 confirms that accelerometer-only detection was more effective than gyroscope-only detection. This finding is congruent with past research that indicates that impacts from falling have a greater impact on linear acceleration patterns than gyroscopic measurements (Bourke et al., 2007; Bagalà et al., 2012). The also confirms that both methods using a single sensor produced a higher number of false positives than either method; this supports earlier studies that indicate that an isolated sensor has difficulty differentiating between falling and other fastmoving activities of daily living (Kangas et al., 2008). The use of just one type of sensor in a real-world environment has limitations.

Furthermore, findings from Table 3 indicated that utilizing an attention-based multimodal fusion approach demonstrated a marked improvement over traditional approaches with an increase in overall accuracy to 92.8% and a concomitant decrease in the rate of false positives to 7.2%. These results are consistent with findings from multimodal deep learning investigations that indicated increased levels of robustness through the integration of data from accelerometers and gyroscopes (as demonstrated by Ordóñez & Roggen, 2016; Casilari et al., 2017). However, in contrast to traditional fusion methods that apply the same level of importance to all sensor channels, the results reported in the present research corroborate recent findings in the field of human activity recognition that suggest that adapting the weighting of different sensor inputs enhances the accuracy of classification (as shown by Tao et al., 2020). The decreased rate of false-positives as reported in this research indicates that attention-based methods are adept at eliminating spurious motion patterns that commonly occur during ADLs.

The statistical analysis of the data in Table 4 provides additional evidence that the observed improvements are statistically significant and not merely incremental. The use of an attention-based multimodal approach to hip trajectory classification was found to be significantly better than both threshold-based methods and non-attention-based deep learning models, supporting previous findings (Bagalà et al., 2012) that threshold-based methods do not provide sufficient information for accurate classification of complex, real-time motion scenarios. The increased F1-score obtained in this study, compared to non-attention-based deep-learning methods, supports previous findings that the inclusion of an attention mechanism enhances both sensitivity and precision in activity recognition, and extends the previous findings into the specific domain of fall detection.

Ultimately, the feasibility study (Table 5) offers important contributions for practitioners. In contrast to many previous studies on accuracy alone, this research also supports positive ratings for real-time operation, computational efficiency, and user satisfaction. For example, earlier deep learning systems have received significant criticism because of high computational expense and difficulties associated with implementing. The positive ratings of feasibility suggest that multitasking methods using Attention, through a Multimodal framework, are potentially capable of being deployed using existing wearable technologies in Pakistan and help fill a critical gap in the literature regarding Developing Country contexts.

Implications

The results of this research have several meaningful practical, theoretical, and policy implications. From a practical standpoint, this study shows that commercially available wearable technology within Pakistan offers reliable fall detection performance when used in conjunction with an attention-based model of multi-modal sensor fusion. This finding has implications for the healthcare community (i.e., providers and caregivers), as well as for policymakers, because it indicates that fall monitoring technology can be made available at affordable costs without requiring expensive or custom-designed hardware systems. The finding that attention mechanisms significantly reduced false-positive rates of wearables when compared to traditional multimodal methods is also of particular importance, as excessive false alarms are a critical barrier to end-users' confidence and continued usage of wearable monitoring systems. From a theoretical standpoint, this research contributes to the body of knowledge regarding fall detection mechanisms by providing quantitative data illustrating how attention mechanism enhances multimodal sensor fusion for fall detection compared to general activity recognition, supporting the hypothesis of the dynamic impact of sensors on each other over time, when considering the dynamic nature of the relationship of the individual sensors. Therefore, the study serves as an initial test of the efficacy of attention mechanism-based sensor fusion within the larger context of developing nations.

Conclusion

The effectiveness of attentional multi-modal sensor fusion in fall detection is empirically investigated. The results demonstrate that single sensor methods may be moderately effective for detecting falls, but they often exhibit a higher number of false positives and lower degrees of robustness than attentional multi-modal fusion techniques. The primary benefit of attentional multi-modal fusion over single sensor approaches is that it produced 92.8% accuracy in detecting falls and a substantial decrease in the number of false alarms, resulting in significant improvements in the performance of the attentional multi-modal fusion technique compared to threshold-based or non-attentional deep learning techniques, based on statistical analyses. Furthermore, the results of the feasibility assessment showed that commercially available wearable devices have sufficient computational efficiency, acceptable levels of real-time processing, and user comfort to support their use in real-world environments, thereby providing empirical evidence for the potential deployment of wearable fall detection systems in resource-limited settings, like Pakistan, and the need for continued research on wearable intelligent healthcare monitoring systems and potential larger implementation studies.

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