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Investigating the Performance of Wearable Motion Sensors on recognizing falls and daily activities via machine learning

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ABSTRACT

With sensor-based wearable technologies, high precision monitoring and recognition of human physical activities in real time is becoming more critical to support the daily living requirements of the elderly. The use of sensor technologies, including accelerometers (A), gyroscopes (G), and magnetometers (M) is mostly encountered in work focused on assistive technology, ambient intelligence, context-aware systems, gait and motion analysis, sports science, and fall detection. The classification performance of four sensor type combinations is investigated through the use of four machine learning algorithms: support vector machines (SVMs), Manhattan k-nearest neighbor classifier (M.k-NN), subspace linear discriminant analysis (SLDA), and ensemble bagged decision tree (EBDT). In this context, a large dataset containing 2520 tests performed by 14 volunteers containing 16 activities of daily living (ADLs) and 20 falls was employed. In binary (fall vs. ADL) and multi-class activity (36 activities) recognition, the highest classification accuracy rate was obtained by the SVM (99.96%) and M.k-NN (95.27%) classifiers, respectively, with the AM sensor type combination in both cases. We also made our dataset publicly available to lay the groundwork for new research.

1. Introduction

Because of demographic changes, developments in healthcare systems have gained momentum recently. One of the main reasons, according to the data of the World Health Organization (WHO), is the regularly increasing percentage of the elderly population in the world [1]. In 2019, 9% (688 million) of the world population is 65 years or over. It is estimated that this ratio will reach nearly 12% (1 billion) in 2030 and 16% (1.6 billion) in 2050 [2]. In this context, developing assistive technologies to support the daily lives of elderly and disabled people, increase their safety and autonomy, detect potentially dangerous events such as falls reliably have become important and challenging research issues [3]. In addition to detecting fall events reliably, research has focused on monitoring and recognizing ADLs to improve the quality-of-life of people in the fall risk groups. Falls are rare events that typically occur in between ADLs and are considered jointly with ADLs in many studies. In this context, activity recognition systems can be used more effectively in applications such as social-physical interaction [4], factory working recognition [5], healthcare, sports science [6], entertainment and interactive games space [7].

Various solutions to automated activity recognition and fall detection have been proposed [8–12]. These can be classified into three main categories according to the type of sensor technology used. Ambient Sensor-Based (ASB), Wearable Sensor-Based (WSB), and Hybrid Sensor-Based (HSB) [11–14].

ASB technologies involve affixing sensors to doors, walls, floor, furniture, etc. to create smart environments that can recognize ADLs and detect falls [11,15,16]. The use of multiple sensor modalities such as acoustic [17,18], infrared [19], vibration [20], and vision-based sensors [21,22] is beneficial. The main advantage of ASB technologies is that the user does not have to affix or carry any sensors or devices on their body that may be obtrusive. This may also eliminate problems related to incorrect placement of the sensors on the body or mixing them up, although some camera systems do require wearing/pasting on special tags or markers. Cameras can provide precise contextual information directly related to the activities [13]. Typically, multiple ambient sensors are placed at fixed locations in the environment which causes the sensor distribution to be complex with low flexibility. Designing smart

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environments may be a suitable choice when the user's daily activities are confined to certain parts of a building. However, when the activities take place both indoors and outdoors and involve going to different places (e.g., running errands, taking a walk, commuting), this approach may not be the best option. It imposes restrictions on the user's mobility since the system operates only in the limited environment being monitored. Also, if the person is not within the field-of-view or the field of operation of the sensor, the sensor cannot function since it is fixed to a certain position in the environment [23,24]. Other people or pets in the environment may easily confuse these systems. Increasing the number of sensors brings additional infrastructure cost to those in need of activity monitoring and in the fall risk group. In addition, vision-based technologies can provide unnecessary information and cause privacy invasion [21,25].

WSB technologies employ sensors that measure motion parameters such as acceleration, velocity, and orientation [11,12]. Sensors developed using Micro-Electro-Mechanical Systems (MEMS) technology, with low cost (under 20 USD), small footprint (under 5 mm), and high functionality (low power and low weight) are suitable for this purpose [26]. Among these sensors, accelerometers, gyroscopes, magnetometers, and barometers are commonly used to examine the displacement of the whole body or the limbs, to observe instant fluctuations in one's activity, and to detect the balance state of the body [27,28]. The most significant advantage of these technologies is their simple design and low installation cost. Therefore, it is not necessary to establish a communication network between the sensors as in the case of ASB technologies. WSB technologies can be used both indoors and outdoors to allow the user to move freely without the restriction of the sensor field-of-view [29,30]. Among the factors that increase the accuracy of activity recognition in these technologies are the use of machine/deep learning techniques [31,32] and the placement of multiple sensor units on different body parts (e.g., head, chest, waist, and limbs) [32,33]. The disadvantages of WSB systems are that users may forget, neglect, or be reluctant to wear them because of the weight and size of the equipment to be worn, especially if multiple sensor units are being used [34]. If the wearables are battery operated, batteries need to be recharged or replaced regularly. Also, the wearable system may not provide the contextual information or suffer the problem of arbitrary data caused by activities [13]. In scenarios where wearables cannot be used (e.g., user having sensitive skin or being forgetful/unable to wear or charge the devices), ASB systems may be preferable. In addition, the targeted device in this research is going to be light, compact, and inexpensive and its integration into accessories such as over-the-clothes belt buckles is going to avoid problems related to sensitive skin.

An alternative approach is to use HSB technologies [11]. Microphone-accelerometer or infrared-microphone sensor pairs are typical examples of the sensor modalities used in this approach [35]. Despite the advantages that this technology provides for activity recognition and fall detection, it also entails some difficulties (e.g., real-time analysis, smart home integration, high processing power, data fusion, and sensor synchronization requirements) [13,36,37].

Although various devices developed for fall detection are commercially available, their false alarm rates are high and it is not easy to test that these devices identify falls correctly. Among the reasons for this is that common activity sets are not used to assess the performance of the developed systems. There exist publicly available datasets as well as studies that acquire and use their own datasets (ADLs and falls) [38,39].

PAMAP2 dataset includes ADLs collected from nine elderly subjects by placing a heart rate monitor and three inertial sensors on the chest, ankle, and arm [40]. The SBHAR dataset was obtained by collecting six different activities from 30 subjects with a smartphone at the waist position and then updated by including six postural transitions [41]. The mHealth dataset consists of 12 daily activities collected from 10 subjects with ECG and three inertial sensors [42]. MobiAct includes a total of 16 activities including 12 ADLs and four falls collected from 66 subjects using the accelerometer and gyroscope of a mobile phone carried in a trouser pocket [43].

The availability of a recently acquired publicly available dataset on fall and daily activities has accelerated the development of fall-classification systems. The multimodal UP-Fall Detection Dataset [44] comprises data acquired from 11 healthy subjects through the use of multiple wearable sensors, cameras, and context-aware sensors while the subjects perform six types of daily activities and five fall types. Consequently, "2019 Challenge UP — Multimodal Fall Detection" competition was organized [45]. This competition stirred considerable interest in fall-detection studies, examples of which are available in the recently published book [46].

Research conducted by Buber and Guvensan [47] involved eight types of ADLs (biking, running, walking, jumping, stairs up/down, standing, and sitting) collected from five volunteers using the built-in tri-axial accelerometer of a mobile phone placed in the front trouser pocket. A sampling frequency of 20 Hz was used, and activity recognition was performed with six classification algorithms (k-NN, K-Star, Naïve Bayes, Bayes Net, Random Forest - RF, and J48) using 10-fold cross validation. The highest performance value of 94% accuracy was obtained with the k-NN algorithm.

Dernbach et al. [48] conducted a study to recognize simple and complex activities collected from 10 volunteers with the accelerometer and gyroscope sensors of a mobile phone, where the position and the orientation of the mobile phone was left to the choice of the user. Sampling rate was set to 80 Hz. Simple activities (running, walking, sitting, biking, lying, standing, stairs up, and driving) are classified with 93% accuracy, while complex activities are classified with 50% accuracy.

Anjum and Ilyas [49] proposed an approach to recognize seven types of activities (stairs up/down, running, walking, driving, biking, and remaining inactive) collected from 10 volunteers by a smartphone carried in various positions. The sampling rate is set to 15 Hz. Among the SVM, k-NN, C4.5, Naïve Bayes classifiers that were used, C4.5 showed the highest performance with 95.2% accuracy.

Saputri et al. [50] considered six types of activities (running, walking, hopping, stairs up/down, and jogging) collected from 27 subjects with a smartphone at 50 Hz sampling rate placed in the front pocket of the trousers. Artificial neural networks provided 93% accuracy in activity recognition.

Bayat et al. [51] proposed a system for the recognition of six activity types (walking, stairs up/down, slow running, fast running, and aerobic dance) collected from four volunteers by a smartphone. The sampling rate of the system was 100 Hz. A classification accuracy of 91.15% was obtained with a combination of LogitBoost, Multilayer Sensor, and SVM algorithms.

Figueiredo et al. [52] proposed a threshold-based technique for detecting falls with acceleration data from volunteers performing falls (two volunteers) and ADLs (six volunteers). As a result, 100% sensitivity, 93% specificity, and 96.16% accuracy were achieved with SVMs using two-fold cross validation.

Zhao et al. [53] proposed another fall-detection system based on smartphone sensors named as "FallAlarm." The activities considered within the scope of the research are running, walking, and standing stationary while the fall types were: forward, backward, right, and left fall. Among the algorithms used in fall detection, decision trees (DTs) performed better than SVM and Naïve Bayes.

Albert et al. [54] collected acceleration data for four days of activity and fall-like events from 15 volunteers with the accelerometer sensor of the phone set to 20 Hz sampling frequency. Falling and daily activities were classified by testing the cross-validation method and five different classification algorithms (Naïve Bayes, Regularized Logistic Regression (RLR), SVM, DTs, and k-NN).

Kansiz et al. [55] used the accelerometer of a smartphone to collect data on daily activities (jogging, jumping, walking, sitting, standing, and stairs up/down) and falls (forward, backward, sideways, hard and soft falls). The sampling frequency of the accelerometer was set to 20 Hz. Naïve Bayes, DT, and K-Star classification algorithms were considered. It was reported that the highest classification rate was obtained with the K-Star using 10-fold cross validation.

Mehrang et al. [56] investigated activity recognition using a heart rate monitor and a wrist-worn tri-axial accelerometer. In this study, four different activity types (sitting, standing, performing household tasks, and stationary cycling) were performed by 20 male volunteers. The sampling rate of the sensor was 25 Hz. RF and SVM were employed for activity classification with accuracies 89.2% and 85.6% for leave-one-subject-out cross validation, respectively.

Pavey et al. [57] considered four activity types (sedentary, stationary, walking, and running) collected from 21 volunteers with GENEActiv monitor (non-dominant wrist-worn tri-axial accelerometer) at 30 Hz sampling rate. RF provided 80.1%, 95.7%, 91.7%, and 93.7% accuracy for sedentary, stationary, walking, and running, respectively.

Hsu et al. [58] developed an inertial system and an algorithm that recognizes and classifies ADLs based on this system. In the proposed system, motion signals of 10 activity types (walking, running, upstairs, downstairs, stand up and squat, drinking, take elevator, still, sitting, lying) were collected with the inertial module attached to the wrists and ankles of 10 male volunteers. The sampling frequency of the modules was set to 100 Hz. After windowing the acquired data and performing feature extraction and feature reduction using the nonparametric weighted feature extraction (NWFE) algorithm, activities were classified with the probabilistic neural network (PNN) algorithm with 90.5% accuracy.

Sok et al. [59] proposed an approach for detecting changes in patient mobility in motor-impaired patients and informing clinicians. Data were collected for six activity types (lying, sitting, standing, walking, wheeling, and stair climbing) using the actigraph wGT3X tri-axial accelerometer module placed on the waist of 13 ambulator (9M/4F) participants with spinal cord injury. A classification accuracy of 88.9% was obtained using hidden Markov models (HMMs).

Li et al. [60] conducted a study to recognize baseline activities and transition activities from the signal flow obtained from the sensors. The framework of the study consists of the steps of window segmentation, feature construction, cluster analysis for action aggregation with K-Means, activity segmentation and classification, respectively. The proposed method was evaluated on the SBHARPT general dataset (containing the activity types: standing, sitting, lying, walking, walking upstairs, and walking downstairs) general dataset. Six different machine learning techniques (SVM, J48, RF, k-NN, MLP, NB) were used and the highest classification accuracy of 97.34% was achieved with the RF algorithm.

Chen et al. [61] propose a new approach for recognizing activities based on data obtained using smartphone sensors. In the algorithm defined as Ensemble Extreme Learning Machine (EELM), the input weights of the base ELM are initialized using Gaussian Random Projection (GRP). The proposed approach is evaluated on two different datasets consisting of six activity types (walking, walking upstairs, walking downstairs, sitting, standing, laying). When the experimental results were examined, the EELM approach classified the activities in the two datasets with an accuracy of 97.35% [62] and 98.88% [61], respectively.

Chelli and Patzold [63] propose a machine learning framework for the recognition of falls and ADLs. They use acceleration and angular velocity signals to recognize seven activity types (falling, walking, walking upstairs, walking downstairs, sitting, standing, and lying) in two general databases [62,64]. After time-domain and frequency-domain feature extraction from the acquired signals, they evaluate the activity classification performance with k-NN, ANN, Quadratic Support Vector Machine (QSVM), and Ensemble Bagged Tree (EBT) algorithms. With the proposed machine learning framework, k-NN, ANN, QSVM, and EBT algorithms classified activities with 85.8%, 91.8%, 96.1%, and 97.7% accuracy, respectively. Both QSVM and EBT achieved 100% classification accuracy in fall detection.

Hemmatpour et al. [65] investigated fall-detection and prevention systems based on sensors (STMicro STM33DH tri-axial accelerometer and tri-axial gyroscope) integrated into a smartphone. The kinematic features of the fall data (only forward fall) are collected from the sensors with a sampling frequency of 10 Hz and the falls are classified using two machine learning algorithms (DT and SVM). The experimental analysis evaluates fall detection, classification accuracy, and fall avoidance ability of 22 volunteers (19M/3F). The results show that the DT algorithm offers the highest performance in fall detection with 83.9% accuracy.

Hussain et al. [66] proposed a fall-detection approach based on machine learning. The proposed approach used SisFall [67], a publicly available dataset for fall detection that contains 15 types of falls and 19 types of ADLs from 38 subjects. The wearable device, consisting of two accelerometers and a gyroscope, was placed on the waist of the volunteers and the sampling frequency was set to 200 Hz. For fall detection, DT, Logistic Regression (LR), k-NN, and SVM with quadratic kernel function were evaluated. The highest accuracy of 99.98% was achieved with the SVM classifier.

On the upshot, it is important to establish benchmarking standards based on which all these studies can be fairly compared. The use of different classification algorithms in the recognition of falls and ADLs is another important issue for comparing the developed devices [63,68–70]. There exist studies to standardize the movements based on fall vs. ADL (non-fall) and to compare the performance of the different sensor types used [71]. In addition, depending on these standard motion sets, there are also studies to determine the optimal sensor placement for single sensor-based solutions [72,73].

A pertinent issue is the variety of the sensor type combinations used (such as accelerometers, gyroscopes, magnetometers, and barometers) in different studies [29,70,71]. In recent studies, accelerometer data were supplemented by data collected from gyroscopes and magnetometers to improve the classification performance [49,74]. There exist several studies in which a gyroscope is employed by itself or in combination with an accelerometer; for example, in fall detection [75], activity recognition [76], and gait analysis [77]. In [78], an accelerometer and gyroscope are used jointly to detect the intensity of physical activities. In [79], movements of Parkinson and epilepsy disease patients have been analyzed with the same combination. In [80], the effect of the stand-alone use of the magnetometer sensor is examined. Reference [81] describes a study focused on fall-direction classification using all three sensor types. In short, accelerometers are the primary sensors used in the majority of activity recognition and fall-detection studies and most of the relevant information seems to stem from accelerometers. The need for employing additional sensors depends on the variety and complexity of activities to be classified. If the activities are simple and limited in number, for instance, involving just moving and stopping, only an accelerometer may be sufficient to achieve the desired performance level. However, contextual signals may be required if a diverse set of complex activities are to be distinguished. This situation necessitates to test different sensor combinations in activity recognition.

Creating an open dataset according to well-established standards [38,71,82] and conducting research with this dataset allows the research to be comparable with those of others. In the process of creating a dataset, parameters such as the spectrum of activities, variety of subjects, and the number of trials are important. Table 1 presents the parameters and the results of related studies [43–61,63,65,66]. However, heterogeneity in the parameters and the acquired data limits the comparison between different approaches. There is wide variability in the parameters such as the sampling rate, activity types, number of subjects, gender balance, and sensor configuration. We observe in Table 1 that apart from a small number of studies, the diversity of the subjects is low, the variety of the activities is limited, and there is no comprehensive information about the repetition of activities. Very high accuracies can be obtained when a limited number of easily distinguishable activities are performed by a small number of subjects. The same classification performance may not be achieved when unseen subjects are included in the tests or the range of activities is expanded. Some studies focused only on ADLs and did not include falls, which are potentially dangerous events that may occur in between ADLs. None of the studies focused on the contribution of sensors to activity recognition by operating individually or in combination with other sensors within the same study.

In this study, different sensor combinations were tested and the performance of each combination in recognizing falls and ADLs was evaluated through the use of four machine learning algorithms. In addition, participation of equal number of male and female volunteers ensured gender balance and enabled more predictable and realistic results to be obtained.

The approach that we take in this work is a first step towards reducing sensor power consumption and producing sensors/algorithms that can operate in real time through energy harvesting. As a result, the number of sensors in activity recognition devices, power consumption of the module, and the cost of the module can be reduced, and real-time signal processing is simplified. The technical challenge of the study is to bring all of the above-mentioned elements together in a single study and the difficulty of making a fair like-for-like comparison between the different techniques, especially given that this is a fall-detection study. Thus, technical contribution will be provided in the integration of computer-run algorithms with Internet of Things (IoT) technologies due to the high computational volume.

In this study, Simulated Falls and Daily Living Activities Data Set [29,83] acquired from sensor units worn on different body parts of the participants is used. The main motivation for the study is to investigate the classification performances of the sensor type combinations placed at the waist location which is determined to be the best sensor placement position in several studies [72,73]. Four machine learning classifiers are used for this purpose, namely, Support Vector Machine (SVM), Manhattan k-Nearest Neighbor (M.k-NN), Subspace Linear Discriminant Analysis (SLDA), and Ensemble Bagged Decision Tree (EBDT) classifiers. Each method is applied to four sensor type combinations, which are, AGM (accelerometer - gyroscope - magnetometer), AG (accelerometer - gyroscope), AM (accelerometer - magnetometer), and A (accelerometer). With these four sensor type combinations and four machine learning techniques, a total of $4 \times 4 = 16$ different combinations are investigated. This study aims to determine the best sensor type combination as well as the superior machine learning algorithm. To our knowledge, this issue has not been addressed in existing studies. If the best sensor type combination is identified, fall and activity recognition devices can be developed accordingly to achieve more accurate classification results. We have addressed both the binary classification (fall vs. ADL) and the multi-class activity recognition (36 activities) problems.

The rest of this article is organized as follows: In Section 2, the experimental set-up, preprocessing of the acquired data, and the machine learning algorithms used are described. In Section 3, we compare the activity recognition performances of the machine learning algorithms executed by combining the data obtained from different sensor types and discuss the results. In Section 4, we draw conclusions and provide directions for future research.

2. Material and methods

Fig. 1a shows the flowchart and the five basic stages of the study: (1) Preparation of an experimental set-up and the procedure to record the activities of individuals, (2) Collecting data and selecting features, (3) Extraction of useful features from data collected prior to classification, (4) Training the machine learning algorithms selected for activity recognition and fall detection, (5) After training, testing the model obtained and reporting the performance results.

2.1. Experimental set-up

First, the sensor types to be used, their number, and configuration (Fig. 1b) were determined and the experiments for ADLs and falls were designed.

In the experiments, Motion Trackers (MTw) development kit, manufactured by Xsens Technologies, was used [84]. The development kit comprises hardware and software components. The equipment consists of two parts: six MTw sensor units and Awinda Station. Each MTw sensor unit has a tri-axial accelerometer that senses 3D acceleration ($\pm$120 m/s^2), a tri-axial gyroscope that detects 3D angular velocity ($\pm$1200°/s), a tri-axial magnetometer that measures magnetic field in 3D ($\pm$1.5 Gauss), and a barometer that measures atmospheric pressure (300–1100 hPa), the last of which was not used in the experiments. The Awinda Station not only wirelessly collects data from all six MTw units but also charges the units. The MT Manager software package that comes with the MTw Development Kit enables the recording and visualization of data from the sensor units which are analyzed through a graphical interface (Fig. 1b). All sensor units were calibrated, and the sampling frequency was set to 25 Hz. The selection of a suitable sampling rate is important in the recognition of activities and falls. According to [85], the frequency content of human activities ranges between 0 and 20 Hz and 98% of the amplitude with FFT (Fast Fourier Transform) is below 10 Hz. These facts indicate that a sampling frequency of 25 Hz is suitable for our study to avoid extreme power consumption and undersampling.

ADLs and fall actions in our dataset [83] were performed according to the experimental protocol proposed in [82], and the procedure for conducting experiments with human participants was approved by the Erciyes University Ethics Committee (Approval Number 2011/319). Experiments were conducted with 14 volunteers (7M/7F). The age, weight, and height ranges of the female participants were 21.5 $\pm$ 2.5 years, 58.5 $\pm$ 11.5 kg, and 169.5 $\pm$ 12.5 cm, respectively. On the other hand, the corresponding values for the male participants were 24 $\pm$ 3 years, 67.5 $\pm$ 13.5 kg, and 172 $\pm$ 12 cm, respectively.

2.2. Data acquisition

In this study, we employ our previously acquired fall and ADL dataset comprising 2520 (14 volunteers $\times$ 36 activities $\times$ 5 repetitions) records collected from 14 volunteers [83]. The participants

Table 1
Review of the methods and their performance results of the related works for falls and ADLs.

Reference	Dataset	Sensors	Volunteers	Activities	Sampling Rate	Locations	Classifier	Performance
Reiss [40]	PAMAP2	3×A (×2) 3×G 3×M a heart rate monitor	9	18 ADL	100 Hz	chest wrist arm	C4.5 *k*-NN Boosted C4.5 Bagging C4.5 NB	Boosted C4.5: 99.69%
Anguita [41]	SBHAR	3×A 3×G	30	6 ADL	50 Hz	waist	multi-class SVM	multi-class SVM: 96%
Memiş [42]	Mhealth	3×A 3×G 3×M ECG	10	12 ADL	50 Hz	chest right wrist left ankle	SVM *k*-NN NB RF Bagging DT	SVM: 98.4%
Vavoulas [43]	MobiAct	3×A 3×G	66	4 fall 12 ADL	20 Hz	trouser pocket	J48 Logistic regression, MLP *k*-NN	*k*-NN: 97.1%
Buber [47]	not published	3×A	5	7 ADL	20 Hz	front pocket of trouser	J48 *K*-Star BN NB RF *k*-NN	*k*-NN: 94%
Dernbach [48]	not published	3×A 3×G	10	8 ADL	80 Hz	user's choice (position & orientation)	MLP NB BN DT B-FT *K*-star	MLP: 93% 2 s window
Anjum [49]	not published	3×A 3×G GPS	10	7 ADL	15 Hz	hand trouser pocket shirt pocket handbag	NB C4.5 *k*-NN, SVM	C4.5: 95.2%
Saputri [50]	not published	3×A	27	5 ADL	50 Hz	front pocket of trouser	ANN	93%
Bayat [51]	not published	3×A	4	6 ADL	100 Hz	hand	J48 *K*-Star, BN NB RF *k*-NN	MLP & LB & SVM: 91.15% Acc
Figueiredo [52]	not published	3×A 3×G 3×O	8	10 fall 17 ADL	50 Hz 100 Hz	trouser pocket or belt	SVM & threshold algorithms	SVM 96.19%
Zhao [53]	not published	3×A WiFi module	10	74 fall 3 ADL	32 Hz	waist	C 4.5 NB SVM	C 4.5 100% Precision 75.8% Recall
Albert [54]	not published	3×A	15	fall-like events 4 ADL	20 Hz	belt: set position & orientation	C 4.5 NB RLR *k*-NN SVM	RLR: Detection: 98% Classification: 99.6%
Kansiz [55]	not published	3×A	8	104 fall 6 ADL	20 Hz	pocket	J48 *K*-Star NB	*K*-Star average recall: 0.88
Mehrang [56]	not published	3×A a heart rate monitor	20	4 ADL	25 Hz	wrist	RF SVM	RF 89.2% SVM 85.6%
Pavey [57]	not published	3×A	21	4 ADL	30 Hz	wrist	RF	Accuracy: 80.1% (sedentary) 95.7% (stationary) 91.7% (walking) 93.7% (running)
Hsu [58]	not published	3×A 3×G	10	10 ADL	100 Hz	wrist	PNN	90.5% Acc
Sok [59]	not published	3×A	13	6 ADL	-	waist	HMM	88.9% Acc

Table 1 (*continued*)

Reference	Dataset	Sensors	Volunteers	Activities	Sampling Rate	Locations	Classifier	Performance
Li [60]	SBHARPT	3×A 3×G	30	7 ADL	50 Hz	waist	SVM, J48, RF, *k*-NN, MLP, NB	RF 97.34% Acc
Chen [61]	HARUS	3×A 3×G	30	6 ADL	50 Hz	waist	ANN, ELM, SVM, RF, LSTM, EELM	EELM 97.35% Acc
	not published dataset (collected with Huawei P20 Pro)	-	-	6 ADL	-	pants' pocket, shirt's pocket, and backpack.	ANN, ELM, SVM, RF, LSTM, EELM	EELM 98.88% Acc
Chelli [63]	HARUS	3×A 3×G	30	1 fall 6 ADL	50 Hz	waist	*k*-NN, ANN, QSVM, EBT	EBT 96.1% Acc (ADL), QSVM & EBT 100% Acc (fall)
	not published dataset (collected with SHIMMER sensor)	3×A 3×G	30	1 fall 6 ADL	100 Hz	chest and thigh	*k*-NN, ANN, QSVM, EBT	EBT 96.1% Acc (ADLs), QSVM & EBT 100% Acc (fall)
Hemmatpour [65]	not published	3×A 3×G	22	1 fall (forward)	10 Hz	lower back of body near the real Center of Mass	DT	83.9% Acc
Hussain [66]	SisFall	3×A (×2) 3×G		14 fall 19 ADL	200 Hz	waist	DT, LR, *k*-NN, SVM	QSVM 99.98% Acc

B-FT: Best-First Tree, RF: Random Forest, C4.5 DC (WEKA J48), ANN: Artificial Neural Network, C4.5 Decision Tree, DC: Decision Tree, DT: Decision Table, ID3 Decision Tree, *K*-Star, *k*-NN: *k*-Nearest Neighbor, LR: Logistic Regression, RLR: Regularized Logistic Regression, BN: Bayesian Network, MLP: Multi-layer Perceptron, NB: Naïve Bayes, QDA: Quadratic Discriminant Analysis, SVM: Support Vector Machine, PNN: Probabilistic Neural Network, HMM: Hidden Markov Model, LSTM: Long Short Term Memory. In the sensors column, 3×A: tri-axial accelerometer, 3×G: tri-axial gyroscope, 3×M: tri-axial magnetometer, and 3×O: roll, pitch, yaw.

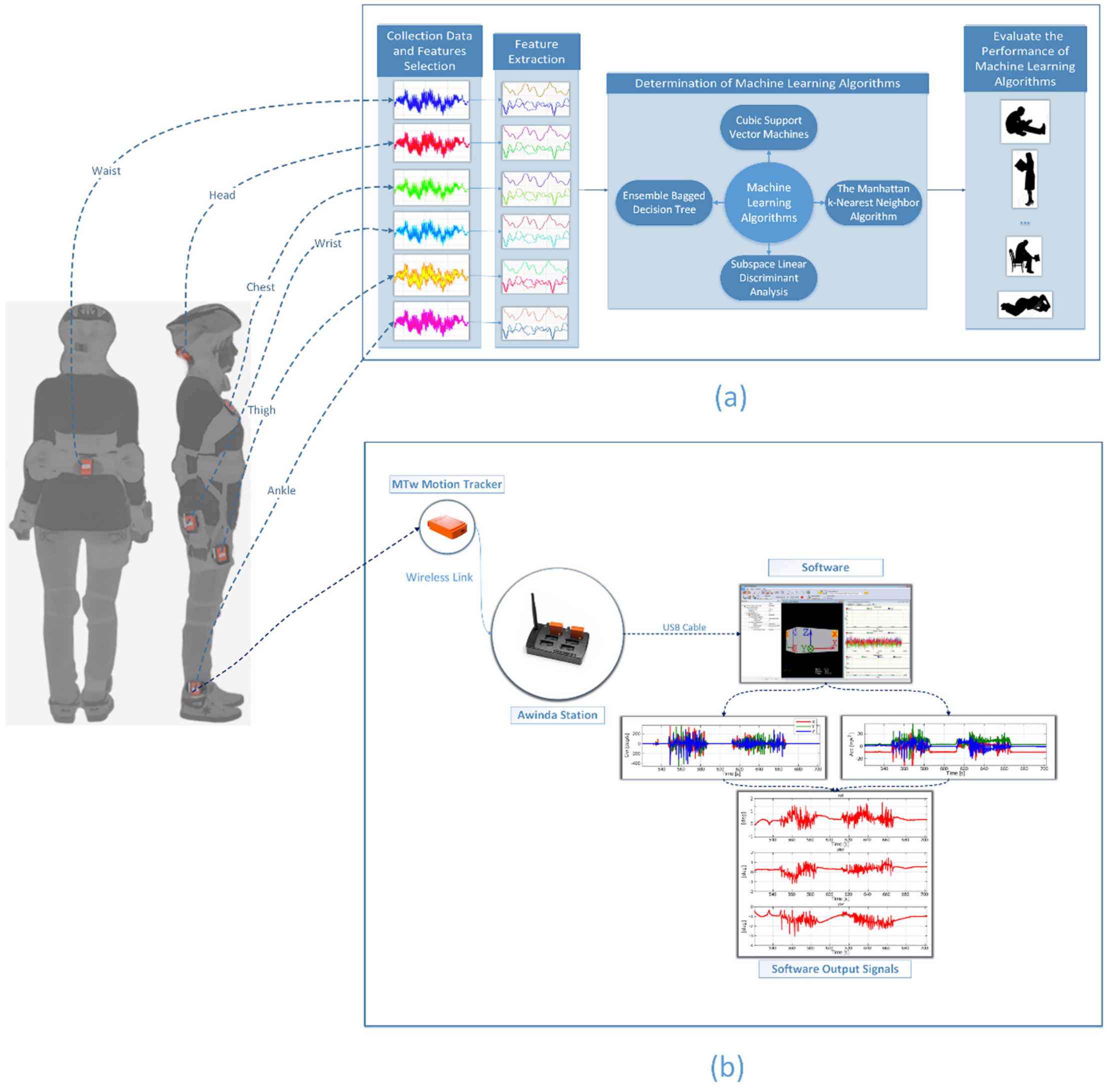

Fig. 1. a) Flowchart of activity recognition. b) The system consisting of MTw sensors and the Awinda station on the body, working phases, and signal acquisition.

performed fall (20 sets) and ADL (16 sets) movements, five repetitions each. The tests were carried out with six sensor units, each with three tri-axial sensors (accelerometer, gyroscope, and magnetometer), affixed to different parts of the volunteers' bodies (head, chest, waist, right wrist, right thigh, and right ankle). Movement types are provided in Table 2.

Many of the ADLs included in the dataset are a subset of real-world ADLs that can easily be confused with falls. As ADLs/falls recorded in the laboratory and those occurring in a natural setting may differ, the mean and peak acceleration values of the recorded voluntary falls were compared with those in [86], where there were some involuntary falls by the elderly, and this comparison is presented in our previous study [29]. As a result, it was observed that the experimental records collected in the study were consistent with the involuntary falls recorded in [86].

In 2014, we developed an automatic fall-detection system with wearable motion sensor units that can be attached to subjects' bodies at six different positions [29].

According to the results obtained in our previous studies in which the MTw sensors were located at the same six positions on the body, we investigated the best sensor placement on the body parts for device ergonomics and to reduce the number of sensor units [72,73]. In both studies, it was observed that the sensor unit in the waist region attained the best activity/fall recognition performance.

Each movement was recorded by the sensor unit at the waist region for a total of 15 s. The peak acceleration value ($A_{\max}$) was detected based on the data collected from the accelerometer:

$$A_{\max} = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{1}$$

To obtain the range of active movement, a two-second time interval was considered before and after the peak acceleration, totaling to a four-second time window, and a total of 101 samples (2-sec $\times$ 25 Hz + 1 sample at the moment of maximum acceleration + 2-sec $\times$ 25 Hz) were taken. The remaining records were not considered. Based on the 101 samples, a 101 $\times$ 9 matrix was constructed using the data from all three axes of the accelerometer, gyroscope, and magnetometer sensors. The structure of the resulting matrix is shown in Fig. 2.

2.3. Feature extraction

Extracted features consist of the minimum, maximum, mean, skewness, kurtosis value, five peaks and five frequency values of the discrete Fourier transform (DFT), and 11 values of the auto-correlation function [37]. Note that the auto-correlation function

Table 2
List of the Activity Types (Falls and ADLs) Considered in the Study.

Experimental ADLs		
#	Label	Description
1	Walking forward	Walking straight forward
2	Walking backward	The opposite of movement 1
3	Jogging slow running	Slow running as athletes do to warm-up
4	Squatting and getting up	Kneeling and getting up again
5	Bending	Bending from the waist to be 90^o
6	Bending and picking	Bending 90^o to pick up an object on the ground
7	Limping	Walking as if one foot is flawed
8	Stumbling	Attached to an object while walking forward to continue walking forward
9	Foot buckling	Pressing the foot for a moment while walking forward and continue to walk forward
10	Coughing	Volunteer coughing or sneezing
11	Sitting on the chair	Volunteer sitting on the floor at the level and comfort of the chair (hard surface)
12	Sitting on the couch	Volunteer sitting on a couch at the level and comfort of the sofa (soft surface)
13	Sitting in the air	Vertical sitting of the volunteer in a squatting position
14	Sitting on the bed	Volunteer sitting vertically on the bed level and comfort (soft surface)
15	Lying bed	Lying vertically to bed
16	Getting up from bed	Moving from lying down to sitting position
Experimental Falls		
#	Label	Description
17	Front lying	Fall forward to the floor
18	Falling forward with protection	Falling forward with the hands protecting himself
19	Falling to knees forward	Falling to knees
20	Falling forward on knees and then reaching out	First, fall on knees and then fall to the floor
21	Rising quickly	Rising quickly after falling to the ground
22	Slow stand-up	Slowly standoff after falling to the ground
23	Right in front	Moving to the right side after falling to the floor forward
24	Left-handed	Move forward to the left after falling to the floor
25	Sitting backwards	Sitting backward on the floor
26	Back lying	Falling backwards onto the ground
27	Right-handed	Right-handed after falling back to the right side
28	Left-handed	Hand-backed after falling back to the left
29	Right-handed	Falling onto the right arm
30	Right-to-side quick-rise	Quickly after falling to the ground on the right arm
31	Side-left	Falling to the ground on the left arm
32	Side-left quick rise	Left-arm quickly fall after falling onto the floor
33	Falling out of bed	Rolling down to the floor while lying in bed
34	Falling from the podium	Slipping as you walk on the podium
35	Fainting	Falling to the ground by fainting
36	Fainting wall	During fainting, it hits the wall and slowly slips off the wall

evaluated at zero lag corresponds to the variance. This makes a total of 26 features for each recording which were calculated using the formulas given below. Thus, a total of 26 values were calculated for each column of the matrix which is represented by an $N \times 1$ vector $d = [d_1, d_2,..., d_N]^T$, where $N = 101$.

$$mean\,(d) : \mu = \frac{1}{N}\sum_{i=1}^{N} d_i \tag{2}$$

$$variance\,(d) : \sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (d_i - \mu)^2 \tag{3}$$

$$skewness(d) = \frac{1}{N\sigma^3}\sum_{i=1}^{N} (d_i - \mu)^3 \tag{4}$$

$$kurtosis(d) = \frac{1}{N\sigma^4}\sum_{i=1}^{N} (d_i - \mu)^4 \tag{5}$$

$$autocorrelation\,(d) :$$

$$R_{ss}\,(\Delta) = \frac{1}{N-\Delta}\sum_{i=0}^{N-\Delta-1} (d_i - \mu)\,(d_{i-\Delta} - \mu) \tag{6}$$

$$\Delta = 0, 1, ..., N-1$$

$$\mathrm{DFT}\,(k) = \sum_{i=0}^{N-1} d_i e^{-\frac{j2\pi ki}{N}} \qquad k = 0, 1, ..., N-1 \tag{7}$$

Table 3
Sensor Type Combinations. Y: Yes, N: No.

Combinations	Accelerometer	Gyroscope	Magnetometer
A	Y	N	N
AG	Y	Y	N
AM	Y	N	Y
AGM	Y	Y	Y

In this study, four combinations of the sensor types available in the MTw sensor unit in the waist area are considered, as shown in Table 3, and the activity classification performance of the combinations are investigated.

When all three axes of a sensor are taken into consideration, the length of the feature vectors extracted for each combination is 234 (26 $\times$ 9) for AGM, 156 (26 $\times$ 6) for AG and AM, and 78 (26 $\times$ 3) for A (Table 4).

2.4. Description of the machine learning algorithms

Machine learning algorithms process and interpret the input data to extract useful information. In this study, features were extracted based on raw data collected through the sensor units which are then used as input to the classifiers. When an algorithm recognizes an activity, the developed model associates the input data with the labeled activity.

We have implemented four state-of-the-art machine learning algorithms to recognize activities and compared the classification

Table 4
Features Extracted from the Data Combinations. Number of Extracted Features (NEF); Total Number of Extracted Features (TNEF).

	min		max		mean		skewness		kurtosis		DFT		autocorrelation	
(a) AGM Data														
TNEF: 234	Ax	1	Ax	1	Ax	1	Ax	1	Ax	1	Ax	10	Ax	11
	Ay	1	Ay	1	Ay	1	Ay	1	Ay	1	Ay	10	Ay	11
	Az	1	Az	1	Az	1	Az	1	Az	1	Az	10	Az	11
	Gx	1	Gx	1	Gx	1	Gx	1	Gx	1	Gx	10	Gx	11
	Gy	1	Gy	1	Gy	1	Gy	1	Gy	1	Gy	10	Gy	11
	Gz	1	Gz	1	Gz	1	Gz	1	Gz	1	Gz	10	Gz	11
	Mx	1	Mx	1	Mx	1	Mx	1	Mx	1	Mx	10	Mx	11
	My	1	My	1	My	1	My	1	My	1	My	10	My	11
	Mz	1	Mz	1	Mz	1	Mz	1	Mz	1	Mz	10	Mz	11
NEF		9		9		9		9		9		90		99
(b) AG Data														
TNEF: 156	Ax	1	Ax	1	Ax	1	Ax	1	Ax	1	Ax	10	Ax	11
	Ay	1	Ay	1	Ay	1	Ay	1	Ay	1	Ay	10	Ay	11
	Az	1	Az	1	Az	1	Az	1	Az	1	Az	10	Az	11
	Gx	1	Gx	1	Gx	1	Gx	1	Gx	1	Gx	10	Gx	11
	Gy	1	Gy	1	Gy	1	Gy	1	Gy	1	Gy	10	Gy	11
	Gz	1	Gz	1	Gz	1	Gz	1	Gz	1	Gz	10	Gz	11
NEF		6		6		6		6		6		60		66
(c) AM Data														
TNEF: 156	Ax	1	Ax	1	Ax	1	Ax	1	Ax	1	Ax	10	Ax	11
	Ay	1	Ay	1	Ay	1	Ay	1	Ay	1	Ay	10	Ay	11
	Az	1	Az	1	Az	1	Az	1	Az	1	Az	10	Az	11
	Mx	1	Mx	1	Mx	1	Mx	1	Mx	1	Mx	10	Mx	11
	My	1	My	1	My	1	My	1	My	1	My	10	My	11
	Mz	1	Mz	1	Mz	1	Mz	1	Mz	1	Mz	10	Mz	11
NEF		6		6		6		6		6		60		66
(d) A Data														
TNEF: 78	Ax	1	Ax	1	Ax	1	Ax	1	Ax	1	Ax	10	Ax	11
	Ay	1	Ay	1	Ay	1	Ay	1	Ay	1	Ay	10	Ay	11
	Az	1	Az	1	Az	1	Az	1	Az	1	Az	10	Az	11
NEF		3		3		3		3		3		30		33

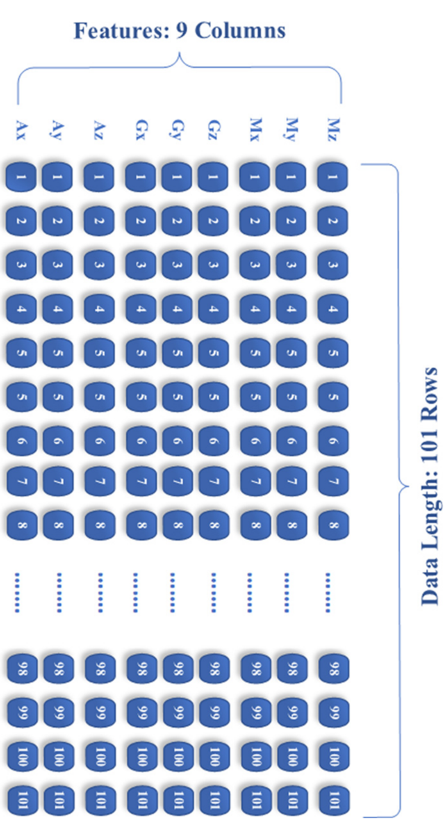

Fig. 2. Structure of the data matrix obtained as a result of preprocessing.

performances of these algorithms using specific metrics. These algorithms are briefly described below.

2.4.1. *Support Vector Machines (SVMs)*

This is a supervised learning algorithm that aims to maximize the width between the support points determined based on the decision boundary [87]. The standard form of SVM is a linear classifier. However, SVM has been developed to make nonlinear classifications by using the kernel method. In this study, the SVM model was tested with three different hyperparameters, namely, the specific kernel types used in the algorithm ('linear', 'poly', 'rbf', and 'sigmoid'), the value of the regulation parameter C (0.1, 0.3, 0.5, 0.7, 0.9, 1.0, 1.3, 1.5, 1.7, 2.0), and the degree of the polynomial kernel function 'poly' (2, 3, 4, 5). SVM model shows the best performance for binary and multi-class activity recognition with $C = 1$, 'linear' kernel type with sensor type combination AM, and $C = 0.1$, 'linear' kernel type with sensor type combination AGM, respectively.

2.4.2. *The Manhattan k-Nearest Neighbor Classifier (M.k-NN)*

In the k-nearest neighbor algorithm, the object to be classified is assigned to the class of the nearest neighbor according to the feature values [88]. This is done by calculating the distance to assign a new sample from the test data to similar samples clustered in the training data. Since the number of neighbors involved in the classification is indicated by the integer-valued parameter k, the algorithm is called the k-nearest neighbor algorithm. Determining a suitable value for the k parameter is important for successful performance of the algorithm. Employing small values of k increases the variance but reduces the stability of the results. If larger k values are used, increased bias and reduced sensitivity are obtained. In this study, Manhattan distance is used as the distance metric. The mathematical formula $D(\boldsymbol{x}, \boldsymbol{y}) = \sum_{i=1}^{m} |x_i - y_i|$ for calculating the Manhattan distance between two feature vectors ($\boldsymbol{x}$, $\boldsymbol{y}$) in m-dimensional space is the sum of the absolute distances between the elements of the two feature vectors in each dimension. The k parameter values of 1,3,5,7,9,11,13,15 have been tested and the best result was obtained with the value of $k = 1$ in all sensor type combinations. Therefore, a test sample is assigned to the same class as its nearest neighbor.

2.4.3. Linear Discriminant Analysis (LDA)

Linear discriminant analysis (LDA) is a multi-variate statistical analysis method used to define and classify sample clusters. The LDA allows multiple continuous arguments to be separated linearly according to a categorically dependent variable considered as a data class. This ensures that the distance between classes increases as much as possible while minimizing the distance between members of each class [89]. Initially, it was possible to use LDA only for binary classification, but with the advancements in computing power and technology, it is currently possible to classify more than two categories.

2.4.4. Decision Trees (DTs)

Decision Trees are hierarchical and nonparametric classifiers commonly used in data classification, also known as classification and regression trees [88]. A DT, like real tree, consists of roots, branches, and leaves. However, unlike a real tree, there are root node, leafy or leafless internal node, and leaf node parts where the DT gives the final classification results. After the model has been trained, starting from the root node, the data sequence is split in each hierarchy according to a classification rule (IF-THEN rule). Depending on the structure of the DT, the division can be binary, tertiary, or multiple. After performing the entire division process, the model classifies an activity as a fall or an ADL.

2.4.5. Ensemble classifiers

The main motivation to use an ensemble classifier, which is a combination of different classification algorithms, is to achieve improved classification performance [88]. Different methods such as boosting, bagging, voting, and subspacing have been developed to use multiple classifiers at the same time.

DTs are known to suffer from the bias-variance trade-off. There is a large bias with simple trees and a large variance with complex trees. Ensemble methods combine several DTs to produce better predictive performance than utilizing a single DT. The main principle behind the ensemble model is that a group of weak learners' function together to form a strong learner.

Bagging and boosting are the ensemble methods developed first. In these methods, many models are built in order to prevent the classifier from memorizing data and reducing variance. In the bagging method, this involves taking a number of samples from the dataset to be used to train the models and training a model for each of these samples. The final prediction is obtained by averaging the predictions acquired from all trained models. In the boosting method, new models are obtained which learn to fix the prediction errors of the built models. Each of the built models makes predictions that can be weighted according to the sensitivity ratios, and the resulting predictions are combined to determine the final prediction. In both of these approaches, the final classifier is determined as the one that collects the most votes from the DTs obtained during the sampling of many models. While the same type of models are built in bagging and boosting methods, different types of models are employed in the voting procedure. In addition, various statistical methods are used in the voting method to combine the predictions obtained from the models. Subspace learning techniques have a significant role, especially with the LDA scheme that engaged to determine a specific discriminant subspace of low dimension [90]. This method attempts to reduce the correlation between estimators in an ensemble by training them on random samples of features instead of the entire feature set.

In this study, the following two ensemble classifiers are examined:

Subspace Linear Discriminant Analysis (SLDA): The parameters of this algorithm are the number of learners $n = 10, 50, 100, 500, 1000, 1500$, subspace dimension $= 2$, and the number of features (max features) to draw from X input variables to train each base estimator (10, 20, 30, 40, 50). The best result was obtained with the parameter values $n = 10$, max features=50 for binary classification and $n = 500$ and max features=50 for multi-class activity recognition, in both cases with the sensor type combination AM.

Ensemble Bagged Decision Tree (EBDT): Number of learners (n) of EBDT tried were also $n = 10, 50, 100, 500, 1000, 1500$. The best result was obtained with the value of $n = 500$ for binary classification with sensor type combinations AGM, AM, and with $n = 1500$ for multi-class activity recognition with sensor type combination AGM.

2.5. Evaluating the performance of machine learning algorithms

Selection of the performance evaluation criteria is critical in assessing how well the machine learning algorithms classify. The selected metrics affect how the performances of the algorithms are evaluated and how comparisons are made. One of the best ways to evaluate the classification performance of the developed model is to classify data that have not been encountered before (unseen data), with known class labels.

In this study, Repeated Random Sub-Sampling (RRSS) cross-validation technique was used to assess the classification performance with less variability [91]. In this method, the data are randomly partitioned into two independent clusters: a training set and a test set. The former is used to improve the model, while the latter is used to verify the accuracy of the model. The dataset can be partitioned into the training and test sets in different ways by the user. The random partitioning of the data can be repeated arbitrarily often. The final classification accuracy is calculated by averaging the accuracy value obtained at each repetition. In this study, the dataset is randomly split into $m = 10$ equal partitions and RRSS is applied. The training set consists of $m - 1$ partitions and the remaining partition is used as the test (validation) set. The random partitioning is repeated 10 times and the resulting accuracies are averaged out. Thus, every record gets a chance to be verified.

One of the most commonly used criteria for evaluating classification performance of algorithms is the *accuracy* performance metric which is a measure of the proportion of correct classifications in all cases examined. This criterion, which is a statistical quantity, is calculated by means of a confusion matrix, which also serves to assess performance. In binary classification, the accuracy criterion is calculated as follows:

$$Accuracy\ (Acc) = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \times 100 \tag{8}$$

In the equation, T_n indicates the negative samples that are correctly classified, T_p represents the positive samples that are correctly classified, F_p indicates the negative samples that are misclassified as positive, and F_n denotes the positive samples that are misclassified as negative. To summarize, the symbols in binary classification (fall/ADL) are:

T_p: true positive; actually fall, classification correct
T_n: true negative; actually ADL, classification correct
F_p: false positive; actually ADL, misclassification as a fall
F_n: false negative; actually fall, misclassification as an ADL

Table 5
Comparison of the Binary (Fall/ADL) Classification Performance of the Four Machine Learning Algorithms with Data from Four Sensor Type Combinations.

(a) SVM	AGM		AG		AM		A	
	Confusion Matrices							
	Classified Fall	Classified ADL	Classified Fall	Classified ADL	Classified Fall	Classified ADL	Classified Fall	Classified ADL
Actually Fall	1399	1	1399	1	1400	0	1399	1
Actually ADL	1	1119	2	1118	1	1119	1	1119
Acc (%)	99.92		99.88		99.96		99.92	
Se (%)	99.92		99.92		100		99.92	
Sp (%)	99.91		99.82		99.92		99.91	
(b) EBDT	AGM		AG		AM		A	
	Confusion Matrices							
	Classified Fall	Classified ADL	Classified Fall	Classified ADL	Classified Fall	Classified ADL	Classified Fall	Classified ADL
Actually Fall	1395	5	1392	8	1395	5	1393	7
Actually ADL	7	1113	9	1111	7	1113	6	1114
Acc (%)	99.52		99.32		99.52		99.48	
Se (%)	99.64		99.42		99.64		99.50	
Sp (%)	99.37		99.19		99.37		99.46	
(c) SLDA	AGM		AG		AM		A	
	Confusion Matrices							
	Classified Fall	Classified ADL	Classified Fall	Classified ADL	Classified Fall	Classified ADL	Classified Fall	Classified ADL
Actually Fall	1389	11	1386	14	1394	6	1390	10
Actually ADL	16	1104	17	1103	16	1104	15	1105
Acc (%)	98.92		98.76		99.12		99.00	
Se (%)	99.21		99.00		99.57		99.28	
Sp (%)	98.57		98.48		98.57		98.66	
(d) M.*k*-NN	AGM		AG		AM		A	
	Confusion Matrices							
	Classified Fall	Classified ADL	Classified Fall	Classified ADL	Classified Fall	Classified ADL	Classified Fall	Classified ADL
Actually Fall	1399	1	1398	2	1399	1	1398	2
Actually ADL	1	1119	3	1117	2	1118	1	1119
Acc (%)	99.92		99.80		99.88		99.88	
Se (%)	99.92		99.85		99.92		99.85	
Sp (%)	99.91		99.73		99.82		99.91	

Besides the accuracy measure, other commonly used criteria for performance evaluation are *sensitivity* and *specificity* measures.

Sensitivity (Se) shows the proportion of correctly classified falls in all positive samples:

$$Sensitivity\,(Se) = \frac{T_p}{T_p + F_n} \times 100 \tag{9}$$

Specificity (Sp) represents the proportion of correctly classified falls in all negative samples:

$$Specificity\,(Sp) = \frac{T_n}{T_n + F_p} \times 100 \tag{10}$$

3. Results and discussion

3.1. Confusion matrices

3.1.1. Confusion matrices with binary classification

ADLs and falls were classified through binary classification, employing four state-of-the-art machine learning algorithms and data from the four sensor type combinations. Accuracy, sensitivity, and specificity performance metrics were calculated to analyze the classification performance and the results are presented in Table 5. Among the four classifiers, the highest accuracy was obtained with SVM. Accuracies for the AGM, AG, AM, and A sensor type combinations are 99.92%, 99.88%, 99.96%, 99.92%, respectively, the highest (99.96%) being obtained with the AM sensor type combination.

3.1.2. Confusion matrices for the classification of multiple classes (36 activities)

In the multi-class activity recognition problem, data belonging to 36 activities for each sensor type combination (AGM, AG, AM, A) were classified with the four machine learning algorithms and confusion matrices were obtained in order to observe the performance of these algorithms for each activity. In Table 6, we present the performance of the M.*k*-NN on the AM data, reflected as a confusion matrix for the 36 activities. The first column of the table lists the actual (true) activities while the first row indicates the classified activities. The values along the diagonal of the confusion matrix correspond to the number of correctly classified activities,

Table 6
Representation of the Classification Results of 36 Activities with Confusion Matrix on AM Data Format by Using M.*k*-NN Algorithm.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
1	57	0	0	0	0	0	12	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
4	0	0	0	65	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	1	1	68	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	10	0	0	0	0	0	57	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	69	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	1	0	0	0	0	0	4	9	56	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	1	0	0	0	0	0	0	69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	2	0	0	0	0	0	0	0	0	68	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	66	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	65	3	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	62	0	0	0	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	67	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0	1	61	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	2	60	1	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	5	63	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	69	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	67	0	1	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	69	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	67	3	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	68	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	68	1	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	66	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	68	0	0	1
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	68	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	69	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70

Table 7
Comparison of the Multi-Class (36 Activities) Activity Recognition Performance of the Four Machine Learning Algorithms with Data from Four Sensor Type Combinations.

	AGM	AG	AM	A
Classifier	mean ± std (%)			
SVM	93.49 ± 1.75	92.46 ± 1.83	91.98 ± 1.78	92.77 ± 1.28
EBDT	93.80 ± 1.20	93.69 ± 1.23	93.61 ± 1.39	93.05 ± 1.46
SLDA	83.41 ± 2.57	83.25 ± 2.44	85.07 ± 2.11	84.96 ± 1.85
M.*k*-NN	92.46 ± 1.53	89.99 ± 1.76	95.27 ± 1.41	93.96 ± 1.63

and the non-zero values on the off diagonals indicate the number of incorrectly classified activities. The link for the classification performance of the 36 activities for the other three algorithms is shared for researchers to review.

3.2. Performance ratios of classification

Accuracy values for each of the four sensor type combinations were calculated and examined and the classifier with the highest accuracy rate was identified for that particular sensor type combination. The following mean and standard deviation (std) values were obtained based on 10 repetitions of RRSS (Table 7).

When the classification performances of the algorithms for the 36 activities are examined in Table 7, using M.k-NN (where $k = 1$), accuracy rates obtained using AGM, AG, AM, and A sensor type combinations are 92.46%, 89.99%, 95.27%, and 93.96%, respectively. Note that the highest accuracy of 95.27% is obtained with the AM sensor type combination and the M.k-NN classifier.

3.3. Classifier decision processing time

In this study, preprocessing and classification operations were performed using Python version 3.6 on a laptop computer with 2.60 GHz octa-core 64-bit Intel Core i7 processor, 16 GB of RAM, and 64-bit Microsoft Windows 10 Home operating system.

Tables 8 and 9 display the mean and the standard deviation values obtained over the 10 repetitions of the classification algorithms, respectively. In these tables, we compare the calculation requirements of the four machine learning algorithms according to the sensor type combination for both binary and multi-class activity recognition problems in terms of the training and test times required on the dataset. In terms of the training time, algorithms with the highest and lowest computation time in binary classification are EBDT with the sensor type combination AG and M.k-NN with the sensor type combination A, respectively. In multi-class activity recognition, algorithms with the highest and lowest computation time are EBDT with the sensor type combination AGM and M.k-NN with the sensor type combination A, respectively. In terms of the test time, algorithms with the highest and lowest computation time in binary classification are EBDT with the sensor type combination A and both SVM and SLDA with the sensor type combination AM, respectively. In the multi-class problem, algorithms with the highest and lowest computation time are SLDA with the sensor type combination AG and M.k-NN with the sensor type combination AM, respectively.

3.3.1. Training Time

Table 8
Training Time of the Data Combinations for Binary and Multi-Class Activity Recognition (36 Activities).

	Binary Classification (Fall/ADL)			
	AGM	AG	AM	A
Classifier	mean ± std (sec)			
SVM	0.636 ± 0.188	0.166 ± 0.128	0.092 ± 0.005	0.117 ± 0.091
EBDT	516.9 ± 78.07	599.5 ± 83.89	41.75 ± 18.17	580.4 ± 89.38
SLDA	0.358 ± 0.009	20.68 ± 2.832	0.351 ± 0.013	4.172 ± 3.842
M.*k*-NN	0.173 ± 0.008	0.261 ± 0.082	0.209 ± 0.059	0.057 ± 0.004
	Multi-Class Activity Recognition (36 Activities)			
	AGM	AG	AM	A
Classifier	mean ± std (sec)			
SVM	1.465 ± 0.801	0.505 ± 0.218	0.917 ± 0.587	0.597 ± 0.487
EBDT	1222 ± 100.3	292.2 ± 17.79	572.6 ± 29.01	237.9 ± 35.04
SLDA	13.86 ± 8.176	195.7 ± 63.39	68.97 ± 35.20	63.27 ± 15.67
M.*k*-NN	1.073 ± 0.112	0.631 ± 0.277	0.443 ± 0.190	0.183 ± 0.102

3.3.2. Testing Time

Table 9
Testing Time of the Data Combinations for Binary and Multi-Class Activity Recognition (36 Activities).

	Binary Classification (Fall/ADL)			
	AGM	AG	AM	A
Classifier	mean ± std (sec)			
SVM	0.062 ± 0.088	0.004 ± 0.001	0.003 ± 0.001	0.007 ± 0.001
EBDT	0.702 ± 0.677	1.054 ± 1.001	0.093 ± 0.088	1.575 ± 1.120
SLDA	0.004 ± 0.001	0.126 ± 0.084	0.003 ± 0.001	0.028 ± 0.049
M.*k*-NN	0.317 ± 0.009	0.327 ± 0.099	0.408 ± 0.191	0.107 ± 0.007
	Multi-Class Activity Recognition (36 Activities)			
	AGM	AG	AM	A
Classifier	mean ± std (sec)			
SVM	0.479 ± 0.265	0.143 ± 0.071	0.254 ± 0.158	0.133 ± 0.110
EBDT	1.004 ± 0.379	0.392 ± 0.171	0.531 ± 0.067	0.401 ± 0.193
SLDA	0.270 ± 0.163	2.945 ± 2.134	1.346 ± 0.821	0.909 ± 0.241
M.*k*-NN	1.950 ± 0.137	0.727 ± 0.354	0.063 ± 0.010	1.015 ± 0.402

4. Conclusions

In this study, the effects of four sensor type combinations of a sensor unit affixed to the waist region of the human body were analyzed using four state-of-the-art machine learning algorithms. According to the results of the analysis, when all sensor type combinations are evaluated, successful results are obtained in the classification of falls and ADLs.

When examined in terms of binary classification (fall vs. ADL), sensor type combinations, and classification algorithms, the sensor type A by itself attains a high classification rate in general. In addition, it is observed that better results are obtained with the sensor type combination AM in classification with SVMs. Due to these high accuracy rates and small proportional differences in binary classification, we can state that it is difficult to draw a general conclusion about the effect of the sensor type combinations on binary classification. However, in the multi-class problem of classifying 36 activities, we can see the effect of sensor type combinations on the classification performance based on the accuracy rates. As the number of sensor types included in the combinations is reduced, the classification accuracies become lower, as expected. A similar conclusion can be drawn for the training and testing time requirements of the machine learning algorithms in sensor type combinations.

The selected classifiers are considered successful in distinguishing falls and ADLs with high levels of accuracy. New experiments and data collection procedures are planned for future studies to extend this study in different directions. Accuracy is expected to fall down as the amount and variability of the data increase. Although the size of the dataset is not investigated in this study, it is necessary to enlarge it further to examine the stability of the model and the effects of the parameters. It can be done by identifying different attributes to increase the accuracy rates degrading with increasing data size. It is envisaged to be stored in a cloud-like environment to ensure that it is easily accessible by other researchers at any time to conduct further studies.

To improve the accuracy and stability of the model in future studies, changes can be made to the partitioning of the dataset to select training and test datasets differently and other cross-validation techniques such as P-fold or leave-one-subject-out may be employed instead of RRSS.

Through this study, we examine the effect of different sensor type combinations. Thus, by reducing the number of sensors, we are taking the first step in the development of a system that is lighter, has a long battery life, and is less expensive, allowing the ease of wearability. In the future, we plan to examine which axes of which sensor types are essential for fall detection. In cooperation with some companies, we aim to design a self-powered device with body-energy harvesting capability, easily integrated with other systems, and most importantly, with high sensitivity and lower cost. Thus, hardware design constraints will be minimized. In addition, in traditional methods, analyzing the raw data of each new dataset or sensor type and extracting the features suitable for the model will require signal processing and domain expertise. This is not a scalable approach. For this reason, in our ongoing study, the activity recognition performance of deep learning techniques that can adapt to new dataset and sensor types quickly by automatically extracting features from raw data are being evaluated to eliminate software-related limitations. In fall detection, it is crucial to reach emergency assistance directly by the systems communicating among themselves without the user having to do anything. As the movements can be predicted accurately, reporting methods can be used to provide the necessary information to other devices that the users in the fall risk group carry or to remote points. This can be achieved by the communication of the sensor units through IoT technology [92,93].

CRediT authorship contribution statement

Erhan Kavuncuoğlu implemented the machine learning classifiers and contributed to the writing and editing of the manuscript. Esma Uzunhisarcıklı reviewed the manuscript and made suggestions for correction. Billur Barshan contributed significantly to the writing and organization of the manuscript. Ahmet Turan Özdemir supervised the study, coordinated the experiments, analyzed the experimental data, made suggestions on machine learning techniques, and made contributions to the writing and editing of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and material

Availability of data and material: The dataset used in the work is shared as open source from the link below. (https://archive.ics.uci.edu/ml/datasets/Simulated+Falls+and+Daily+Living+Activities+Data+Set).

The classification performance of the 36 activities for other algorithms is shared at the link below for researchers to review. (https://drive.google.com/drive/folders/18j49fN7o-GAhrGKRhwyveIOVYCPKBfsC?usp=sharing).

Code availability

Not applicable.

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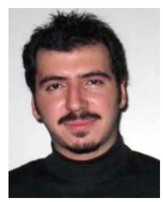

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