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Review

# Human activity recognition with smartphone-integrated sensors: A survey

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A R T I C L E I N F O

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A B S T R A C T

*Human Activity Recognition (HAR)* is an essential area of research related to the ability of smartphones to retrieve information through embedded sensors and recognize the activity that humans are performing. Researchers have recognized people's activities by processing the data received from the sensors with Machine Learning Models. This work is intended to be a hands-on survey with practical's tables capable of guiding the reader through the sensors used in modern smartphones and highly cited developed machine learning models that perform human activity recognition. Several papers in the literature have been studied, paying attention to the preprocessing, feature extraction, feature selection, and classification techniques of the HAR system. In addition, several summary tables illustrating HAR approaches have been provided: most popular human activities in the literature with paper references, the most popular datasets available for download (*Analyzing their characteristics, such as the number of subjects involved, the activities recorded, and the sensors with online-availability*), *co-occurrences between activities and sensors, and a summary table showing the performance obtained by researchers*. =The paper's goal is to recommend, through the discussion phase and thanks to the tables, the current state of the art on this topic.

## 1. Introduction

*Human Activity Recognition (HAR)* identifies physical activities performed by a physical person by analyzing signals recorded by digital devices. Thanks to the recent spread of the *Internet of Things (IoT)*, it has become increasingly common to adopt HAR to recognize activities of daily living. Some examples of activities could be sitting, standing, climbing stairs, and walking. Detecting such activities has numerous applications ranging from neurological disease progression analysis to gaming and many more. Smartphones have many sensors which could be used to detect activities: accelerometer, gyroscope, magnetometer, and so on. The combination of them could lead to activity recognition through a common smartphone (Vyas et al., 2017).

Several assumptions and hypotheses shall be considered when designing a Human Activity Recognition (HAR) system: Advances in traditional recognition methods have successfully focused on finding meaningful information from raw data. However, the main challenge is that HAR models demonstrate effectiveness primarily in controlled environments and for specific tasks. As a result, performance in complex HAR tasks depends on the Feature Extraction techniques adopted and the limitations of domain knowledge. In this context, no direct and unambiguous solutions emerge to infer human actions from sensory information in a general way. The scientific literature presents varied choices for experimental settings, data types, tasks, and sensors. Moreover, data from such sensors incorporate intrinsic elements such as the temporal nature of the data, storage, and so on. Conducting a specific survey on human activity recognition using smartphones is imperative. This investigation provides the reader with a direct and practical approach to building a robust HAR system. The main idea is also to provide a detailed study plan, especially for people who are inept in this domain.

The survey focuses strongly on Human Activity Recognition approaches using smartphones that provide the reader with a direct, practical, and easy-to-understand approach to building a robust HAR system. In addition, smartphone sensors were studied in more detail to understand their potential applications, thus finding the optimal configuration. These aspects are fundamental to building a HAR system. This investigation also aims to conduct an in-depth study of HAR architectures using standard machine learning (also known as *Shallow Learning*) and *Deep Learning* techniques. The main innovation, besides the careful structuring of the paper, is the composition of several summary tables that can be used to guide the approach and for quick

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reference by the reader:

1. *Activities found in Literature with the corresponding reference in* Table 4: This table collects scientific papers from the past five years and groups the scientific papers that specifically addressed them by HAR activities. Readers who want to study only one activity could consult the included references. In addition, the histogram below the table has also been added for quick understanding.
2. *Co-occurrences between activities and sensors found in Literature with the corresponding reference in* Table 5: This *table* collects the scientific papers from the last five years and groups not only the activities from the previous work but also the sensors better to detail the search for the correct literature reference. In addition, the histogram below the table has also been added for quick understanding. This table is helpful to emphasize our detailed analysis of the sensors. In addition, for quick understanding, the histogram below the table has also been added.
3. *Summary and comparison among the different datasets found in Literature in* Table 6: This table collects the scientific *datasets* of the last five years inherent to HAR models and makes a careful analysis of them considering several characteristics, namely: *Name of Devices, Number of users, Sensor, Activities, Laboratory/Real, Raw data/pre-processed, Availability*. The table promotes quick readability of the essential features and convenience in finding the suitable dataset and downloading it simultaneously from the link.
4. *Summary of the experimentation settings with performance scores found in the Literature in* Table 7: This *table* collects scientific papers from the last five years and summarizes their performance. The table favors the choice of the dataset to the model used to favor better performance. In addition, for quick understanding, the histogram below (Fig. 4) that analyzes the contrast of using Shallow/Deep models in HAR approaches has also been added.

**Table 1**
Surveys on HAR methods.

| Ref. | Description |
|---|---|
| (Vyas et al., 2017) | It covers smartphone sensors, sampling rate, location, and orientation. Furthermore, the study focuses on the recognition of the number of activities. Additionally, different classification methods used for the recognition process are evaluated. Finally, the various challenges and facets of these studies are discussed. |
| (Slim et al., 2019) | The authors examined state of the art in recognizing human activity based on acceleration components. The online and offline activity recognition systems, traditional machine learning algorithms, and Deep Learning have been defined. Forty-eight studies qualitatively compare activities, devices used, learning patterns, datasets, and recognition accuracy. Finally, the different challenges and problems of these studies are discussed. |
| (Gupta et al., 2020) | This work includes three popular methods of activity recognition, namely HAR using pose estimation (vision-based), smartphone sensors, and wearable sensors. The pros and cons of the technologies are also discussed by considering a comparison of their accuracy. |
| (Thakur & Biswas, 2020) | It summarizes recognizing human physical activity from mobile phone sensors. The analysis is based on three parameters: human activity, smartphone position, location, and classification method. The accuracy of the other classification methods for various activities is compared. The limitations of the different classifiers are also discussed. Finally, real applications enabled by activity recognition are introduced. |
| (KH & Ibrahim, 2021) | The authors compared HAR works between 2010 and 2020 with smartphone sensors. The comparison charts highlight: the type of sensor used, the activities, the positioning of the sensor, the type of HAR system (offline, online), the processing device, the classifier (variety of algorithms), and the levels of system accuracy. |

The selected surveys in Table 1 did not go into all these aspects, especially the survey tables analyzed and viewed above. Finally, a careful discussion of relevant results is provided to advise the reader to use suitable models, datasets, and tips to create an optimal HAR system.

The organization of the work is the following: Chapter 2 describes sensors present in smartphones and used for HAR. Chapter 3 explains various architectures for HAR: It starts by explaining the different pre-processing techniques and feature extraction, feature selection, and classification. Chapter 4 illustrates summary tables on human activities, datasets, and performance on various state-of-the-art works. Chapter 5 provides Discussions and observations concerning the design and technology choices to address the problem. Chapter 6 contains the most used applications of a HAR system, and Chapter 7 sketches conclusions and final considerations.

## 2. Smartphone sensors

Smartphones have a variety of sensors, including GPS, Accelerometers, Gyroscopes, Magnetometers, Proximity Sensors, Brightness Sensors, and more, all of which have specific uses:

- *Accelerometer*: Recognizes changes in position. They are often found in electronic gadgets, essential for screen orientation, and not mainly made for very accurate activity recognition.
- *Gyroscope*: Tracks motions of a smartphone in three dimensions. Flipping the gadget over will silence calls, among other phone functions like gaming and navigation.
- *Magnetometer*: This device is mainly used to determine cardinal directions. Combined with accelerometers, they can operate as a compass and find substantial metallic objects.
- *Proximity Sensor*: Uses electromagnetic fields to detect adjacent objects without making contact. It is essential for preventing unintentional screen touches when on the phone and may be used to recognize hand gestures.
- *Brightness Sensor*: Adjusts screen brightness by detecting ambient light. It can offer the best possible screen viewing while preserving battery life. They are sometimes used in smart homes to change the illumination based on the surroundings.
- *GPS Receiver*: This device receives satellite signals and uses them to pinpoint its location. Useful for tracking, navigation, and location-based suggestions.
- *Other Sensors*: Smartphones come with various other sensors, including thermometers, fingerprint scanners, NFC, and others, but not all are useful for activity identification jobs. The most extensively used sensors in contemporary smartphones are the topic of this overview.

**Table 2**
Data description of the sensors found in the Literature.

| Sensor Name | Data Description | Unit of Measurement |
|---|---|---|
| Accelerometer | x, y, z axis | $m/s^2$ |
| Gyroscope | x, y, z axis | $rad/s$ |
| Magnetometer | x, y, z axis | $\mu T$ |
| Proximity Sensor | Distance from object | $cm$ |
| Brightness Sensor | Illuminance intensity | $lux$ |
| GPS receiver | Estimated Location Accuracy | $m$ |
| | Time in UTC concerning the position found | $ms$ |
| | Latitude detected | *degrees* |
| | Longitude detected | *degrees* |

**Table 3**
References analyzed in the Classification Phase.

| Classification Model | References |
|---|---|
| J48 | (Hnoohom et al., 2017), (Catal et al., 2015), (Wannenburg & Malekian, 2017), (Micucci et al., 2017) |
| Random Forest | (Bayat et al., 2014), (Xu et al., 2018), (Attal et al., 2015), (Micucci et al., 2017) |
| Support Vector Machines | (Bayat et al., 2014), (Abdull Sukor et al., 2018), (Wan et al., 2020), (Jain & Kanhangad, 2018), (Wannenburg & Malekian, 2017), (Attal et al., 2015), (Akhavian & Behzadan, 2016), (Micucci et al., 2017) |
| K-Nearest Neighbors | (Jain & Kanhangad, 2018), (Ignatov & Strijov, 2015), (Wannenburg & Malekian, 2017), (Attal et al., 2015), (Akhavian & Behzadan, 2016), (Micucci et al., 2017) |
| Naïve Bayes | (Wang et al., 2016), (Rodrigues & Mestria, 2016), (Wannenburg & Malekian, 2017) |
| Logistic Regression | (Catal et al., 2015), (Akhavian & Behzadan, 2016) |
| Gaussian Mixture Models | (Attal et al., 2015) |
| Hidden Markov Models | (Kim et al., 2016), (Zhang, 2015), (Attal et al., 2015), (Ronao & Cho, 2017), (San-Segundo et al., 2018) |
| Convolutional Neural Network | (Zeng et al., 2014), (Chen & Xue, 2015), (Almaslukh et al., 2018), (Panwar et al., 2017), (Ha & Choi, 2016), (Wan et al., 2020), (Yao et al., 2017), (Xu et al., 2018), (Mario, 2019), (Lee et al., 2017), (Jordao et al., 2018), (Ignatov, 2018), (Zhou et al., 2019), (Matsui et al., 2017). |
| Long Short-Term Memory | (Wan et al., 2020), (San-Segundo et al., 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Yu & Qin, 2018), (Chen et al., 2017), (Tao et al., 2016), (Milenkoski et al., 2018) |
| Multi-Layer Perceptron | (Nweke et al., 2019), (Abdull Sukor et al., 2018), (Bayat et al., 2014), (Wannenburg & Malekian, 2017), (Catal et al., 2015), (Wan et al., 2020), (Rodrigues & Mestria, 2016), (Ogbuabor & La, 2018), (Voicu et al., 2019), (Pires et al., 2020) |

### 2.1. Other sensors

A modern smartphone can have many other sensors, such as a thermometer, fingerprint sensor, NFC, barometer, heart rate monitor, pedometer, and humidity sensor. However, given the purpose of this work, there are two main reasons why should have focused on these sensors. First, sensors such as fingerprints and NFC are not helpful for activity recognition tasks. There is no example of the use of these sensors in the literature. Secondly, focusing on the most common sensors embedded in modern smartphones is essential. We need to get sensor data from different devices and ensure that the selected sensors are widely adopted in modern smartphones. Table 2 summarizes the previously explained sensors and reports the measurement units typically adopted. Table 2 summarizes the previously explained sensors, reporting the measure units typically adopted.Table 3.

## 3. Architecture of a HAR system

A HAR system's architecture comprises three main components: Data Acquisition, Features Engineering, and Classification. Data Acquisition mainly deals with collecting and storing data from all the sensors. At the same time, for the Features Engineering phase, most authors used time-domain features as well as frequency-domain features. This process involves the following steps:

- *Pre-processing*: Some operations help filter and prepare the raw data to be processed;
- *Features Extraction*: combining existing features to produce a more useful one;
- *Features Selection*: consists in selecting, among the existing, the most valuable features to train on;
- *Classification*: concerns the learning techniques that use the pre-processed data from the previous stage.

The architecture is shown in Fig. 1. The main component of the data acquisition phase is the sensors' measure of various attributes, i.e., acceleration, location, audio, temperature, etc….

### 3.1. Data acquisition

There are four types of attributes that can be collected:

- *Environmental Attributes:* features that depend on the surrounding environment (e.g., *humidity, temperature, noise, and light levels*). These provide contextual information useful to discriminate the activity performed by the users. For instance, if the user operates in a noisy environment, they are more likely to walk or run rather than sleep. These parameters might be helpful to increase the accuracy of the recognition model, but alone they are insufficient to produce a sufficiently accurate recognition model.
- *Motion and Orientation*: An accelerometer and a gyroscope can be used to build an accurate and reliable recognition model (Nweke et al., 2019). Triaxial accelerometers are typically used to measure the total acceleration at every instant, requiring a gyroscope to isolate the gravity from the user-initiated acceleration. The gravity magnitude is fixed but can be decomposed along three axes to produce information about the device's Orientation. Instead, the user acceleration is given by the instantaneous acceleration caused by the user's movements. The accelerometer allows us to understand the acceleration on three axes x, y, and z. The axes allow many human activities to be recognized by discriminating walking from the lower to the upper plane, thanks to the z-axis. Moreover, a gyroscope can also measure the rotation rate along the three axes of the device, which is helpful since virtually all activities include swinging movements (e.g., swinging an arm during a run). For this reason, the position of the accelerometer is an essential factor. For instance, placing an accelerometer inside the trouser pocket can help recognize activities like walking and running. However, it can hardly differentiate between activities that do not involve leg movements, like standing still or driving a car.
- *Location*: GPS and GLONASS are the most widely used positioning systems integrated with most modern smartphones. There are two ways to use position sensors in HAR: the first is to use the position to provide contextual information about the activity (Jordao et al., 2018). For instance, if the user is at home, it is unlikely that he could be swimming or riding a bus, but he might be eating or resting. The second way is to use the longitude variations to calculate the user's speed and course during an activity. This can be useful for recognizing activities where speed and course are vital, like driving a car, running, and walking. Even so, using position sensors comes with many problems: firstly, they are unsuitable for indoor activities or activities performed in areas where the signal is weak; moreover, the GPS/GLONASS systems are expensive in CPU usage and energy consumption (Jordao et al., 2018).
- *Vital Sign*: Heart rate, respiration rate, skin temperature, and more signals can be used to obtain a more accurate recognition model (Nweke et al., 2019). However, this is not always true, in fact, Tapia et al. (2007), which used a triaxial accelerometer and a heart rate monitor, concluded that the heart rate is not helpful in activity recognition, especially during transitions from intense to moderate activities, because the heart rate is slow to fall to normal levels. Therefore, a low-level intensity activity performed after a high-

**Table 4**
Activities found in Literature with the corresponding reference.

| Activity | Reference |
|---|---|
| Walking | (Zeng et al., 2014), (Wang et al., 2016), (Chen & Xue, 2015), (Almaslukh et al., 2018), (Bayat et al., 2014), (Abdull Sukor et al., 2018), (Rodrigues & Mestria, 2016), (Ha & Choi, 2016), (Wan et al., 2020), (Inoue et al., 2017), (Yao et al., 2017), (Kim et al., 2016), (Jain & Kanhangad, 2018), (Xu et al., 2018), (Xu et al., 2018), (Mario, 2019), (Ogbuabor & La, 2018), (Lee et al., 2017), (Zebin et al., 2018), (Hernandez et al., 2019), (Ignatov & Strijov, 2015), (Hnoohom et al., 2017), (Zhang, 2015), (Yu & Qin, 2018), (Voicu et al., 2019), (Chen et al., 2017), (Tao et al., 2016), (Kolosnjaji & Eckert, 2018), (Jordao et al., 2018), (Catal et al., 2015), (Pires et al., 2020), (Walse et al., 2016), (Wannenburg & Malekian, 2017), (Attal et al., 2015), (Milenkoski et al., 2018), (Ignatov, 2018), (San-Segundo et al., 2018), (Zhou et al., 2019), (Dobbins & Rawassizadeh, 2018), (Lu et al., 2017), (Micucci et al., 2017), (Matsui et al., 2017), (Lara et al., 2012), (Tapia et al., 2007), (Sztyler et al., 2017), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Qi et al., 2019), (Hassan et al., 2018), (Bayat et al., 2014), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Jansi & Amutha, 2018), (Ullah et al., 2019), (Gattulli et al., 2023), (Convertini et al., 2023), (Garcia-Gonzalez et al., 2023), (Sardar et al., 2022), (Tan et al., 2022), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Zhang et al., 2016), (Ronao & Cho, 2014), (Zhang et al., 2015) |
| Jogging | (Zeng et al., 2014), (Chen & Xue, 2015), (Almaslukh et al., 2018), (Bayat et al., 2014), (Ha & Choi, 2016), (Inoue et al., 2017), (Jain & Kanhangad, 2018), (Xu et al., 2018), (Ignatov & Strijov, 2015), (Tao et al., 2016), (Kolosnjaji & Eckert, 2018), (Catal et al., 2015), (Wannenburg & Malekian, 2017), (Milenkoski et al., 2018), (Ignatov, 2018), (Matsui et al., 2017), (Sztyler et al., 2017), (Qi et al., 2019), (Jansi & Amutha, 2018), (Gattulli et al., 2023) |
| Stairs up | (Zeng et al., 2014), (Abdull Sukor et al., 2018), (Ha & Choi, 2016), (Inoue et al., 2017), (Yao et al., 2017), (Mario, 2019), (Chen et al., 2017), (Jordao et al., 2018), (Walse et al., 2016), (Attal et al., 2015), (San-Segundo et al., 2018), (Dobbins & Rawassizadeh, 2018), (Lara et al., 2012), (Tapia et al., 2007), (Sztyler et al., 2017), (Bayat et al., 2014), (Ghate & Sweetlin Hemalatha, 2021) |
| Stairs down | (Zeng et al., 2014), (Abdull Sukor et al., 2018), (Ha & Choi, 2016), (Wan et al., 2020), (Inoue et al., 2017), (Yao et al., 2017), (Mario, 2019), (Chen et al., 2017), (Jordao et al., 2018), (Walse et al., 2016), (Attal et al., 2015), (San-Segundo et al., 2018), (Dobbins & Rawassizadeh, 2018), (Lara et al., 2012), (Tapia et al., 2007), (Sztyler et al., 2017), (Bayat et al., 2014), (Ghate & Sweetlin Hemalatha, 2021) |
| Laying Down | (Zeng et al., 2014), (Wang et al., 2016), (Almaslukh et al., 2018), (Abdull Sukor et al., 2018), (Ha & Choi, 2016), (Wan et al., 2020), (Inoue et al., 2017), (Kim et al., 2016), (Ogbuabor & La, 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Hnoohom et al., 2017), (Yu & Qin, 2018), (Chen et al., 2017), (Walse et al., 2016), (Wannenburg & Malekian, 2017), (Attal et al., 2015), (Ignatov, 2018), (Micucci et al., 2017), (Sztyler et al., 2017), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Qi et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Jansi & Amutha, 2018), (Ullah et al., 2019), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Ronao & Cho, 2014), (Zhang et al., 2015) |
| Sitting | (Zeng et al., 2014), (Wang et al., 2016), (Almaslukh et al., 2018), (Abdull Sukor et al., 2018), (Rodrigues & Mestria, 2016), (Ha & Choi, 2016), (Wan et al., 2020), (Inoue et al., 2017), (Yao et al., 2017), (Kim et al., 2016), (Xu et al., 2018), (Ogbuabor & La, 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Ignatov & Strijov, 2015), (Hnoohom et al., 2017), (Yu & Qin, 2018), (Voicu et al., 2019), (Chen et al., 2017), (Kolosnjaji & Eckert, 2018), (Catal et al., 2015), (Walse et al., 2016), (Wannenburg & Malekian, 2017), (Attal et al., 2015), (Milenkoski et al., 2018), (Ignatov, 2018), (San-Segundo et al., 2018), (Dobbins & Rawassizadeh, 2018), (Micucci et al., 2017), (Lara et al., 2012), (Tapia et al., 2007), (Sztyler et al., 2017), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Qi et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Jansi & Amutha, 2018), (Ullah et al., 2019), (Gattulli et al., 2023), (Convertini et al., 2023), (Sardar et al., 2022), (Tan et al., 2022), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Zhang et al., 2016), (Ronao & Cho, 2014), (Zhang et al., 2015) |
| Standing | (Zeng et al., 2014), (Wang et al., 2016), (Almaslukh et al., 2018), (Abdull Sukor et al., 2018), (Rodrigues & Mestria, 2016), (Ha & Choi, 2016), (Wan et al., 2020), (Inoue et al., 2017), (Yao et al., 2017), (Kim et al., 2016), (Xu et al., 2018), (Xu et al., 2018), (Ogbuabor & La, 2018), (Lee et al., 2017), (Zebin et al., 2018), (Hernandez et al., 2019), (Ignatov & Strijov, 2015), (Hnoohom et al., 2017), (Zhang, 2015), (Yu & Qin, 2018), (Voicu et al., 2019), (Chen et al., 2017), (Kolosnjaji & Eckert, 2018), (Catal et al., 2015), (Pires et al., 2020), (Walse et al., 2016), (Wannenburg & Malekian, 2017), (Attal et al., 2015), (Milenkoski et al., 2018), (Ignatov, 2018), (San-Segundo et al., 2018), (Zhou et al., 2019), (Dobbins & Rawassizadeh, 2018), (Micucci et al., 2017), (Matsui et al., 2017), (Tapia et al., 2007), (Sztyler et al., 2017), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Qi et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin |

(*continued on next page*)

**Table 4** (*continued*)

| Activity | Reference |
|---|---|
| | Hemalatha, 2021), (Jansi & Amutha, 2018), (Ullah et al., 2019), (Sardar et al., 2022), (Tan et al., 2022), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Zhang et al., 2016), (Ronao & Cho, 2014), (Zhang et al., 2015) |
| Upstairs | (Wang et al., 2016), (Chen & Xue, 2015), (Almaslukh et al., 2018), (Bayat et al., 2014), (Rodrigues & Mestria, 2016), (Inoue et al., 2017), (Kim et al., 2016), (Jain & Kanhangad, 2018), (Xu et al., 2018), (Xu et al., 2018), (Ogbuabor & La, 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Ignatov & Strijov, 2015), (Hnoohom et al., 2017), (Zhang, 2015), (Yu & Qin, 2018), (Voicu et al., 2019), (Tao et al., 2016), (Kolosnjaji & Eckert, 2018), (Catal et al., 2015), (Pires et al., 2020), (Milenkoski et al., 2018), (Ignatov, 2018), (Zhou et al., 2019), (Micucci et al., 2017), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Qi et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Jansi & Amutha, 2018), (Ullah et al., 2019), (Tan et al., 2022), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Zhang et al., 2016), (Ronao & Cho, 2014), (Zhang et al., 2015) |
| Downstairs | (Wang et al., 2016), (Chen & Xue, 2015), (Almaslukh et al., 2018), (Bayat et al., 2014), (Inoue et al., 2017), (Kim et al., 2016), (Jain & Kanhangad, 2018), (Xu et al., 2018), (Xu et al., 2018), (Ogbuabor & La, 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Ignatov & Strijov, 2015), (Hnoohom et al., 2017), (Zhang, 2015), (Yu & Qin, 2018), (Voicu et al., 2019), (Tao et al., 2016), (Kolosnjaji & Eckert, 2018), (Catal et al., 2015), (Pires et al., 2020), (Ignatov, 2018), (Zhou et al., 2019), (Micucci et al., 2017), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Qi et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Jansi & Amutha, 2018), (Ullah et al., 2019), (Tan et al., 2022), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Zhang et al., 2016), (Ronao & Cho, 2014), (Zhang et al., 2015) |
| Falling | (Chen & Xue, 2015), (Gattulli et al., 2023), (Convertini et al., 2023) |
| Running | (Chen & Xue, 2015), (Almaslukh et al., 2018), (Bayat et al., 2014), (Ha & Choi, 2016), (Wan et al., 2020), (Xu et al., 2018), (Mario, 2019), (Lee et al., 2017), (Voicu et al., 2019), (Chen et al., 2017), (Tao et al., 2016), (Pires et al., 2020), (Lu et al., 2017), (Matsui et al., 2017), (Lara et al., 2012), (Tapia et al., 2007), (Sztyler et al., 2017), (Gattulli et al., 2023), (Convertini et al., 2023), (Zhang et al., 2016), (Zhang et al., 2015) |
| Jumping | (Chen & Xue, 2015), (Almaslukh et al., 2018), (Ha & Choi, 2016), (Xu et al., 2018), (Mario, 2019), (Tao et al., 2016), (Micucci et al., 2017), (Sztyler et al., 2017), (Qi et al., 2019), (Jansi & Amutha, 2018), (Gattulli et al., 2023), (Convertini et al., 2023) |
| Aerobic Dancing | (Bayat et al., 2014) |
| Sleeping | (Zhang et al., 2016) |
| Elevator up, Elevator down | (Zhang et al., 2016), (Zhou et al., 2019) |
| Waist bends forward, Relaxing, Frontal elevation of arms, Knees bending | (Ha & Choi, 2016) |
| Cycling | (Ha & Choi, 2016), (Wan et al., 2020), (Yao et al., 2017), (Zhang, 2015), (San-Segundo et al., 2018), (Dobbins & Rawassizadeh, 2018), (Matsui et al., 2017), (Tapia et al., 2007) |
| Nordic walking | (Wan et al., 2020) |
| Watching TV, Computer work, Vacuum cleaning, Folding laundry, House cleaning | (Wan et al., 2020), (Chen et al., 2017) |
| Car driving | (Wan et al., 2020), (Matsui et al., 2017), (Garcia-Gonzalez et al., 2023) |
| Ironing | (Wan et al., 2020), (Chen et al., 2017) |
| Playing soccer, Rope jumping | (Wan et al., 2020) |
| Write notes, Open engine hood, Close engine hood, Check door gaps, Open door, Close door, Open/close two doors, Check trunk gap, Open/close trunk, Check the steering wheel | (Zeng et al., 2014), (Ha et al., 2015) |
| Open then close the fridge, Open then close the dishwasher, Open then close three drawers (at different heights), Open then close door 1/2, Open then close door 2, Toggle the lights on then off, Clean the table, Drink while standing, Drink while seated | (Zeng et al., 2014), (Zhang et al., 2016) |
| Pour milk into a cup, Put kettle onto charging point, Reach out for the power switch on the wall, Drink a glass of water while waiting for kettle to boil, Reach out to switch off the kettle, Pour hot water from the kettle into cup, Fetch milk from the shelf, Pour milk into cup, Put the bottle of milk back on shelf, Have a sip and taste the drink, Have another sip while walking back to desk, Unlock drawer, Retrieve biscuits from drawer, Eat a biscuit, Lock drawer, Have a drink, Fetch cup from desk, Place cup on kitchen surface, Fetch kettle, Pour out extra water from kettle, Fetch cup from kitchen surface, | (Panwar et al., 2017) |
| Brush own teeth, Comb own hair, get up from the bed, lie down on the bed, sit down on a chair, Stand up from a chair, Drink from a glass, Pour water into a glass, Use the telephone | (Jordao et al., 2018) |
| Sawing, Hammering, turning a wrench, Loading, Hauling, Unloading, Returning | (Akhavian & Behzadan, 2016) |

**Table 5**
Co-occurrences between activities and sensors found in Literature with the corresponding reference.

| Activity | Sensor | Reference |
|---|---|---|
| Walking | Accelerometer | (Zeng et al., 2014), (Chen & Xue, 2015), (Almaslukh et al., 2018), (Bayat et al., 2014), (Abdull Sukor et al., 2018), (Rodrigues & Mestria, 2016), (Wan et al., 2020), (Inoue et al., 2017), (Kim et al., 2016), (Xu et al., 2018), (Xu et al., 2018), (Mario, 2019), (Lee et al., 2017), (Ignatov & Strijov, 2015), (Hnoohom et al., 2017), (Zhang, 2015), (Tao et al., 2016), (Kolosnjaji & Eckert, 2018), (Jordao et al., 2018), (Catal et al., 2015), (Pires et al., 2020), (Wannenburg & Malekian, 2017), (Milenkoski et al., 2018), (Ignatov, 2018), (San-Segundo et al., 2018), (Dobbins & Rawassizadeh, 2018), (Lu et al., 2017), (Micucci et al., 2017), (Sztyler et al., 2017), (Ghate & Sweetlin Hemalatha, 2021), (Gattulli et al., 2023), (Convertini et al., 2023), (Zhang et al., 2016), (Zhang et al., 2015) |
| | Accelerometer + gyroscope | (Wang et al., 2016), (Ha & Choi, 2016), (Yao et al., 2017), (Jain & Kanhangad, 2018), (Ogbuabor & La, 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Yu & Qin, 2018), (Chen et al., 2017), (Walse et al., 2016), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Ullah et al., 2019), (Tan et al., 2022), (Bernaś et al., 2022), (Sardar et al., 2022), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Ronao & Cho, 2014) |
| | Accelerometer + gyroscope + magnetometer | (Voicu et al., 2019), (Attal et al., 2015), (Matsui et al., 2017), (Qi et al., 2019), (Jansi & Amutha, 2018) |
| | Accelerometer + gyroscope + magnetometer + barometer | (Zhou et al., 2019) |
| | Accelerometer + vital sign | (Lara et al., 2012), (Tapia et al., 2007) |
| Jogging | Accelerometer | (Zeng et al., 2014), (Chen & Xue, 2015), (Almaslukh et al., 2018), (Bayat et al., 2014), (Inoue et al., 2017), (Xu et al., 2018), (Ignatov & Strijov, 2015), (Tao et al., 2016), (Kolosnjaji & Eckert, 2018), (Catal et al., 2015), (Wannenburg & Malekian, 2017), (Milenkoski et al., 2018), (Ignatov, 2018), (Sztyler et al., 2017), (Ghate & Sweetlin Hemalatha, 2021), (Gattulli et al., 2023), (Convertini et al., 2023) |
| | Accelerometer + gyroscope | (Ha & Choi, 2016), (Jain & Kanhangad, 2018) |
| | Accelerometer + gyroscope + magnetometer | (Matsui et al., 2017), (Qi et al., 2019), (Jansi & Amutha, 2018) |
| Stairs up | Accelerometer | (Zeng et al., 2014), (Abdull Sukor et al., 2018), (Wan et al., 2020), (Inoue et al., 2017), (Mario, 2019), (Jordao et al., 2018), (San-Segundo et al., 2018), (Dobbins & Rawassizadeh, 2018), (Sztyler et al., 2017), (Ghate & Sweetlin Hemalatha, 2021) |
| | Accelerometer + gyroscope | (Ha & Choi, 2016), (Yao et al., 2017), (Chen et al., 2017), (Walse et al., 2016) |
| | Accelerometer + gyroscope + magnetometer | (Attal et al., 2015) |
| | Accelerometer + vital sign | (Lara et al., 2012), (Tapia et al., 2007) |
| Stairs down | Accelerometer | (Zeng et al., 2014), (Abdull Sukor et al., 2018), (Wan et al., 2020), (Inoue et al., 2017), (Mario, 2019), (Jordao et al., 2018), (San-Segundo et al., 2018), (Dobbins & Rawassizadeh, 2018), (Sztyler et al., 2017), (Ghate & Sweetlin Hemalatha, 2021) |
| | Accelerometer + gyroscope | (Ha & Choi, 2016), (Yao et al., 2017), (Chen et al., 2017), (Walse et al., 2016) |
| | Accelerometer + gyroscope + magnetometer | (Attal et al., 2015) |
| | Accelerometer + vital sign | (Lara et al., 2012), (Tapia et al., 2007) |
| Laying Down | Accelerometer | (Zeng et al., 2014), (Almaslukh et al., 2018), (Abdull Sukor et al., 2018), (Wan et al., 2020), (Inoue et al., 2017), (Kim et al., 2016), (Hnoohom et al., 2017), (Wannenburg & Malekian, 2017), (Ignatov, 2018), (Micucci et al., 2017), (Sztyler et al., 2017), (Zhang et al., 2015) |
| | Accelerometer + gyroscope | (Wang et al., 2016), (Ha & Choi, 2016), (Ogbuabor & La, 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Yu & Qin, 2018), (Chen et al., 2017), (Walse et al., 2016), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Ullah et al., 2019), |

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**Table 5** (*continued*)

| Activity | Sensor | Reference |
|---|---|---|
| | | (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Ronao & Cho, 2014) |
| | Accelerometer + gyroscope + magnetometer | (Attal et al., 2015), (Qi et al., 2019), (Jansi & Amutha, 2018) |
| Sitting | Accelerometer | (Zeng et al., 2014), (Almaslukh et al., 2018), (Abdull Sukor et al., 2018), (Rodrigues & Mestria, 2016), (Wan et al., 2020), (Inoue et al., 2017), (Kim et al., 2016), (Xu et al., 2018), (Ignatov & Strijov, 2015), (Hnoohom et al., 2017), (Kolosnjaji & Eckert, 2018), (Catal et al., 2015), (Wannenburg & Malekian, 2017), (Milenkoski et al., 2018), (Ignatov, 2018), (San-Segundo et al., 2018), (Dobbins & Rawassizadeh, 2018), (Micucci et al., 2017), (Sztyler et al., 2017), (Ghate & Sweetlin Hemalatha, 2021), (Gattulli et al., 2023), (Zhang et al., 2016), (Zhang et al., 2015) |
| | Accelerometer + gyroscope | (Wang et al., 2016), (Ha & Choi, 2016), (Yao et al., 2017), (Ogbuabor & La, 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Yu & Qin, 2018), (Chen et al., 2017), (Walse et al., 2016), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Ullah et al., 2019), (Bernaś et al., 2022), (Sardar et al., 2022), (Tan et al., 2022), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Ronao & Cho, 2014) |
| | Accelerometer + gyroscope + magnetometer | (Voicu et al., 2019), (Attal et al., 2015), (Qi et al., 2019), (Jansi & Amutha, 2018) |
| | Accelerometer + vital sign | (Lara et al., 2012), (Tapia et al., 2007) |
| Standing | Accelerometer | (Zeng et al., 2014), (Almaslukh et al., 2018), (Abdull Sukor et al., 2018), (Rodrigues & Mestria, 2016), (Wan et al., 2020), (Inoue et al., 2017), (Kim et al., 2016), (Xu et al., 2018), (Xu et al., 2018), (Lee et al., 2017), (Ignatov & Strijov, 2015), (Hnoohom et al., 2017), (Zhang, 2015), (Kolosnjaji & Eckert, 2018), (Catal et al., 2015), (Pires et al., 2020), (Wannenburg & Malekian, 2017), (Milenkoski et al., 2018), (Ignatov, 2018), (San-Segundo et al., 2018), (Dobbins & Rawassizadeh, 2018), (Micucci et al., 2017), (Sztyler et al., 2017), (Ghate & Sweetlin Hemalatha, 2021), (Gattulli et al., 2023), (Convertini et al., 2023), (Zhang et al., 2016), (Zhang et al., 2015) |
| | Accelerometer + gyroscope | (Wang et al., 2016), (Ha & Choi, 2016), (Yao et al., 2017), (Ogbuabor & La, 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Yu & Qin, 2018), (Chen et al., 2017), (Walse et al., 2016), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Ullah et al., 2019), (Sardar et al., 2022), (Tan et al., 2022), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Ronao & Cho, 2014) |
| | Accelerometer + gyroscope + magnetometer | (Voicu et al., 2019), (Attal et al., 2015), (Matsui et al., 2017), (Qi et al., 2019), (Jansi & Amutha, 2018) |
| | Accelerometer + gyroscope + magnetometer + barometer | (Zhou et al., 2019) |
| | Accelerometer + vital sign | (Tapia et al., 2007) |
| Upstairs | Accelerometer | (Chen & Xue, 2015), (Almaslukh et al., 2018), (Bayat et al., 2014), (Rodrigues & Mestria, 2016), (Inoue et al., 2017), (Kim et al., 2016), (Xu et al., 2018), (Xu et al., 2018), (Ignatov & Strijov, 2015), (Hnoohom et al., 2017), (Zhang, 2015), (Tao et al., 2016), (Kolosnjaji & Eckert, 2018), (Catal et al., 2015), (Pires et al., 2020), (Milenkoski et al., 2018), (Ignatov, 2018), (Micucci et al., 2017), (Zhang et al., 2016), (Zhang et al., 2015) |
| | Accelerometer + gyroscope | (Wang et al., 2016), (Jain & Kanhangad, 2018), (Ogbuabor & La, 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Yu & Qin, 2018), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Ullah et al., 2019), (Tan et al., 2022), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Ronao & Cho, 2014) |
| | Accelerometer + gyroscope + magnetometer | (Voicu et al., 2019), (Qi et al., 2019), (Jansi & Amutha, 2018) |
| | Accelerometer + gyroscope + magnetometer + barometer | (Zhou et al., 2019) |
| Downstairs | Accelerometer | (Chen & Xue, 2015), (Almaslukh et al., 2018), (Bayat et al., 2014), (Inoue et al., 2017), (Kim et al., 2016), (Xu et al., 2018), (Xu et al., 2018), ( |

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**Table 5** (*continued*)

| Activity | Sensor | Reference |
|---|---|---|
| | | Ignatov & Strijov, 2015), (Hnoohom et al., 2017), (Zhang, 2015), (Tao et al., 2016), (Kolosnjaji & Eckert, 2018), (Catal et al., 2015), (Pires et al., 2020), (Ignatov, 2018), (Micucci et al., 2017), (Zhang et al., 2016), (Zhang et al., 2015) |
| | Accelerometer + gyroscope | (Wang et al., 2016), (Jain & Kanhangad, 2018), (Ogbuabor & La, 2018), (Zebin et al., 2018), (Hernandez et al., 2019), (Yu & Qin, 2018), (Yu et al., 2018), (Chen et al., 2019), (Zhu et al., 2019), (Hassan et al., 2018), (Gholamreza & AlModarresi, 2021), (Zebin et al., 2019), (Mohammed Hashim & Amutha, 2021), (Deep & Zheng, 2019), (Ghate & Sweetlin Hemalatha, 2021), (Ullah et al., 2019), (Tan et al., 2022), (Ronao & Cho, 2017), (Ronao & Cho, 2016), (Ronao & Cho, 2014) |
| | Accelerometer + gyroscope + magnetometer | (Voicu et al., 2019), (Qi et al., 2019), (Jansi & Amutha, 2018) |
| | Accelerometer + gyroscope + magnetometer + barometer | (Zhou et al., 2019) |
| Falling | Accelerometer | (Chen & Xue, 2015), (Gattulli et al., 2023), (Convertini et al., 2023) |
| Running | Accelerometer | (Chen & Xue, 2015), (Almaslukh et al., 2018), (Bayat et al., 2014), (Wan et al., 2020), (Xu et al., 2018), (Mario, 2019), (Lee et al., 2017), (Tao et al., 2016), (Pires et al., 2020), (Lu et al., 2017), (Sztyler et al., 2017), (Gattulli et al., 2023), (Convertini et al., 2023), (Zhang et al., 2016), (Zhang et al., 2015) |
| | Accelerometer + gyroscope | (Ha & Choi, 2016), (Chen et al., 2017), (Bernaś et al., 2022) |
| | Accelerometer + gyroscope + magnetometer | (Voicu et al., 2019), (Matsui et al., 2017) |
| | Accelerometer + vital sign | (Lara et al., 2012), (Tapia et al., 2007) |
| Jumping | Accelerometer | (Chen & Xue, 2015), (Almaslukh et al., 2018), (Xu et al., 2018), (Mario, 2019), (Tao et al., 2016), (Micucci et al., 2017), (Sztyler et al., 2017), (Gattulli et al., 2023), (Convertini et al., 2023) |
| | Accelerometer + gyroscope | (Ha & Choi, 2016), (Bernaś et al., 2022) |
| | Accelerometer + gyroscope + magnetometer | (Qi et al., 2019), (Jansi & Amutha, 2018) |
| Aerobic Dancing | Accelerometer | (Bayat et al., 2014) |
| Relaxing | Accelerometer + gyroscope | (Ha & Choi, 2016) |
| Sleeping | Accelerometer | (Zhang et al., 2016) |
| | Accelerometer | (Zhang et al., 2016) |
| Elevator up | Accelerometer + gyroscope + magnetometer + barometer | (Zhou et al., 2019) |
| | Accelerometer | (Zhang et al., 2016) |
| Elevator down | Accelerometer + gyroscope + magnetometer + barometer | (Zhou et al., 2019) |
| Waist bends forward, Frontal elevation of arms, Knees bending | Accelerometer + gyroscope | (Ha & Choi, 2016) |
| | Accelerometer | (Wan et al., 2020), (Zhang, 2015), (San-Segundo et al., 2018), (Dobbins & Rawassizadeh, 2018) |
| Cycling | Accelerometer + gyroscope | (Ha & Choi, 2016), (Yao et al., 2017) |
| | Accelerometer + gyroscope + magnetometer | (Matsui et al., 2017) |
| | Accelerometer + vital sign | (Tapia et al., 2007) |
| Nordic walking | Accelerometer | (Wan et al., 2020) |
| Watching tv | Accelerometer | (Wan et al., 2020) |
| | Accelerometer + gyroscope | (Chen et al., 2017) |
| Computer work | Accelerometer | (Wan et al., 2020) |
| | Accelerometer + gyroscope | (Chen et al., 2017) |
| Car driving | Accelerometer | (Wan et al., 2020), (Garcia-Gonzalez et al., 2023) |
| | Accelerometer + gyroscope + magnetometer | (Matsui et al., 2017) |
| Vacuum cleaning | Accelerometer | (Wan et al., 2020) |
| | Accelerometer + gyroscope | (Chen et al., 2017) |

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**Table 5** (*continued*)

| Activity | Sensor | Reference |
|---|---|---|
| Ironing | Accelerometer | (Wan et al., 2020) |
| | Accelerometer + gyroscope | (Chen et al., 2017) |
| Folding laundry | Accelerometer | (Wan et al., 2020) |
| | Accelerometer + gyroscope | (Chen et al., 2017) |
| House cleaning | Accelerometer | (Wan et al., 2020) |
| | Accelerometer + gyroscope | (Chen et al., 2017) |
| Playing soccer, Rope jumping | Accelerometer | (Wan et al., 2020) |
| Write notes | Accelerometer | (Zeng et al., 2014) |
| | Accelerometer + gyroscope | (Ha et al., 2015) |
| Open engine hood | Accelerometer | (Zeng et al., 2014) |
| | Accelerometer + gyroscope | (Ha et al., 2015) |
| Close engine hood | Accelerometer | (Zeng et al., 2014) |
| | Accelerometer + gyroscope | (Ha et al., 2015) |
| Check door gaps | Accelerometer | (Zeng et al., 2014) |
| | Accelerometer + gyroscope | (Ha et al., 2015) |
| Open door | Accelerometer | (Zeng et al., 2014) |
| | Accelerometer + gyroscope | (Ha et al., 2015) |
| Close door | Accelerometer | (Zeng et al., 2014) |
| | Accelerometer + gyroscope | (Ha et al., 2015) |
| Open/close two doors | Accelerometer | (Zeng et al., 2014) |
| | Accelerometer + gyroscope | (Ha et al., 2015) |
| Check trunk gap | Accelerometer | (Zeng et al., 2014) |
| | Accelerometer + gyroscope | (Ha et al., 2015) |
| Open/close trunk | Accelerometer | (Zeng et al., 2014) |
| | Accelerometer + gyroscope | (Ha et al., 2015) |
| Check steering wheel | Accelerometer | (Zeng et al., 2014) |
| | Accelerometer + gyroscope | (Ha et al., 2015) |
| Open then close the fridge, Open then close the dishwasher, Open then close 3 drawers (at different heights), Open then close door 1/2, Toggle the lights on then off, Clean the table, Drink while standing, Drink while seated | Accelerometer | (Zeng et al., 2014), (Zhang et al., 2016) |
| Fetch cup from the desk, Place cup on kitchen surface, Fetch kettle, Pour out extra water from kettle, Put kettle onto charging point, Reach out for the power switch on the wall, Drink a glass of water while waiting for kettle to boil, Reach out to switch off the kettle, Pour hot water from the kettle into cup, Fetch milk from the shelf, Pour milk into cup, Pour milk into cup, Put the bottle of milk back on shelf, Fetch cup from kitchen surface, Have a sip and taste the drink, Have another sip while walking back to desk, Unlock drawer, Retrieve biscuits from drawer, Eat a biscuit, Lock drawer, Have a drink. | Accelerometer | (Panwar et al., 2017) |
| Brush own teeth, Comb own hair, get up from the bed, lie down on the bed, sit down on a chair, stand up from a chair, drink from a glass, pour water into a glass, use the telephone | Accelerometer | (Jordao et al., 2018) |
| Sawing, Hammering, turning a wrench, Loading, Hauling, Unloading, Returning | Accelerometer + gyroscope | (Akhavian & Behzadan, 2016) |

**Table 6**
Summary and comparison among the different datasets found in Literature. Legend: Name of Devices(D), Number of users (NoD), Sensor(S), Activities(A), Laboratory/Real(L/RW), Raw data/pre-processed (RD/PP), Availability (Av).

| D | NoD | S | A | L/RW | RD/PP | Av |
|---|---|---|---|---|---|---|
| UniMiB SHAR | Unknown (30 subjects) | Accelerometer | Falling (Falling Forward, Backward, Right, Left, Hitting An Obstacle, With Protective Strategies, Backward Without Protective Strategies, Syncope), Walking, Running, Climbing Stairs, Descending Stairs, Jumping, Lying Down From Standing, Sitting | L | RD | Public and available online https://paperswithcode.com/dataset/unimib-shar |
| USC - HAD | MotionNode (14 users) | Accelerometer; Gyroscope; Magnetometer | Running forward, Jumping, Sitting, Standing, Sleeping, Walking forward, Walking left, Walking right, ElevatorUp ElevatorDown, Walking upstairs, Walking downstairs | RW | RD | Public and available online https://sipi.usc.edu/had/ |
| HAR using smartphone | Samsung Galaxy S2 (30 users) | Accelerometer Gyroscope | Walking downstairs, Sitting, Standing, Laying, Walking, Walking upstairs | L | PP | Public and available online https://archive.ics.uci.edu/ml/datasets /Human+Activity+Recognition+Using+Smartphones (Anguita et al., 2013) |
| Real-world HAR | Unknown (9 users) | Accelerometer; GPS; Gyroscope; Light sensor; Magnetometer; Sound Level Data | Walking, Stairs up, Stairs down, Sitting, Standing, Laying, Running, Jogging, Jumping | RW | RD | Public and available online https://sensor.informatik.uni-mannheim.de/ |
| Unknown | Unknown | Accelerometer | Check_trunk_gap, Open/close trunk, Check steering wheel, Write notes, Open_engine hood, Close_engine_hood, Check_door_gaps, Open_door, Close_door, Open/close two doors | L | PP | Public and available online (Stiefmeier et al., 2008) |
| WISDM: Wireless Sensor Data Mining | Nexus One; TC Hero; Motorola BackFlip (36 users) | Accelerometer | Walking, Jogging, Upstairs, Downstairs, Sitting, Standing | L | D/PP | Public and available online (Kwapisz et al., 2011) |
| Actitracker | Android smartphone (29 users) | Accelerometer | Walking, Jogging, Stairs, Sitting, Standing, Laying down | RW | RD/PP | Public and available online (Weiss et al., 2016) |
| Opportunity | Unknown device name (4 users) | Gyroscopes; Accelerometers; GPS; objects accelerometers; 2Dgyroscopes; switches | Prepare coffee, Drink coffee, Start, Groom Relax, Prepare sandwich, Eat sandwich, CleanupBreak | RW | PP | Public and available online https://archive.ics.uci.edu/ml/datasets /opportunity+activity+recognition (Roggen et al., 2023) |
| Pamap2 | Colibri wireless inertial measurement units<br>Unknown device name | Accelerometer; Gyroscope Magnetometer Heart rate monitor | Watching TV, Computer work, Car driving, Ascending stairs, Descending stairs, Vacuum cleaning, Ironing, Folding laundry, House cleaning, Playing soccer, Rope jumping, Laying, Sitting, Standing Walking, Running, Cycling, Nordic Walking | RW | RD | Public and available online https://archive.ics.uci.edu/ml/datasets/ pamap2+physical+activity+monitoring |
| HHAR | LGWatches; SamsungGalaxy; GearSamsung Galaxy S3 mini; Samsung Galaxy S3; LG Nexus 4; Samsung Galaxy S+ (9 users) | Accelerometer; Gyroscope | Biking Sitting Standing Walking Stair up Stair down | RW | RD | Public and available online https://archive.ics.uci.edu/ml/ datasets/heterogeneity+activity+recognition (Stisen et al., 2015) |

intensity activity can be mistakenly classified as the latter (Tapia et al., 2007).

### 3.2. Features extraction

Feature extraction is a part of activity recognition. *Frequency-domain* and *Time-domain features* are used to perform this approach. *Time-domain features* use average, range, variance, skewness, kurtosis, median etc. The *frequency-domain features* are Correlation, Peak Power, Spectral Power, Peak Frequency, Different Frequency Bands, and Spectral Entropy.

Some of the common *frequency-domain* features *time-domain* and used for HAR are: The *Time-domain features* include *skewness, kurtosis, variance, range, average, median, etc.*, which are used in HAR papers (Wang et al., 2016; Abdull Sukor et al., 2018; Kim et al., 2016). Kim et al. used two simple features in their work applied to the accelerometer: mean and standard deviation (Kim et al., 2016):

$$\mu^k = \sum_{i=1}^{T} a_i^k \tag{1}$$

Moreover, the standard deviation is:

$$\sigma^k = \sqrt{\sum_{i=1}^{T} \left(a_i^k - \mu_k\right)^2} \tag{2}$$

where $a_i^k$ and $T$ are the $i$-th accelerometer data of the $k$-axis and the length of sequence, respectively. Hnoohom et al. (2017) used several time-domain features, among which the Signal Magnitude area. This feature is referred to a statistical measure of the magnitude of a varying quantity, defined as (Hnoohom et al., 2017):

**Table 7**
Summary of the experimentation settings with performance scores found in the Literature, sorted concerning the year of publication.

| Paper | PP or FE | Classification | Dataset | Sensor | Performances | Year of publication |
|---|---|---|---|---|---|---|
| (Gattulli et al., 2023) | Sliding Window, Raw Data | CNN, Bi-LSTM | **Unimib SHAR** (Falling (Falling Forward, Backward, Right, Left, Hitting An Obstacle, With Protective Strategies, Backward Without Protective Strategies, Syncope), Walking, Running, Climbing Stairs, Descending Stairs, Jumping, Lying Down From Standing, Sitting)<br>**Dataset Uniba** (Walking, Running, Jumping, Sitting, Falling (Forward, Backward, Right, And Left)) | Accelerometer | **Average Accuracy DatasetUniba:**<br>91 % CNN<br>90 % Bi-LSTM<br>**Average Accuracy UnimibShar:**<br>97 % CNN<br>76 % Bi-LSTM | **2023** |
| (Convertini et al., 2023) | Sliding Window, Discrete Fourier Transform | SVM.NuSVC, Bernoulli Naïve Bayes, Random Forest Classifier, Bayesian Ridge, CNN, LSTM, Bi - LSTM | **Dataset Uniba** (Walking, Running, Jumping, Sitting, Falling (Forward, Backward, Right, And Left)) | Accelerometer | **Average Accuracy DatasetUniba:**<br>91 % CNN | |
| (Garcia-Gonzalez et al., 2023) | Sliding Window | CNN separabile in profondità (DS-CNN) e LSTM bidirezionale (Bi-LSTM) | **A Public Domain Dataset For Real-life Human Activity Recognition Using Smartphone Sensors:**<br>Inactive: not carrying the mobile phone.<br>Active: carrying the mobile phone, moving, but not going to a particular place.<br>Walking<br>Driving: Moving in a means of transport powered by an engine. This would include cars, buses, motorbikes, trucks and any similar. | Accelerometer, Gyroscope, Magnetometer and GPS | **Accuracy:**<br>94.80 % (DS-CNN)-LSTM | |
| (Bernaś et al., 2022) | Sliding Window, Raw Data | LSTM RNN | **Ibigworld Dataset** (Walk, Run, Squat, Jump, Lie Down, Swing Arms, Sit and Stand) | Accelerometer Gyroscope | **Accuracy:**<br>99.59 % LSTM RNN | **2022** |
| (Sardar et al., 2022) | Sliding Window, Mean, Median, Variance and Standard Deviation | LSTM, Random Forest, Decision Tree, KNN, SVM | **KAU-COVID19-AR-Dataset** (Walking, Handwashing, Standing, Sitting, Hand Sanitizing, Nose–Eyes Touching, Handshake Drink water) | Accelerometer, Gyroscope, Speed and GPS | **Accuracy:**<br>97,33 % Random Forest | |
| (Tan et al., 2022) | Sliding Window, Overlapping | Ensemble (ELA): GRU, CNN, DNN | **UCI HAR** (Sitting, Standing and Laying down, Walking, Walking upstairs, Walking downstairs) | Accelerometer Gyroscope | **Average Accuracy:**<br>96.7 % | |
| (Mohammed Hashim & Amutha, 2021) | Sliding Window;<br>Z-Score Standardization<br>FFDRT | Random forest | **HAR using smartphone** (Walking downstairs, Sitting, Standing, Laying, Walking, Walking upstairs) | Accelerometer Gyroscope | **Accuracy**<br>92,72 % | |
| (Ghate & Sweetlin Hemalatha, 2021) | Sliding Window; | CNN + LSTM<br>CNN + RF | **HAR using smartphone** (Sitting, Standing, Laying, Walking, Walking upstairs, Walking downstairs)<br>**WISDM** (Jogging, Walking, Upstairs, Downstairs, Sitting, Standing) | Accelerometer (WISDM);<br>Accelerometer Gyroscope | **Accuracy WISDM:**<br>94 % CNN + LSTM<br>97,77 % CNN + RF<br>**Accuracy HAR:**<br>97 % CNN + LSTM<br>98,2% CNN + RF | **2021** |
| (Gholamreza & AlModarresi, 2021) | Sliding Window;<br>FFT | 1D CNN<br>2D CNN | **HAR using smartphone** (Walking downstairs, Sitting, Walking upstairs, Standing, Laying) | Accelerometer Gyroscope | **Accuracy**<br>90,51 % 1D CNN<br>95,69 % 2D CNN | |
| (Wan et al., 2020) | Sliding Window | CNN<br>LSTM<br>BLSTM<br>MLP | **HAR using smartphone** (Walking downstairs, Sitting, Standing, Laying, Walking, walking upstairs)<br>**Pamap2** (Vacuum cleaning, Ironing, Folding laundry, House cleaning, Playing soccer, Rope jumping, Laying, Sitting, Standing, Walking, Running, Cycling, Nordic Walking, Watching TV, Computer work, Car driving, Ascending stairs, Descending stairs) | Accelerometer | **Accuracy**<br>92,71 % HAR<br>91,00 % Pamap2<br>**Accuracy**<br>89,01 % HAR<br>85,86 % Pamap2<br>**Accuracy**<br>89,4% HAR<br>89,52 % Pamap2<br>**Accuracy**<br>86,83 % HAR<br>82,07 % Pamap2 | **2020** |

(continued on next page)

**Table 7** (*continued*)

| Paper | PP or FE | Classification | Dataset | Sensor | Performances | Year of publication |
|---|---|---|---|---|---|---|
| | | SVM | | | **Accuracy**<br>90,5% HAR<br>84,07 % Pamap2 | |
| (Deep & Zheng, 2019) | Sliding Window; | CNN + LSTM | **HAR using smartphone** (Walking downstairs, Sitting, Walking, Walking upstairs, Standing, Laying) | Accelerometer; Gyroscope | **Accuracy**<br>93,40 % | **2019** |
| (Ullah et al., 2019) | Sliding Window; | LSTM | **HAR using smartphone** (Walking, walking upstairs, walking downstairs, Sitting, Standing, Laying) | Accelerometer; Gyroscope | **Accuracy**<br>93,13 % | |
| (Jain & Kanhangad, 2018) | Sliding Window;<br>Magnitude Signals;<br>Histogram Of Gradient;<br>Fourier Descriptor | SVM<br>K-NN | **HAR using smartphone** (Sitting, Standing, Laying, Walking, Walking upstairs, Walking downstairs) | Accelerometer<br>Gyroscope | **Accuracy**<br>97,12 %<br>**Accuracy**<br>91,75 % | |
| (Xu et al., 2018) | Sliding Window;<br>Z-Score Standardization | CNN | **WISDM** (Jogging, Walking, Upstairs, Downstairs, Sitting, Standing) | Accelerometer | **Accuracy**<br>91,97 % | |
| (Ogbuabor & La, 2018) | Sliding Window;<br>Magnitude Signals; | MLP | **HAR using smartphone** (Laying, Walking, Walking upstairs, Walking downstairs, Sitting, Standing) | Accelerometer<br>Gyroscope | **Accuracy**<br>92 % Accelerometer<br>80 % Gyroscope<br>95 % Both | **2018** |
| (San-Segundo et al., 2018) | Sliding Window;<br>Z-Score Standardization | LSTM | **HHAR** (Biking, Sitting, Standing, Walking, Stair up, Stair down) | Accelerometer | **F-score:**<br>87,3 | |
| (Yu et al., 2018) | Sliding Window; | LSTM | **HAR using smartphone** (Walking downstairs, Sitting, Standing, Laying, Walking, Walking upstairs) | Accelerometer<br>Gyroscope | **Accuracy**<br>94,34 % | |
| (Ignatov, 2018) | Sliding Window | CNN | **WISDM** (Jogging, Walking, Upstairs, Downstairs, Sitting, Standing)<br>**HAR using smartphone** (Walking, Walking upstairs, Walking downstairs, Sitting, Standing, Laying) | Accelerometer | **Accuracy**<br>93,32 % WISDM<br>94,35 % HAR | |
| (Yu & Qin, 2018) | Sliding Window | Bi-LSTM | **UCI HAR** (Sitting, Standing and Laying down, Walking, Walking upstairs, Walking downstairs) | Accelerometer<br>Gyroscope | **Accuracy:**<br>93,79 % | |
| (Almaslukh et al., 2018) | Sliding Window<br>Mean | CNN | **Real-World HAR** (climbing downstairs, climbing upstairs, jumping, lying, standing, sitting, running/jogging, and walking) | Accelerometer | **Precision**<br>**0,79** | |
| (Chen et al., 2017) | Sliding Window | LSTM | **Pamap2** (Laying, Sitting, Nordic Walking, Watching TV, Computer work, Car driving, Vacuum cleaning, Ironing, Folding laundry, House cleaning, Playing soccer, Ascending stairs, Descending stairs, Rope jumping, Standing, Walking, Running, Cycling) | Accelerometer<br>Gyroscope | **Accuracy:**<br>82.57 % | **2017** |
| (Ronao & Cho, 2017) | Sliding Window;<br>Z-Score Standardization<br>Correlation<br>PCA<br>LDA | HMM | **HAR using smartphone** (Walking, Walking upstairs, Walking downstairs, Sitting, Standing, Laying)<br>**USC-HAD** (Walking downstairs, Running forward, Jumping, Sitting, Standing, Sleeping, Elevator up, Elevator down, Walking forward, Walking left, Walking right, Walking upstairs) | Accelerometer<br>Gyroscope | **Accuracy**<br>93,18 % HAR<br>67,07 % USC-HAD | |
| (Ha et al., 2015) | Sliding Window | CNN | **Skoda** (Write notes, Open engine hood, Close engine hood, Check door gaps, Open door, Close door. Open/close two doors, Check trunk gap, Open/close trunk, Check steering wheel) | Accelerometer<br>Gyroscope | **Accuracy**<br>97,92 % | |
| (Walse et al., 2016) | Sliding Window;<br>PCA | MLP | **HAR using smartphone** (Walking, Walking upstairs, Walking downstairs, Sitting, Standing, Laying) | Accelerometer<br>Gyroscope | **Accuracy**<br>96,17 % | **2016** |
| (Zhang et al., 2016) | Sliding Window | DNN | **Opportunity** (Start, Drink coffee, Prepare sandwich, Eat sandwich, Cleanup, Break, Groom, Relax, Prepare coffee)<br>**USC-HAD** (Walking downstairs, Running forward, Jumping, Sitting, Standing, Sleeping, Elevator up, Elevator down, Walking forward, | Accelerometer | **Accuracy**<br>82,3% Opportunity<br>91,17 % USC-HAD | |

(*continued on next page*)

**Table 7** (*continued*)

| Paper | PP or FE | Classification | Dataset | Sensor | Performances | Year of publication |
|---|---|---|---|---|---|---|
| | | | Walking left, Walking right, Walking upstairs) | | | |
| (Ronao & Cho, 2016) | Sliding Window; FFT | Deep CNN | **HAR using smartphone** (Walking, Walking upstairs, Walking downstairs, Sitting, Standing, Laying) | Accelerometer Gyroscope | **Accuracy** 95,75 % | |
| (Ignatov & Strijov, 2015) | Event-Defined Window (Custom Algorithm For) Segmentation | K-NN | **Actitracker** (Walking, Jogging, Stairs, Sitting, Standing, Laying down) | Accelerometer | **Accuracy:** 96 % | |
| (Kim et al., 2016) | Sliding Window | HMM | **HAR using smartphone** (Sitting, Standing, Laying, Walking, Walking upstairs, Walking downstairs) | Accelerometer | **Accuracy** 83,51 % | |
| (Catal et al., 2015) | Sliding Window | Ensemble learning with vote (J48, Logistic Regression, MLP) | **WISDM** (Jogging, Walking, Upstairs, Downstairs, Sitting, Standing) | Accelerometer | **Accuracy** 91,62 % | |
| (Kolosnjaji & Eckert, 2018) | Fft; Autoencoder (Pre-Trained Network For F.E) | (4-layers) ANN | **HAR using smartphone** (Sitting, Standing, Laying, Walking, Walking upstairs, Walking downstairs) **WISDM** (Jogging, Walking, Upstairs, Downstairs, Sitting, Standing) | Accelerometer | **Precision** 77,01 % HAR 80,02 % WISDM | **2015** |
| (Zeng et al., 2014) | Sliding Window | CNN | **Skoda** (Open/close two doors, Check trunk gap, Open/close trunk, Write notes, Open engine hood, Close engine hood, Check door gaps, Open door, Close door, Check steering wheel) **Actitracker** (Sitting, Standing, Lying down, Walking, Jogging, Stairs) **Opportunity** (Drink coffee, prepare sandwich, Eat sandwich, Cleanup, Start, Groom, Relax, prepare coffee, Break) | Accelerometer | **Accuracy** 86,18 % Skoda 91,00 % Actitracker 75,83 % Opportunity | |
| (Ronao & Cho, 2014) | Sliding window; Z-score standardization RF features selection | HMM | **HAR using smartphone** (Sitting, Standing, Laying, Walking, Walking upstairs, Walking downstairs) | Accelerometer Gyroscope | **Accuracy** 91,76 % | **2014** |

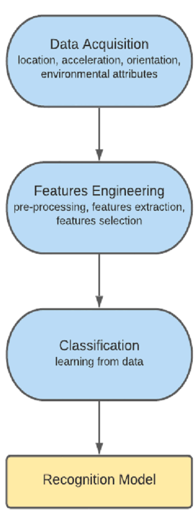


**Fig. 1.** The general HAR system architecture.

$$sma_{xyz} = \frac{1}{3}\left(\sum_{j=1}^{N}|S_{xi}| + \sum_{j=1}^{N}|S_{yi}| + \sum_{j=1}^{N}|S_{zi}|\right) \tag{3}$$

The *Frequency-domain features* used to frequency spectrum with accelerometer and gyroscope (Wang et al., 2016; Jain & Kanhangad, 2018; Ignatov & Strijov, 2015).

$$X(f) = \sum_{i=0}^{N-1} x_i e^{-j2\pi fi/N} \tag{4}$$

Variable X is frequency spectrum, f is the f-th Fourier coefficient, N is the size of the sliding window:

$$X(f) = \sum_{i=0}^{N-1} a_i + jb_i \tag{5}$$

With $a_i = x_i\cos(\frac{2\pi fi}{N})$ and $b_i = x_i\sin(\frac{2\pi fi}{N})$. In HAR system is used the *Power Spectral Density (PSD)* with accelerometer sensor for this activity driving, cycling, running, walking (Abdull Sukor et al., 2018). The *Power Spectral Density* is calculated as follow:

$$P(f) = \frac{1}{N}\sum_{i=0}^{N-1} a_i^2 + b_i^2 \tag{6}$$

Entropy is generally used in HAR systems with accelerometer sensors (Abdull Sukor et al., 2018). This feature is discriminant between activities with the same PSD but different movements patterns (Abdull Sukor et al., 2018):

$$H(f) = \frac{1}{N}\sum_{i=0}^{N-1} c_i\log(c_i), c_i = \frac{\sqrt{a_i^2 + b_i^2}}{\sum_{k=0}^{N-1}\sqrt{a_i^2 + b_i^2}} \tag{7}$$

The DC (PDS at frequency 0 Hz) is used in HAR with an accelerometer, is defined as the sum its squared spectral normalized coefficients (Bayat et al., 2014):

$$DC = \frac{1}{N}\sum_{i=0}^{N-1} a_i^2 \tag{8}$$

The Correlation between axes is very useful for differentiating activities in only one direction (Wannenburg & Malekian, 2017; Hnoohom et al., 2017). The formula is as follows. The HAR system uses Other frequency-domain features based on spectral energy (Abdull Sukor et al., 2018).

$$c_{xy} = \frac{\sum_{i=1}^{N}(S_{xi} - mean(S_x))(S_{yi} - mean(S_y))}{\sqrt{\sum_{i=1}^{N}(S_{xi} - mean(S_x))^2 \bullet (S_{yi} - mean(S_y))^2}} \tag{9}$$

### 3.3. Features selection

Feature Selection is another important phase in HAR System. The HAR system's performance depends on the dimensions of the feature space or vector. Shallow learning algorithms need discriminating features. This curse of the dimensionality problem with classifier performance decrease. One way to reduce the data dimensionality problem, an essential topic in Machine Learning and Data Mining, is to apply Feature Selection algorithms. These algorithms are very important because they are used to discard the less discriminating features and keep the most discriminating features for the problem addressed. This procedure aims to reduce the complexity and time of computation and improve the final classification.

There is a critical feature selection named *Principal Component Analysis (PCA)*. That is a linear technique that transports the original features into new mutually uncorrelated features. The PCA (new feature) rearranges the Raw Features into a new low-dimensional space. In this new space, the principal components are arranged from most significant to lowest (then omitted). More articles use PCA (Wang et al., 2016; Abdull Sukor et al., 2018; Ignatov & Strijov, 2015; Kolosnjaji & Eckert, 2018; Walse et al., 2016; Akhavian & Behzadan, 2016).

*Linear Discriminant Analysis (LDA)* is associated with principal component analysis (PCA). These two methods find linear combinations of variables (Ronao & Cho, 2017). The LDA method is a feature projection in a new space of lower dimensions. This situation minimizing their within-class variability while maximizes the between-class separability.

*Independent Component Analysis (ICA)* solves *Blind Source Separation (BSS)*. This technique is used for non-Gaussian data. The ICA aims to find separate components, and original features can be expressed as a linear combination.

In *Factors Analysis (FA)* the features are grouped by their correlation. FA represents groups of certain highly correlated features that have small correlations regarding some factor with specific features of other groups.

### 3.4. Classification

The feature extracted/selected is essential for classification ML algorithms. In the HAR system, the input data patterns are associated with the activities (classes) under consideration. The definition of Machine Learning has two types of approaches: *Supervised* and *Unsupervised*.

In *Supervised Learning,* generally, the training set includes already labeled features. In contrast, in *Unsupervised Learning*, the training data are not labeled. Activity recognition is usually treated as a supervised machine learning problem since the desired outputs are controlled, and an unsupervised model may result in a more complex model. Supervised learning approaches include many modules, for example, *Decision Tree classifiers such as the J48 and Random Forest (RF), K-Nearest Neighbours (K-NN), Support Vector Machines (SVM), Logistic Regression (LR), Naïve Bayes (NB) and Artificial Neural Networks (ANNs)*. Those require entirely labeled activity data. The unsupervised learning approaches, *Hidden Markov Models (HMMs)*, *Gaussian Mixture Models (GMMs), and* Clustering algorithms infer the labels from the data. In the following sections, the classification techniques mentioned above are briefly described.

#### 3.4.1. K-nearest neighbors

K-Nearest Neighbor (KNN) is a supervised learning algorithm for regression and classification. The algorithm calculates the probability that the input data belongs to training data class *"K",* and the class contains the highest likelihood of being selected. KNN predicts the class by calculating the distance between the test data and all training points by choosing the K number of points near the test data.

Ignatov (2018) applied the K-NN classification to differentiate between six human activities (Jogging, Walking, Upstairs, Downstairs, Sitting, and Standing in the WISDM dataset) using both time-domain and frequency-domain features obtained from smartphone three-axial accelerometers. This approach has shown high precision and nearly 96 % recognition accuracy (Ignatov & Strijov, 2015).

Wannenburg and Malekian (2017) makes a comparison among different classifiers. They extracted both time-domain and frequency-domain features obtained from the smartphone three-axial accelerometer and used the WEKA framework for the feature selection task with five human activities (Jogging, Laying, Walking, Sitting, Standing). As for the classifiers, they compare SVM, ANN, NB, Tree, k-Star, and K-NN with k equals 1 and k equals to 5. The K-NN gives the best result with k equals 1 achieving 99.01 % accuracy, followed by the K-NN with k equals 5, which achieved a 99.0 % score for accuracy (Wannenburg & Malekian, 2017).

#### 3.4.2. Support vector machine

Support Vector Machine (SVM) is a statistical learning theory. It is a non-linear classification using kernel methods. The kernel methods protect data from high dimensional space using a non-linear kernel function. SVM is a binary classifier.

Bayat et al. (2014) compared the SVM with other classifiers. Using low-pass filters for features selection, they achieved 72.24 % of accuracy, trying to recognize six different activities (*Slow Walking, Fast Walking, Running, Stairs-Up, Stairs-Down, and (Aerobic) Dancing*). Moreover, they combined the SVM with other classifiers to achieve higher accuracy results. Using SVM combined with the Multilayer Perceptron, they obtained 91.15 % of accuracy in identifying the same six activities (Bayat et al., 2014).

Abdull Sukor et al. (2018) used the SVM to recognize three different activities (*Standing, Sitting, Laying, Stairs Up, Stairs Down, and Walking*). They extracted both time-domain and frequency-domain features and used the PCA to reduce dimensionality. This approach achieved 92.87 % accuracy, outperforming the same configuration without using the PCA for dimensionality reduction (which achieved 90.19 % Accuracy) (Abdull Sukor et al., 2018).

Jain and Kanhangad (2018) used the SVM as a classifier and compared achieved accuracy using time-domain, frequency-domain, and both features with this activity *Walking, Walking Downstairs, Walking Upstairs, Standing, Sitting, Laying, Stand-to-Sit, Sit-to-Stand, Sit-to-Lie, Lie-to-Sit, Stand-to-Lie, Lie-to-Stand*. The result shows that the time-domain works better than frequency-domain features achieving 94.57 % accuracy against the 93.82 %. However, using both features, the average accuracy in recognizing the six proposed activities increases, achieving 97.12 % (Jain & Kanhangad, 2018).

#### 3.4.3. Random forest

Random Forest (RF) combines with the Bootstrap Aggregation Method (Bagging) and Randomization in the selection of nodes in the construction of the Decision Tree. The output is a majority vote of the different decisions in each tree. The RF model requires huge, labeled data (Twomey et al., 2018).

Xu et al. (2018) proposed a classification methodology to recognize six activities using a wearable device's acceleration data. They compared the classification accuracy of the RF with the ANN and DT classifiers. The result showed that RF achieved the best accuracy, compared with other classifiers, in recognizing walking, jumping, and running activities (Xu et al., 2018).

#### 3.4.4. Gaussian mixture model

A Gaussian Mixture Model (GMM) is a probabilistic model used to represent Normally Distributed subpopulations within an overall population. The GMM parameters are estimated using the Expectation-Maximization algorithm (EM).

In HAR systems, separate GMMs can be used for different tasks. GMM does not guarantee convergence to the global minimum many times. The tasks used are Standing, Sitting, Sitting to sitting on the floor, Sitting on the floor, Laying down, Laying down to sitting on the floor, Standing, Ascending on stairs, and Walking with 73 % accuracy and 96 % specificity.

### 3.4.5. Markov chains and Hidden Markov models

Markov chain (stochastic discrete-time process covering a finite number of states) fits the sequential model data well. It is often used in a more general *Hidden Markov Model (HMM)* model. In this case, each activity is represented by a specific state.

The Hidden Markov Model (HMM) is a stochastic statistical process. It is helpful for modeling time series. One disadvantage of the HMM model is that it often fails to guarantee convergence to the global minimum. Sensor data are time series, and in fact, this approach can help their implementation. This approach observes micro variations useful for the final classification (Nweke et al., 2019). Hidden states are critical to decree an activity in HAR approaches. After training, the most probable sequence of detected activities is decremented by Viterbi's algorithm (Zhang, 2015).

Kim et al. (2016) used the HMM extended in the HMM Ensemble Model to improve discriminative power with activity Walking, walking upstairs, walking downstairs, Sitting, Standing, and Laying (UCI HAR Dataset). This latter uses the Decision Template method to integrate the probabilities of multiple HMMs concerning an observation sequence. This method, combined with extracting two simple features (such as mean and standard deviation), only achieved 83.51 % accuracy in recognizing seven different activities (Kim et al., 2016).

Zhang (2015) used HMM in combination with Deep Neural Networks with the activity Riding, Walking, walking upstairs, walking upstairs, Standing, and Walking downstairs. A critical step of training an HMM is to learn the observation model. It could be helpful to use DNNs for modeling the observation probability distribution of HMMs. With this technique, the authors achieved 93.37 % accuracy in recognizing five different activities, outperforming other HMM-based classification methods such as HMM-RF and HMM-GMM (Zhang, 2015).

Ronao and Cho (2017) uses the Continuous HMM in a hierarchical architecture. This architecture allows the inherent hierarchical characteristics of the tasks to be exploited. Instead, CHMMs use continuous observation densities such as sensor signals, which are advantageous. Moreover, the hierarchical structure allows different feature subsets for various subclasses while minimizing feature computation time. The authors achieved 92.94 % accuracy in identifying the six other activities of the HAR dataset (*Downstairs, Sitting, Standing, Laying, Walking, Upstairs*) and 56.33 % accuracy for the twelve different activities of the USC-HAD dataset (*Sleeping, Elevator Up, Walking Right, Walking Upstairs, Walking Downstairs, Running Forward, Jumping Up, Walking Forward, Walking Left, Sitting, Standing, Elevator Down*) (Ronao & Cho, 2017).

### 3.4.6. Artificial neural networks and multilayer perceptron

Artificial Neural Networks (ANNs) can automatically learn and approximate nonlinear feature combinations to recognize discriminant classes optimally (Twomey et al., 2018). ANNs attempt to optimize input parameters via neuron passage, activation function, and weights. The objective is to regularize them through back-propagation (Kolosnjaji & Eckert, 2018). Minimizing error by optimizing input parameters without using feature extraction methods practical more Shallow Learning models. In modern HAR systems, ANN can be combined with other classifiers to construct a heterogeneous algorithm (Hnoohom et al., 2017; Catal et al., 2015). The disadvantage of ANN networks is that they require a large amount of data for the training phase and thus HAR Datasets.

The MLP network is an ANN with a multilayer feedforward architecture. The MLP is based on nonlinear activations for hidden units (Nweke et al., 2019). The MLP tries to minimize the error function between the outputs it estimates and the desired outputs. The MLP approach is good for nonlinear classifications. In fact, in HAR studies, the MLP network has been used in a wide range of studies:

Ogbuabor and La (2018) investigated the role of gyroscope and accelerometer sensors in a HAR system using an MLP classifier with six activities (*Walking, Sitting, Laying, Walking Downstairs, walking upstairs and standing*). The accelerometer performs better than the gyroscope, with an overall accuracy of 92 %. Combining the accelerometer and gyroscope performed better with 95 % accuracy (Ogbuabor & La, 2018).

Wan et al. (2020) proposes a smartphone inertial accelerometer-based architecture with typical daily activities (Nordic walking, Watching TV, Walking, Running, Cycling, Computer work, Laying, Sitting, and Standing). The preprocessing is done with denoising, and CNN, LSTM, BLSTM, MLP, and SVM models are utilized on the UCI and Pamap2 datasets. With UCI Dataset, the MLP accuracy is 0.8683 %, and with Pamap2 Dataset, the accuracy is 0.8207 %, better respecting other models (Wan et al., 2020). The best model is CNN.

Voicu et al. (2019) proposes a HAR system for three smartphone sensors: an accelerometer, gyroscope, and gravity sensor. The activity is Walking, Running, Sitting, Standing, Upstairs, and Downstairs. The best overall accuracy was obtained with these three experiment configurations, i.e., External implementation 5-s window accelerometer and gyroscope at wrist and in the pocket, External implementation 15-s window accelerometer and gyroscope at the wrist, External implementation 30-s window accelerometer and gyroscope at the wrist. Respectively Overall accuracy equals 94 %, 94 %, and 97 % (Voicu et al., 2019).

### 3.4.7. Convolutional neural network

CNNs, called ConvNets, are widely used extensions of MLPs that have seen great success in computer vision tasks (Nweke et al., 2019). Convolutions represent a critical difference between CNNs and other NNs in layers of the network that induce weight sharing. Convolutional layers via neurons and deep layers learn and optimize input features. Each neuron is implemented as a receptive field that connects it to previous layers. CNNs also typically have pooling layers for down sampling, usually performing average or max pooling to reduce the feature maps' spatial resolution. These layers are typically stacked on each other and used in conjunction with dense layers, creating a deep architecture. The architecture of CNNs, which typically refers to the number of layers, the size of each layer, the choice of activation functions, etc., is diverse.

A wide variety of studies have been conducted with CNNs, and the three most recent will be shown in these examples:

Zhou et al. (2019) proposes a pedestrian activities recognition method based on a CNN with nine activities: still, walk, upstairs, up the elevator, up the escalator, down the elevator, down the escalator, downstairs, and turning. The experiments achieve approximately 98 % accuracy. The smartphone sensors used are accelerometers, magnetometers, gyroscopes, and barometers collected with various types of smartphones (Zhou et al., 2019).

Wan et al. (2020) proposes a smartphone inertial accelerometer-based architecture with typical daily activities (*Cycling, Nordic walking, Laying, Sitting, Watching TV, Computer work, Standing, Walking, and Running*). The preprocessing is done with denoising, and CNN, LSTM, BLSTM, MLP, and SVM models are utilized on the UCI and Pamap2 datasets. With UCI Dataset, the CNN accuracy is 0.9271 %, and with Pamap2 Dataset, the accuracy is 0.9100 %, better respecting other models (Wan et al., 2020).

Mario (2019) proposes a method to detect activity with a single tri-axial accelerometer with activity Walking, Running, Jumping, Climbing Up, and Climbing down. A CNN is used with a sliding window with 50 % overlap to extract 5 s of acceleration from a square horizontal-vertical. The results outperform by around 8 % concerning the authors of the dataset with p-fold cross-validation (Mario, 2019).

#### 3.4.8. Recurrent neural networks (RNNs) and long short-term memory

Recurrent Neural Networks (RNNs) are built upon feedforward NNs by allowing recurrent edges, i.e., edges that adjacent span timesteps in the network. These results are helpful for problems where data is not independent of time or space, as RNNs can pass specific information across different timesteps (Yao et al., 2017; Inoue et al., 2017). The most widely used RNNs are Long Short-Term Memory (LSTM) networks (Nweke et al., 2019). LSTMs introduced the concept of a memory cell replacing the traditional nodes in hidden layers, storing states for given periods. LSTMs and Bidirectional LSTMs have been shown to learn time dependencies and perform well in various tasks.

A wide variety of studies have been conducted with LSTM, and the three most recent will be shown in these examples:

Zebin et al. (2018) proposes an LSTM model for six life activities (Walking on a level surface, walking upstairs, walking downstairs, sitting, standing, laying) classification with raw accelerometer and gyroscope data. The LSTM achieves 92 % average accuracy in a multi-class scenario (Zebin et al., 2018).

Hernandez et al. (2019) proposes a HAR system with a smartphone accelerometer and gyroscope data. The model used is bidirectional long short-term memory (Bi-LSTM) network. The activities are sitting, standing, laying, walking, walking upstairs, and walking downstairs. The overall accuracy is 92.67 % (Hernandez et al., 2019).

Milenkoski et al. (2018) proposes a lightweight algorithm for activity detection based on LSTM networks and other models such as J48, Logistic Regression, MLP, and Straw Man with raw accelerometer data. The activity is Downstairs, Jogging, Sitting, Standing, Upstairs, and Walking. The LSTM model only achieves over 95 % accuracy with Walking, Sitting, and Standing activities (Milenkoski et al., 2018).

#### 3.4.9. Other classification techniques used in activity recognition

Another paradigm for HAR is one of the fuzzy logic methods derived from fuzzy set theory. The approach is sufficient to identify static postures, such as standing, laying down, and sitting (Acampora et al., 2012). Few studies have found good performance in fall detection. Fuzzy logic employs methods to construct appropriate membership functions and to combine and interpret fuzzy rules.

Another classification technique is the *Naive Bayes classifier*. For HAR systems, the NB approach shows a similar level of accuracy compared to other classification methods (Wang et al., 2016; Wannenburg & Malekian, 2017; Rodrigues & Mestria, 2016).

## 4. Activities, datasets, and performances of HAR

This chapter takes on a vital role in the survey. Its importance derives from the in-depth exposition of three key elements: the Activities, the Datasets, and the Performance. Each of these aspects is treated in detail and constitutes a sub-chapter.

The first sub-chapter is devoted to the analysis of *Activities*. Here, the various activities involved in the scope being surveyed will be examined and presented in detail. The various activities will be explored, their distinctive characteristics outlined, and their importance highlighted within the landscape under review. The second sub-chapter is reserved for an in-depth discussion of the *Datasets* used. The data sources employed for the activities under consideration will be exposed. Specifics of the datasets will be presented, including size, types of data collected, and collection methods. In addition, the relevance of the datasets in influencing the overall results and evaluations of the activities analyzed will be discussed. The third and final sub-chapter deals with *Performance*. Here, a detailed analysis of Performance related to the activities considered will be conducted based on the data provided by the datasets. Metrics and indicators will be examined to assess the effectiveness of the methodologies employed in the different activities. Any strengths and limitations of the observed Performance will also be identified.

### 4.1. Activities

The section summarizes all the activities found in the Literature, with an in-depth study of all sensors used to recognize each activity. In this section, Table 4 maps the type of activity (or task) with the reference of authors that used that specific task in their study.

The graph below summarizes the information shown in the previous table. All the activities with a frequency equal to or less than 3 activities are not reported (Fig. 2).

- Total number of activities: 29;
- Total number of references provided: 437;

Averages and statistics:

- Average number of referrals per activity: 437 / 29 ≈ 15.07 (rounded to two decimal places)
- Maximum number of references for an activity: 72 (for “Laying Down,” “Sitting,” “Standing,” “Upstairs,” “Downstairs”)
- Minimum number of references for an activity: 1 (for several activities)

Moreover, the sensors used to recognize the activities shown in the previous table are listed below (Table 5).

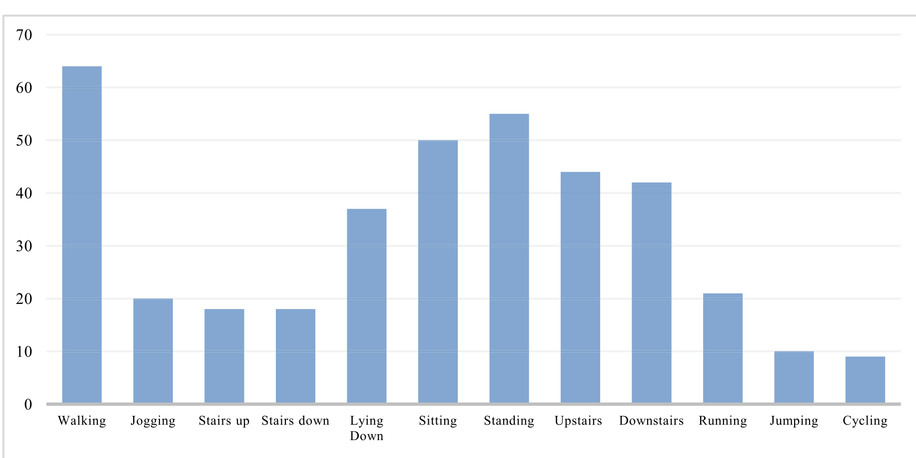


**Fig. 2.** Frequency of activities found in Literature. The x-axis shows the human activities, while the y-axis shows the frequency of use of the activities in the scientific papers analyzed.

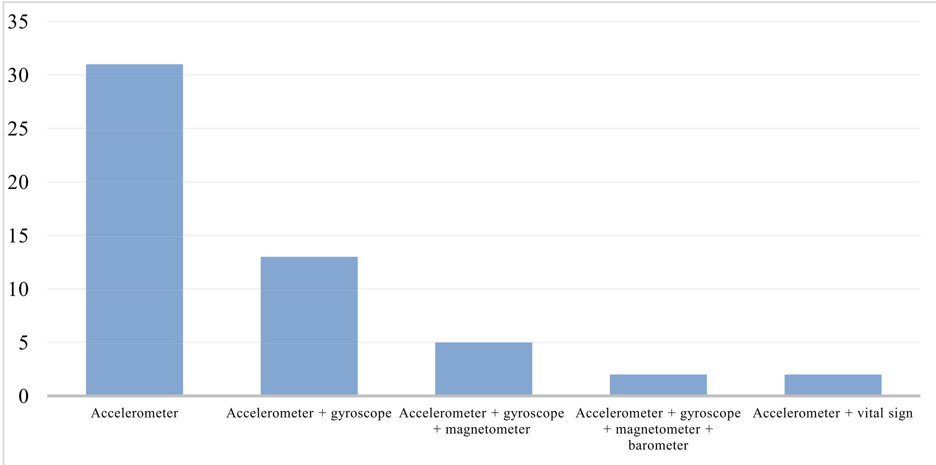


**Fig. 3.** Frequency of sensors found in Literature. The x-axis shows the sensors, while the y-axis shows the frequency of use in the scientific papers analyzed.

It is noticeable from Tables 4 and 5 that some activities occur more often in the literature. Moreover, it is possible to see that some sensors, or combinations of sensors, have been investigated much more than others. To get a clearer idea of the situation, consult the following graphs (Fig. 3).

### 4.2. Dataset

Although different authors have adopted different datasets, Table 6 provides a complete overview of the most used and publicly available Dataset. A brief description of the three most used availability datasets will be shown below:

WISDM: The following dataset contains data collected by the WISDM research team through controlled laboratory conditions. The team gathered a population of users with Android smartphones while carrying out daily activities. The smartphone was placed in the front trouser pocket. The activities that have been detected are *Downstairs, Sitting, Walking, Jogging, Upstairs, and Standing*. Data collection was supervised to ensure data quality. The data was collected thanks to an application created by the authors and performed on each participant's Android phone. The application allows you to collect sensor data (e.g., *GPS, accelerometer*). The authors collected accelerometer data every 50 Hz in all cases.

Actitracker: This dataset was created by the WISDM research team, the same as the previous dataset. In principle, these two datasets are very similar since the number of subjects that performed the activities and the recorded sensor used is the same as the previous dataset. The main difference with the WISDM dataset is that this dataset contains *"real-world"* data, whereas in the previous one, the data was collected through controlled laboratory conditions. Moreover, 225 subjects were involved in the activity recording phase. The activities are sitting, standing, walking, jogging, stairs, Laying down. This dataset provides raw, labeled, unlabeled, and transformed data labeled and unlabeled.

Har using a smartphone: The study team collected data considering a statistical population of 30 volunteers (19 to 48 years old). The experiments were done by manually labeling the data. The device was a Samsung Galaxy S2, and the detected activities were climbing stairs, Lying down, descending stairs, sitting, walking, and standing with the smartphone positioned at the waist. The study team captured the triaxial linear acceleration and triaxial angular velocity at a constant 50 Hz speed of the accelerometer and gyroscope. The signals have been pre-processed by applying noise filters. Sampling was done in sliding windows with a fixed of 2.56 s and 50 % overlap (128 reads/window). A feature vector was obtained from each window by calculating time and frequency domain variables.

For each record, the authors provide the following:

- Triaxial acceleration (total acceleration) and estimated body acceleration (accelerometer);
- Triaxial angular velocity (gyroscope);
- A vector of 561 characteristics with time and frequency domain variables;

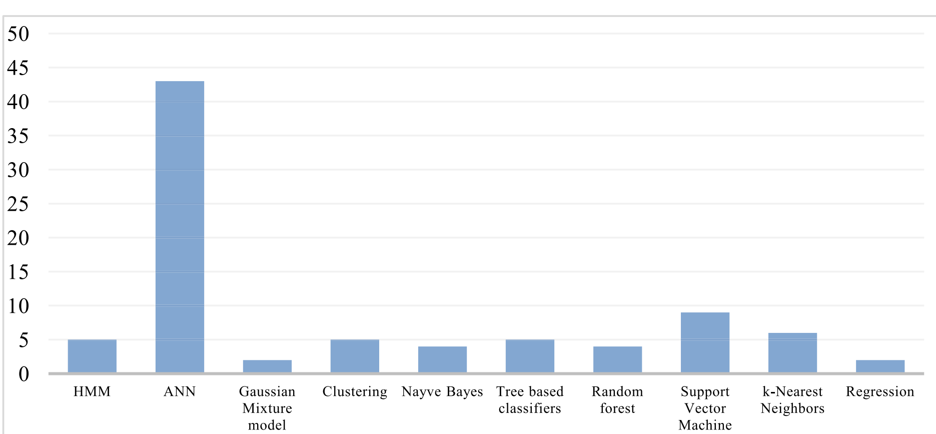


**Fig. 4.** Shallow Learning and Deep Learning Classification Algorithms. The x-axis shows the Machine Learning Shallow/Deep Models, while the y-axis shows the frequency of use of the shallow/deep models in the scientific papers analyzed correlated to the HAR approach.

- The label of the performed activity;
- Subject ID.

### 4.3. Performance

This section is devoted to reporting performance obtained by different systems when adopting solutions previously described. Although many results cannot be compared because they adopted other testing conditions even if the adopted dataset was the same, Table 7 summarizes the highest performing. Another view is the graph in Fig. 4.

This research has suggested several techniques and structures (Table 7) to enhance the precision of contemporary HAR models. One among them is the *Fast Feature Dimensionality Reduction Technique (FFDRT)*, which reduces feature dimensionality by overcoming the issues of power limitations of smartphones without losing degrees of accuracy (Mohammed Hashim & Amutha, 2021).

In the literature, other models prefer the synergy of CNNs with different architectures, such as LSTMs and GRUs, creating more complex networks that increase performance (Ghate & Sweetlin Hemalatha, 2021). CNN-LSTM integration has found superior temporal understanding helpful for dynamic HAR recognition (Deep & Zheng, 2019). CNN architectures with 1D and 2D kernels capture sensor data dependencies. Instead, Fast Fourier Transform (FFT) powerfully amplifies the results (Gholamreza & AlModarresi, 2021). Stacked LSTM networks were considered to help with smartphone behavior identification for incremental learning (Ullah et al., 2019). Deep convolution neural network models have also been proposed to emphasize location-independent recognition for high accuracy of activity and location (Almaslukh et al., 2018).

For the *"Device heterogeneity challenge,"* various feature extraction, normalization, and deep CNN techniques have been proposed to improve HAR among different devices (San-Segundo et al., 2018). Then, *Continuous Hidden Markov Models (CHMMs)* were introduced to exploit activity hierarchy and achieve better classification performance (Ronao & Cho, 2017; Ronao & Cho, 2014). To enrich the methods employed and capture temporal and spatial dependencies in sensor data, multimodal CNNs with 2D kernels have been presented, outperforming traditional methods (Ha et al., 2015). However, dimensionality reduction through PCA and neural networks such as MLP provide excellent performance without compromising accuracy (Walse et al., 2016).

Although deep learning techniques (CNN-LSTM) have dominated the HAR landscape, there is also a modern inclination toward ensemble and hybrid approaches. These methods leverage the strengths of multiple models to improve recognition accuracy (Catal et al., 2015; Kim et al., 2016).

The methods, strategies, and models used in the 2022–2023 scientific papers are the same as in previous years. On the other hand, they propose several concepts that could improve current research and future progress. In particular, the HAR architecture has been used by (Gattulli et al., 2023; Convertini et al., 2023) to detect Bullying and Cyberbullying in Behavioural Biometrics. The earliest years these models will be available on modern smartphones are 2023 and 2024.

## 5. Discussion

This chapter covers a discussion focusing on the central aspects of the study, including *"Points in Common"* about the scientific papers reviewed in the survey. The *"Advantages"* and *"Disadvantages"* arising from these commonalities and differences are examined in depth, shedding light on their implications for the overall goals of the research. As it progresses to the *"Future Developments,"* it is necessary to extend the research. At the same time, a meticulous assessment of the associated "*Risks*" is presented, pointing out potential pitfalls that must be considered in subsequent undertakings. A mention is made of the *"Best"* and *"Worst"* results regarding accuracy. By meticulously dissecting the results, decipher how much the research aligns with the set goals. To tangibly illustrate these notions, *"Realistic Examples"* are introduced, clarifying the practical implications of the study results in real-world scenarios. By consolidating these examples, it was provided an essential reference for subsequent attempts to develop the present work.

*Points in Common*: In the reality of *Human Activity Recognition (HAR)*, several research projects share a similar theme, but all have unique aspects. Accelerometer and gyroscope data take center stage as they are critical to understanding a user's real-time movements and activities. These sensors are commonly used to measure daily activities, fitness, and health. They are ubiquitous in smartphones and wearable devices. This work includes machine learning techniques such as ensemble and hidden Markov models. Methods include Principal Component Analysis (PCA), Multilayer Perceptron (MLP), and Convolutional Neural Networks (CNN), all of which are carefully used to improve the accuracy of activity recognition.

The temporal factor is crucial because activity detection depends heavily on the temporal element of sensor data. Various works study temporal interdependencies and sequential patterns in time series data and exploit these temporal features using CNNs, HMMs, and continuous HMMs for better recognition performance.

A hierarchical approach (exploring the decomposition of complex actions into simpler components using two-level models and sequential HMMs) improves overall recognition accuracy and promotes more precise activity classification.

Datasets such as the UCI-HAR and WISDM datasets play a crucial role and provide a standardized framework for evaluating the effectiveness of different strategies. These datasets support collective efforts to develop HAR through thorough and fair evaluation. The proposed method focuses on ease of use and real-time detection, consistent with the feasibility of using smartphones as data collection tools in real-world situations.

*Advantages*: The model's adaptability, which enables application across several domains and use cases, is one of its significant strengths. Numerous potential use cases, ranging from health monitoring to fitness tracking, demonstrate the suggested models' versatility and wide range of applications.

High accuracy is achieved by combining a CNN-based strategy and a two-stage HMM approach. These methods provide enhanced privacy by eliminating the requirement for personal information, a significant problem they address. According to (Kolosnjaji & Eckert, 2018), privacy-focused strategies can protect sensitive data and improve model applicability to different user groups. In a modern environment where data security and user confidentiality are paramount, an emphasis on data protection is crucial.

Another significant advantage is successfully capturing local relationships in the data using Convolutional Neural Networks (CNN). It also includes a two-stage Hidden Markov Model (HMM). A variety of technologies provide multiple ways to represent and understand data.

*Disadvantages*: There are several disadvantages to using sophisticated models like Convolutional Neural Networks (CNNs).

First, its implementation necessitates significant resources, which restricts deplorability in some situations. Furthermore, the complexity of these models could increase the chance of overfitting, reducing their generalizability.

Another drawback is the lack of publicly available datasets designed for Human Activity Recognition (HAR). This limitation makes the design and evaluation of HAR models more complex and hinders further development of this topic. Additionally, over-reliance on essential features to extract identifying information can compromise the method's ability to identify subtle patterns in the data. This limitation highlights the need for more sophisticated methods to understand human activity fully. Advanced models come with risks such as possible overfitting to datasets, reduced generalizability, and reduced reliability in both theoretical and real-world scenarios and situations.

Future Developments: In considering future developments in Human Activity Recognition (HAR), various avenues have been explored to enhance the applicability of methods in daily life.

- To extend the utility of these systems and contribute to a deeper understanding of Human Behavior, it has been proposed that their scope should be expanded to include activities such as cooking and cleaning. Additionally, it is proposed to integrate HAR models into mobile devices to improve accessibility and real-time responsiveness. This potential for direct implementation on smartphones is consistent with the prevalence of mobile devices in daily life and highlights the need for fast and effective activity recognition.
- Recommendations were provided to improve feature extraction methods. This can provide new insights into the interpretation of time series data. Exploring comprehensive, manually created, and automatically learned feature extraction methods remains a common theme across publications. Technologies such as genetic programming are thought to pursue the expression of ideal traits continuously.
- Key research areas focus on the feasibility of incorporating recognition models directly into smartphones for real-time activity recognition. This is consistent with the increasing demand for efficient identification methods due to the proliferation of mobile devices.
- Several research proposals aim to advance the HAR field, including projects focused on expanding datasets and testing sensitive data. These efforts aim to enhance the robustness and versatility of detection systems and enable their application to various tasks.
- A promising research approach is the integration of optimization approaches with unsupervised pre-training of models, which could contribute to improving recognition accuracy and finding new ways to describe features. These proposed strategies open new opportunities to improve HAR methodologies and address the challenges of this evolving field.

*Best/Worst Results Regarding Accuracy:* The analysis of best and worst results concerning accuracy in human activity recognition reveals intriguing findings.

A Two-Stage *Hidden Markov Model (HMM)* framework showed the best performance and state-of-the-art CNN-based methods showed good accuracy. The success of these models involves using advanced techniques such as ensemble techniques, hierarchical hidden Markov models, convolutional neural networks, and deep neural networks. The field has benefited greatly from new methods that consistently produce better or at least comparable results and represent significant progress in identifying human activities.

The Two-Stage *Continuous Hidden Markov Model (CHMM)* is characterized by its hierarchical classification, which enables efficient feature utilization and achieves the highest reported accuracy. The *CNN-based approach* demonstrated strong discriminative feature extraction capabilities and outperformed state-of-the-art methods, confirming its breakthrough effectiveness. In contrast, the accuracy of the HMM approach (Kim et al., 2016) is lower at 83.51 % compared to the innovative method, ranking it as the worst option in terms of performance in the context of this analysis.

*Realistic Examples:*

*Health Monitoring:* The HAR study can provide clinicians with a tool to monitor daily activities and detect abnormalities during the patient's routine. HAR is also helpful in Parkinson's disease screening to accurately identify symptoms and monitor the course of the condition by tracking its evolution, which is described in terms of the severity of the disease during a time (Ong et al., 2019). Additionally, the HAR monitors patients' rehabilitation to provide a more accurate status of their health condition and assist them in assessing their improvements (Ong et al., 2019). Real-world examples of "*Health Monitoring*" are focal in HAR. These models, for example, can monitor whether a patient in accident rehabilitation is performing the activities (exercises) prescribed by the physician; Can be applied to patient care, therapy, and fitness tracking. Reflects wide-ranging impact on wellness and medical fields;

*Safety*: HAR systems can automatically send alerts if the user falls (Chen & Xue, 2015). In this case, an automatic message can be sent to their relatives, or an automated emergency call could be triggered to save the patient. Smartphones could be used instead of specialized wearable systems (Janidarmian et al., 2017), they have greater flexibility because they do not need to be tied to a receiver and have many response methods, such as sending a text message, an email, or an automatic call. Additionally, smartphones are cheaper, and users can afford a greater audience. Chen et al. proposed a pervasive fall detection system based on mobile phones. Yao et al. proposed a system that automatically detects dangerous vehicle maneuvers to prevent car accidents (Chen & Xue, 2015). The solution required a mobile phone placed in the vehicle, whose accelerometer, gyroscope, and magnetometer are used to collect data and compare it against typical dangerous driving patterns obtained from real driving tests (Yao et al., 2017). Real-world examples of "safety" can be related to the person's safety. These HAR models can monitor bullying activities with the purpose of prevention. It may be helpful to send a smartphone alert to caregivers immediately when a fall, push, or run activity is detected;

*Context-aware Behavior:* HAR can be used to customize the device's behaviors according to the high-level activity that the user is performing, such as "at work" or "walking home"; for instance, the system may be able to turn off incoming calls or set the device mode to silent while the user is working, or if the user is exercising it may play music from a pre-selected playlist. When the user moves, reading the screen is more complex and dangerous. This problem can be overcome by recognizing the user context to automatically adapt the interface and the display methods, thus improving the user experience. Also, the phone volume may be automatically adjusted and increased while the user is walking, and it is subjected to extra noise caused by motion. Real-world examples in "*Context-aware behavior*" can be related to behavioral biometrics topics. Training HAR models is helpful in continuous authentication approaches. They can be related to Touch Dynamics approaches and can thus enhance smartphone security;

*Fitness Tracking:* Fitness tracking monitors metrics such as steps taken, calories burned, and heartbeat. Some advanced systems can observe much more sophisticated metrics, such as climbing floors and sleep quality. Modern smartphones include a built-in accelerometer, a gyroscope, and a global positioning system such as GPS or GLONASS, making fitness tracking available to a broad audience. While specialized devices such as wristbands or sports watches are of a particular purpose, a smartphone is instead a general-purpose device not purchased explicitly by users exclusively interested in activity tracking. Real-world examples in "fitness tracking" can be focal to detect whether one is performing an exercise well. Training HAR models helps monitor parameters such as steps taken, calories burned, and heart rate.

## 6. Conclusions

*Human Activity Recognition (HAR)* is defined as the problem of identifying a physical activity performed by an individual as a function of a motion-tracked in each environment. This work is an extensive survey regarding the most widely used sensors, detectors, datasets, and classifiers to identify the most performing state-of-the-art techniques for HAR. Since the context of this work is to start implementing HAR methodologies, it is necessary to consider the most natural position for carrying the smartphone. When not used, the most natural place to store a smartphone is in your pocket. Moreover, the literature shows that the waist is the best position to perform the HAR task (Mario, 2019; Lara et al., 2012; Sztyler et al., 2017). For this reason, it is necessary to consider all datasets that contain records of devices brought in the waist. Several studies have been made to understand the differences in classification performances when smartphones are carried in hand and waist (Bayat et al., 2014; San-Segundo et al., 2018). The classification performances with the smartphone carried in the waist were generally

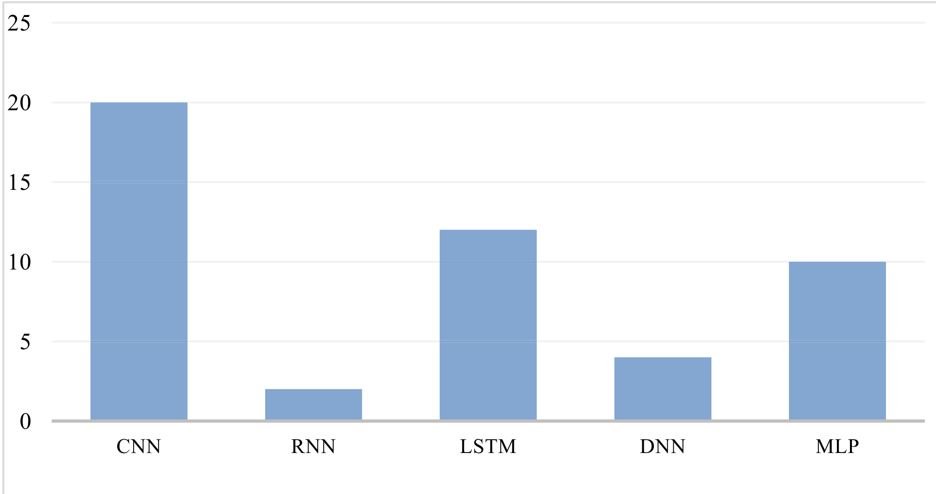


**Fig. 5.** Deep Learning Classification Algorithm. The x-axis shows the Machine Learning Deep Models, while the y-axis shows the frequency of use of the deep models in the scientific papers analyzed correlated to the HAR approach.

better. The literature also shows that accelerometers and gyroscopes are the most used smartphone sensors. The accelerometer generally performs better than the gyroscope, but by combining these two sensors, it is possible to get better classification results (Wang et al., 2016; Ogbuabor & La, 2018; Hnoohom et al., 2017). In most documents, the most easily distinguishable activities are Standing, Laying, Walking Downstairs, Sitting, Walking, and Walking Upstairs. Many activities need to be more easily differentiated from the three axes of the accelerometer. To favor them, the gyroscope could accumulate in the Literature. The most recurrent Datasets in Literature are the WISDM Lab research team, WISDM, Actitracker, and the UCI research team dataset Har using a smartphone. These three datasets contain waist-recorded data. The first two have only accelerometer-recorded data, while the last includes accelerometer and gyroscope data. For what concerns the classification task, it is possible to see that Convolutional Neural Networks (CNNs) and Long Short-Term Memory Recurrent Neural Networks (LSTM) are the most frequent in the Literature and the ones that seem to lead to the best results (see Fig. 5). More implications and analysis have been added in chapter *"5 Discussion."*.

Moreover, unlike other technologies from the Literature, the Neural Network performs well without using complex feature extraction techniques. This can be an advantage since the proposed scenario requires subjects to use their smartphones, each of which can have different kinds of the previously presented sensors. For this reason, a novice reader might delve further into these technologies to better understand how they perform under other conditions by using the previously mentioned datasets in different ways.

### CRediT authorship contribution statement

**Vincenzo Dentamaro:** Conceptualization, Methodology, Investigation, Validation, Visualization, Writing – review & editing. **Vincenzo Gattulli:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Donato Impedovo:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition, Supervision. **Fabio Manca:** Validation, Investigation, Writing – review & editing, Visualization.

### 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.

### Data availability

No data was used for the research described in the article.

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### References

Abdull Sukor, A. S., Zakaria, A., & Abdul Rahim, N. (2018). Activity recognition using accelerometer sensor and machine learning classifiers. In *Proceedings - 2018 IEEE 14th International Colloquium on Signal Processing and Its Application*, 233-238. doi: 10.1109/CSPA.2018.8368718.

Acampora, G., Foggia, P., Saggese, A., & Vento, M. (2012). Combining neural networks and fuzzy systems for human behavior understanding. In *Proceedings - 2012 IEEE 9th International Conference on Advanced Video and Signal-Based Surveillance*, 88-93. doi: 10.1109/AVSS.2012.25.

Akhavian, R., & Behzadan, A. H. (2016). Smartphone-based construction workers' activity recognition and classification. *Automation in Construction, 198–209*. https://doi.org/10.1016/J.AUTCON.2016.08.015

Almaslukh, B., Artoli, A. M., & Al-Muhtadi, J. (2018). A robust deep learning approach for position-independent smartphone-based human activity recognition. *Sensors*. https://doi.org/10.3390/S18113726

Anguita, D., Ghio, A., Oneto, L., P. X., & Reyes-Ortiz, J. L. (2013). A Public Domain Dataset for Human Activity Recognition Using Smartphones. In *Proceedings of the 21th International European Symposium on Artificial Neural Networks*, 437- 442. Tratto da http://www.i6doc.com/en/livre/?GCOI=28001100131010.

Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., & Amirat, Y. (2015). Physical human activity recognition using wearable sensors. *Sensors, 15*, 31314–31338. https://doi.org/10.3390/S151229858

Bayat, A., Pomplun, M., & Tran, D. A. (2014). A study on human activity recognition using accelerometer data from smartphones. *Procedia Computer Science, 34*, 450–457. https://doi.org/10.1016/J.PROCS.2014.07.009

Bernaś, M., Płaczek, B., & Lewandowski, M. (2022). Ensemble of RNN classifiers for activity detection using a smartphone and supporting nodes. *Sensors, 22*. https://doi.org/10.3390/s22239451

Catal, C., Tufekci, S., Pirmit, E., & Kocabag, G. (2015). On the use of ensemble of classifiers for accelerometer-based activity recognition. *Applied Soft Computing, 37*, 1018–1022. https://doi.org/10.1016/J.ASOC.2015.01.025

Chen, W. H., Betancourt Baca, C. A., & Tou, C. H. (2017). LSTM-RNNs combined with scene information for human activity recognition. In *2017 IEEE 19th International Conference on E-Health Networking, Applications and Services*, 1-6. doi:10.1109/HEALTHCOM.2017.8210846.

Chen, Y., & Xue, Y. (2015). A Deep Learning Approach to Human Activity Recognition Based on Single Accelerometer. In *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics*, 1488–1492. doi:10.1109/SMC.2015.263.

Chen, Z., Jiang, C., & Xie, L. (2019). A novel ensemble ELM for human activity recognition using smartphone sensors. *IEEE Transactions on Industrial Informatics, 15*, 2691–2699. https://doi.org/10.1109/TII.2018.2869843

Convertini, V. N., Gattulli, V., Impedovo, D., & Terrone, G. (2023). Classification bullying/cyberbullying through smartphone sensor and a questionnaire application. *Multimedia Tools and Applications*. https://doi.org/10.1007/S11042-023-17609-7/FIGURES/7

Deep, S., & Zheng, X. (2019). Hybrid model featuring CNN and LSTM architecture for Human Activity Recognition on smartphone sensor data. In *Proceedings - 2019 20th International Conference on Parallel and Distributed Computing, Applications and Technologies*, 259-264. doi:10.1109/PDCAT46702.2019.00055.

Dobbins, C., & Rawassizadeh, R. (2018). Towards clustering of mobile and smartwatch accelerometer data for physical activity recognition. *Informatics, 5*, 29. https://doi.org/10.3390/INFORMATICS5020029

Garcia-Gonzalez, D., Rivero, D., Fernández-Blanco, E., & Luaces, M. (2023). Deep learning models for real-life human activity recognition from smartphone sensor data. Internet of Things. *Internet of Things*. doi:10.1016/j.iot.2023.100925.

Gattulli, V., Impedovo, D., Pirlo, G., & Sarcinella, L. (2023). Human activity recognition for the identification of bullying and cyberbullying using smartphone sensors. *Electronics*. https://doi.org/10.3390/electronics12020261

Ghate, V., & Sweetlin Hemalatha, C. (2021). Hybrid deep learning approaches for smartphone sensor-based human activity recognition. *Multimedia Tools and Applications, 80*, 35585–35604. https://doi.org/10.1007/S11042-020-10478-4/TABLES/4

Gholamreza, M., & AlModarresi, S. (2021). A time-efficient convolutional neural network model in human activity recognition. *Multimedia Tools and Applications, 80*, 19361–19376. https://doi.org/10.1007/S11042-020-10435-1/TABLES/8

Gupta, A., Gupta, K., Gupta, K., & Gupta, K. (2020). A Survey on Human Activity Recognition and Classification. In *Proceedings of the 2020 IEEE International Conference on Communication and Signal Processing*, 915–919. doi:10.1109/ICCSP48568.2020.9182416.

Ha, S., & Choi, S. (2016). Convolutional neural networks for human activity recognition using multiple accelerometer and gyroscope sensors. In *Proceedings of the International Joint Conference on Neural Networks*, 381–388. doi:10.1109/IJCNN.2016.7727224.

Ha, S., Y. J., & Choi, S. (2015). Multi-Modal Convolutional Neural Networks for Activity Recognition. In *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics*, 3017–3022. doi:10.1109/SMC.2015.525.

Hassan, M. M., Uddin, M. Z., Mohamedc, A., & Almogren, A. (2018). A robust human activity recognition system using smartphone sensors and deep learning. *Future Generation Computer Systems, 81*, 307–313. https://doi.org/10.1016/J.FUTURE.2017.11.029

Hernandez, F., Suarez, L. F., Villamizar, J., & Altuve, M. (2019). Human Activity Recognition on Smartphones Using a Bidirectional LSTM Network. In *2019 22nd Symposium on Image, Signal Processing and Artificial Vision*, 1-5. doi:10.1109/STSIVA.2019.8730249.

Hnoohom, N., Mekruksavanich, S., & Jitpattanakul, A. (2017). Human Activity Recognition using Triaxial Acceleration Data from Smartphone and Ensemble Learning. In *Proceedings - 13th International Conference on Signal-Image Technology and Internet-Based Systems*, 408-412. doi:10.1109/SITIS.2017.73.

Ignatov, A. (2018). Real-time human activity recognition from accelerometer data using Convolutional Neural Networks. *Applied Soft Computing, 62*, 915–922. https://doi.org/10.1016/J.ASOC.2017.09.027

Ignatov, A. D., & Strijov, V.v. (2015). Human activity recognition using quasiperiodic time series collected from a single tri-axial accelerometer. *Multimedia Tools and Applications, 7257–7270*. https://doi.org/10.1007/S11042-015-2643-0/TABLES/5

Inoue, M., Inoue, S., & Nishida, T. (2017). Deep recurrent neural network for mobile human activity recognition with high throughput. *Artificial Life and Robotics, 173–185*. https://doi.org/10.48550/arxiv.1611.03607

Jain, A., & Kanhangad, V. (2018). Human activity classification in smartphones using accelerometer and gyroscope sensors. *IEEE Sensors Journal, 18*, 1169–1177. https://doi.org/10.1109/JSEN.2017.2782492

Janidarmian, M., Fekr, A. R., Radecka, K., & Zilic, Z. (2017). A comprehensive analysis on wearable acceleration sensors in human activity recognition. *Sensors, 17*, 529. https://doi.org/10.3390/S17030529

Jansi, R., & Amutha, R. (2018). Sparse representation based classification scheme for human activity recognition using smartphones. *Multimedia Tools and Applications, 11027–11045*. https://doi.org/10.1007/S11042-018-6662-5/FIGURES/4

Jordao, A., Torres, L. A., & Schwartz, W. R. (2018). Novel approaches to human activity recognition based on accelerometer data. *Signal, Image and Video Processing, 12*, 1387–1394. https://doi.org/10.1007/S11760-018-1293-X/TABLES/6

KH, A., & Ibrahim, L. (2021). Survey on human activity recognition using smartphone. *AL-Rafidain Journal of Computer Sciences and Mathematics, 55–67*. https://doi.org/10.33899/CSMJ.2021.168253

Kim, Y. J., Kang, B. N., & Kim, D. (2016). Hidden Markov Model Ensemble for Activity Recognition Using Tri-Axis Accelerometer. In *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015*, 3036–3041. doi:10.1109/SMC.2015.528.

Kolosnjaji, B., & Eckert, C. (2018). Neural network-based user-independent physical activity recognition for mobile devices. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 378–386*. https://doi.org/10.1007/978-3-319-24834-9_44

Kwapisz, J. R., Weiss, G. M., & Moore, S. A. (2011). Activity recognition using cell phone accelerometers. *ACM SIGKDD Explorations Newsletter, 74–82*. https://doi.org/10.1145/1964897.1964918

Lara, Ó. D., Prez, A. J., Labrador, M. A., & Posada, J. D. (2012). Centinela: A human activity recognition system based on acceleration and vital sign data. *Pervasive and Mobile Computing, 8*, 717–729. https://doi.org/10.1016/J.PMCJ.2011.06.004

Lee, S. M., Yoon, S. M., & Cho, H. (2017). Human activity recognition from accelerometer data using Convolutional Neural Network. In *2017 IEEE International Conference on Big Data and Smart Computing*. https://doi.org/10.1109/BIGCOMP.2017.7881728

Lu, Y., Wei, Y., Liu, L., Zhong, J., Sun, L., & Liu, Y. (2017). Towards unsupervised physical activity recognition using smartphone accelerometers. *Multimedia Tools and Applications, 10701–10719*. https://doi.org/10.1007/S11042-015-3188-Y/TABLES/4

Mario, M. O. (2019). Human activity recognition based on single sensor square HV acceleration images and convolutional neural networks. *IEEE Sensors Journal, 19*, 1487–1498. https://doi.org/10.1109/JSEN.2018.2882943

Matsui, S., Inoue, N., Akagi, Y., Nagino, G., & Shinoda, K. (2017). User adaptation of convolutional neural network for human activity recognition. *25th European Signal Processing Conference EUSIPCO, 2017*, 753–757. https://doi.org/10.23919/EUSIPCO.2017.8081308

Micucci, D., Mobilio, M., & Napoletano, P. (2017). UniMiB SHAR: A dataset for human activity recognition using acceleration data from smartphones. *Applied Sciences (Switzerland), 7*. https://doi.org/10.3390/APP7101101

Milenkoski, M., Trivodaliev, K., Kalajdziski, S., Jovanov, M., & Stojkoska, B. R. (2018). Real time human activity recognition on smartphones using LSTM networks. In *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics* (pp. 1126–1131). https://doi.org/10.23919/MIPRO.2018.8400205

Mohammed Hashim, B. A., & Amutha, R. (2021). Human activity recognition based on smartphone using fast feature dimensionality reduction technique. *Journal of Ambient Intelligence and Humanized Computing, 12*, 2365–2374. https://doi.org/10.1007/S12652-020-02351-X/TABLES/10

Nweke, H. F., Teh, Y. W., Mujtaba, G., & Al-garadi, M. A. (2019). Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions. *Information Fusion, 46*, 147–170. https://doi.org/10.1016/J.INFFUS.2018.06.002

Ogbuabor, G., & La, R. (2018). Human Activity Recognition for Healthcare using Smartphones. *ACM International Conference Proceeding Series, 41–46*. https://doi.org/10.1145/3195106.3195157

Ong, D. P., San Pedro, E. J., Valenzuela, M. E., & Tiglao, N. M. (2019). BrainSmart: Ambient Assisted Living System Smartphone App Prototype for Parkinson's Disease Patients. *GHTC 2018 - IEEE Global Humanitarian Technology Conference*, 1–6. https://doi.org/10.1109/GHTC.2018.8601563

Panwar, M., Ram Dyuthi, S., Chandra Prakash, K., Biswas, D., Acharyya, A., Maharatna, K., & Naik, G. R. (2017). CNN based approach for activity recognition using a wrist-worn accelerometer. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 2438–2441). https://doi.org/10.1109/EMBC.2017.8037349

Pires, I. M., Marques, G., Garcia, N. M., Flórez-Revuelta, F., Teixeira, M. C., Zdravevski, E., & Coimbra, M. (2020). Pattern recognition techniques for the identification of activities of daily living using a mobile device accelerometer. *Electronics, 9*, 509. https://doi.org/10.3390/ELECTRONICS9030509

Qi, W., Su, H., Yang, C., Ferrigno, G., de Momi, E., & Aliverti, A. (2019). A fast and robust deep convolutional neural networks for complex human activity recognition using smartphone. *Sensors, 19*, 3731. https://doi.org/10.3390/S19173731

Rodrigues, L. M., & Mestria, M. (2016). Classification methods based on bayes and neural networks for human activity recognition. In *2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery, ICNC-FSKD 2016*, 1141–1146. doi:10.1109/FSKD.2016.7603339.

Roggen, D., Calatroni, A., Rossi, M., Holleczek, T., Förster, K., Tröster, G., & Millan, J.d. (2023). Walk-through the OPPORTUNITY dataset for activity recognition in sensor rich environments. *Project: OPPORTUNITY (Activity and Context Recognition with Opportunistic Sensor Configurations). Tratto da*.

Ronao, C. A., & Cho, S. B. (2014). Human activity recognition using smartphone sensors with two-stage continuous hidden markov models. In *2014 10th International Conference on Natural Computation*. https://doi.org/10.1109/ICNC.2014.6975918

Ronao, C. A., & Cho, S. B. (2016). Human activity recognition with smartphone sensors using deep learning neural networks. *Expert Systems with Applications, 59*, 235–244. https://doi.org/10.1016/J.ESWA.2016.04.032

Ronao, C. A., & Cho, S. B. (2017). Recognizing human activities from smartphone sensors using hierarchical continuous hidden Markov models. *International Journal of Distributed Sensor Networks*. https://doi.org/10.1177/1550147716683687/ASSET/IMAGES/LARGE/10.1177_1550147716683687-FIG2.JPEG

San-Segundo, R., Blunck, H., Moreno-Pimentel, J., Stisen, A., & Gil-Martín, M. (2018). Robust Human Activity Recognition using smartwatches and smartphones. *Engineering Applications of Artificial Intelligence, 72*, 190–202. https://doi.org/10.1016/J.ENGAPPAI.2018.04.002

Sardar, A. W., Ullah, F., Bacha, J., Khan, J., Ali, F., & Lee, S. (2022). Mobile sensors based platform of Human Physical Activities Recognition for COVID-19 spread minimization. *Computers in biology and medicine*. https://doi.org/10.1016/j.compbiomed.2022.105662

Slim, S. O., Atia, A., Elfattah, M. M., & Mostafa, M. S. (2019). Survey on human activity recognition based on acceleration data. *International Journal of Advanced Computer Science and Applications, 84–98*. https://doi.org/10.14569/IJACSA.2019.0100311

Stiefmeier, T., Roggen, D., Ogris, G., Lukowicz, P., & Tröster, G. (2008). Wearable activity tracking in car manufacturing. *IEEE Pervasive Computing, 42–50*. https://doi.org/10.1109/MPRV.2008.40

Stisen, A., Blunck, H., Bhattacharya, S., Prentow, T. S., Kjærgaard, M. B., Dey, A., Jensen, M. M. (2015). Smart devices are different: Assessing and mitigating mobile sensing heterogeneities for activity recognition. In *SenSys 2015 - Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems*, 127–140. doi:10.1145/2809695.2809718.

Sztyler, T., Stuckenschmidt, H., & Petrich, W. (2017). Position-aware activity recognition with wearable devices. *Pervasive and Mobile Computing, 38*, 281–295. https://doi.org/10.1016/J.PMCJ.2017.01.008

Tan, T.-H., Wu, J.-Y., Liu, S.-H., & Gochoo, M. (2022). Human activity recognition using an ensemble learning algorithm with smartphone sensor data. *Electronics*. https://doi.org/10.3390/electronics11030322

Tao, D., Wen, Y., & Hong, R. (2016). Multicolumn bidirectional long short-term memory for mobile devices-based human activity recognition. *IEEE Internet of Things Journal, 3*, 1124–1134. https://doi.org/10.1109/JIOT.2016.2561962

Tapia, E. M., Intille, S. S., Haskell, W., Larson, K., Wright, J., King, A., & Friedman, R. (2007). Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor. *Proceedings - International Symposium on Wearable Computers, ISWC, 37–40*. https://doi.org/10.1109/ISWC.2007.4373774

Thakur, D., & Biswas, S. (2020). Smartphone based human activity monitoring and recognition using ML and DL: A comprehensive survey. *Journal of Ambient Intelligence and Humanized Computing, 11*, 5433–5444. https://doi.org/10.1007/S12652-020-01899-Y

Twomey, N., Diethe, T., Fafoutis, X., Elsts, A., McConville, R., Flach, P., & Craddock, I. (2018). A comprehensive study of activity recognition using accelerometers. *Informatics, 5*, 27. https://doi.org/10.3390/INFORMATICS5020027

Ullah, M., Ullah, H., Khan, S. D., & Cheikh, F. A. (2019). Stacked Lstm network for human activity recognition using smartphone data. *Proceedings - European Workshop on Visual Information Processing, EUVIP, 175–180*. https://doi.org/10.1109/EUVIP47703.2019.8946180

Voicu, R. A., Dobre, C., Bajenaru, L., & Ciobanu, R. I. (2019). Human physical activity recognition using smartphone sensors. *Sensors (Basel, Switzerland)*. doi:10.3390/S19030458.

Vyas, V., Walse, K., & Dharaskar, R. (2017). A Survey on Human Activity Recognition using Smartphone. *Nternational Journal of Advance Research in Computer Science and Management Studies, 5*.

Walse, K. H., Dharaskar, R.v., & Thakare, V. M. (2016). PCA based optimal ANN classifiers for human activity recognition using mobile sensors data. *Smart Innovation, Systems and Technologies, 1*, 429–436. https://doi.org/10.1007/978-3-319-30933-0_43/COVER

Wan, S., Qi, L., Xu, X., Tong, C., & Gu, Z. (2020). Deep learning models for real-time human activity recognition with smartphones. *Mobile Networks and Applications*, 743–755. doi:10.1007/S11036-019-01445-X/FIGURES/7.

Wang, A., Chen, G., Yang, J., Zhao, S., & Chang, C. Y. (2016). A comparative study on human activity recognition using inertial sensors in a smartphone. *IEEE Sensors Journal, 16*, 4566–4578. https://doi.org/10.1109/JSEN.2016.2545708

Wannenburg, J., & Malekian, R. (2017). Physical activity recognition from smartphone accelerometer data for user context awareness sensing. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 47*, 3142–3149. https://doi.org/10.1109/TSMC.2016.2562509

Weiss, G. M., Pulickal, T. T., McHugh, P. T., Ronan, I. H., & Timko, J. L. (2016). Actitracker: A smartphone-based activity recognition system for improving health and well-being. In *Proceedings - 3rd IEEE International Conference on Data Science and Advanced Analytics*, 682–688. doi:10.1109/DSAA.2016.89.

Xu, L., Yang, W., Cao, Y., & Li, Q. (2018). Human activity recognition based on random forests. In *ICNC-FSKD 2017 - 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery*, 548-553. doi:10.1109/FSKD.2017.8393329.

Xu, W., Pang, Y., Yang, Y., & Liu, Y. (2018). Human Activity Recognition Based On Convolutional Neural Network. *Proceedings - International Conference on Pattern Recognition, 165–170*. https://doi.org/10.1109/ICPR.2018.8545435

Yao, S., Hu, S., Zhao, Y., Zhang, A., & Abdelzaher, T. (2017). DeepSense: A unified deep learning framework for time-series mobile sensing data processing. *26th International World Wide Web Conference WWW, 2017*, 351–360. https://doi.org/10.48550/arxiv.1611.01942

Yu, S., & Qin, L. (2018). Human activity recognition with smartphone inertial sensors using bidir-LSTM networks. In *Proceedings - 2018 3rd International Conference on Mechanical, Control and Computer Engineering, ICMCCE 2018*, 219-224. doi:10.1109/ICMCCE.2018.00052.

Yu, T., Chen, J., Yan, N., & Liu, X. (2018). A Multi-Layer Parallel LSTM Network for Human Activity Recognition with Smartphone Sensors. In *2018 10th International Conference on Wireless Communications and Signal Processing, 2018 10th International Conference on Wireless Communications and Signal Processing, WCSP 2018*, 1-6. doi:10.1109/WCSP.2018.8555945.

Zebin, T., Scully, P. J., Peek, N., Casson, A. J., & Ozanyan, K. B. (2019). Design and implementation of a convolutional neural network on an edge computing smartphone for human activity recognition. *IEEE Access, 7*, 133509–133520. https://doi.org/10.1109/ACCESS.2019.2941836

Zebin, T., Sperrin, M., Peek, N., & Casson, A. J. (2018). Human activity recognition from inertial sensor time-series using batch normalized deep LSTM recurrent networks. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 1-4. doi:10.1109/EMBC.2018.8513115.

Zeng, M., Nguyen, L. T., Yu, B., Mengshoel, O. J., Zhu, J., Wu, P., & Zhang, J. (2014). Convolutional Neural Networks for human activity recognition using mobile sensors. In *Proceedings of the 2014 6th International Conference on Mobile Computing, Applications and Services, MobiCASE 2014*, 197-205. doi:10.4108/ICST.MOBICASE.2014.257786.

Zhang, L. W. (2015). Human activity recognition with HMM-DNN model. In *Proceedings of 2015 IEEE 14th International Conference on Cognitive Informatics and Cognitive Computing, ICCI*CC 2015*, 192–197. doi:10.1109/ICCI-CC.2015.7259385.

Zhang, L., Wu, X., & Luo, D. (2015). Real-Time Activity Recognition on Smartphones Using Deep Neural Networks. In *2015 IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom)*, 1236–1242. doi:10.1109/UIC-ATC-ScalCom-CBDCom-IoP.2015.224.

Zhang, L., Wu, X., & Luo, D. (2016). Recognizing human activities from raw accelerometer data using deep neural networks. In *Proceedings - 2015 IEEE 14th International Conference on Machine Learning and Applications, ICMLA 2015*, 865–870. doi:10.1109/ICMLA.2015.48.

Zhou, B., Yang, J., & Li, Q. (2019). Smartphone-based activity recognition for indoor localization using a convolutional neural network. *Sensors, 19*, 621. https://doi.org/10.3390/S19030621

Zhu, Q., Chen, Z., & Soh, Y. C. (2019). A novel semisupervised deep learning method for human activity recognition. *IEEE Transactions on Industrial Informatics, 15*, 3821–3830. https://doi.org/10.1109/TII.2018.2889315