Daily physical activities recognition using wearable devices: a systematic mapping

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Abstract. *Sensors available in wearable devices can monitor their user's physical and mental health by recognizing the daily routine of physical activities. Because the area of human activity recognition can be complex due to a large amount of information, this work aims to facilitate the understanding of the area by providing a systematic mapping. A search using the Scopus database was conducted and resulted in 44 correspondences. The results were then classified according to their usage of primary techniques, preprocessing, feature extraction, sensors, datasets, most found activities, and considerations of lightweight algorithms. To better visualize the data, an online platform was also developed.*

1. Introduction

Recognizing daily human activities automatically can be helpful in many areas designed around user behavior, such as home care support, postoperative trauma, rehabilitation, abnormal activities, exercise, and fitness [Gupta 2020].

There are many ways to detect activities, e.g., using sensors, smartphones, or images [Jobanputra 2019]. Sensor-based detection can include a gyroscope, an accelerometer, wireless technologies, sound sensors, and others [Wang 2019] which can be packed inside a wearable smartphone or attached to the body, while video-based detection uses cameras. The latter does not require the user to wear any object but raises privacy concerns due to the usage of the person's video [Ann 2014], and it is difficult to capture all daily activities since the camera is usually attached to the environment [Ann 2014], not being able to follow the user's activities constantly.

More specifically, wearables are mobile devices created to be worn. They can collect, process, and upload data, but unlike smartphones, they can be more present in daily routines [Seneviratne 2017]. As a result, much information can be extracted, ranging from indoor localization and navigation to financial payments [Seneviratne 2017]. However, wearables stand out in physical and mental health monitoring. This monitoring is done by several sensors in the devices, such as accelerometer and gyroscope, most commonly found in those apparatus, and more specific ones, such as heart rate, temperature, GPS, and oxygen saturation [Seneviratne 2017]. By processing the data provided by those sensors, it can be possible to understand a user's routine and provide feedback and recommendations about their health status.

The usage of wearables has been rising [Spil 2019]. Due to that boom in its usage, the area of Human Activity Recognition (HAR) also followed the same path, and HAR using wearable technology has also been under many studies, from how to analyze and process the data from its sensors to methods that can get that data and process it, recognizing the current activity.

A subarea of HAR is the recognition of activities of daily living (ADL) [Pashmdarfard 2020], such as eating, dressing, bathing, watching television, and sweeping the house [Zheng 2008], and physical exercise, such as walking and running. With the usage of wearables and recognition of daily physical activities, which includes some ADL and physical exercises, it can be possible to understand a user's routine and provide feedback and recommendations about their health status.

As a result of the many studies, many techniques have been developed. However, it can be difficult to assimilate all that knowledge because of all the available data. To understand the recognition of daily physical activities, i.e., what it is capable of, challenges, and which techniques are being mainly used, a great commencement is to use a systematic mapping which is a method of secondary study that can provide an overview of a topic area, identify current gaps or provide background for new research [Kitchenham 2004]. Researchers can use it and, if necessary, it can precede a systematic review [Barbosa 2011], which is more specific and in-depth.

This work aims to provide background for future researchers on daily physical activity recognition using wearables by providing a systematic mapping. Not only that but there will be a focus on the user's ease and practicality. Because of that, there will be a restriction on the types of wearables considered: smartwatches, smartbands, wristbands, earbuds, and smartglasses. Although there are other wearable devices, such as smart clothing [Cho 2009], they are not commonly available since some are still in development, as is the case of smart clothing, or have found a specific niche. Therefore, this work focuses only on those devices easily found on the market since they are more common and available.

Furthermore, some works propose the fusion of data from multiple devices. That would force users to necessarily possess these equipment sets to benefit from the proposed system. Therefore, this work focuses only on research that uses only one piece of equipment.

The remaining of this work is organized as follows: the related works are presented in Section 2. The methodology used in this work is introduced in Section 3. Section 4 presents and discusses the mapping results. Finally, the conclusion is stated at the end, in Section 5.

2. Related Works

It is searched in Scopus[1] for systematic works with the following keywords: "Systematic," "Wearable," and "HAR," or "Human Activity Recognition," or "Human

[1] Scopus search is found at: https://www.scopus.com/search/form.uri?display=advanced

Activity Decoding" in title, abstract, or keywords. Scopus is considered one of the best databases for searching articles [Falagas 2008]. Its content is obtained from the archives of 60 major publishers. These major publishers include Springer Nature, Wiley Blackwell, Taylor & Francis, IEEE, American Physical Science, and Elsevier [Scopus 2020]. As of March 2023, it only generated four results. Although all are systematic works, only one of them is a systematic mapping. The others are an evaluation of techniques, a study, and a review. They are seen next.

The work of [De Nardin 2020] systematically mapped 21 papers published between 2010 and 2019 to identify resources as variables and associated values used in developing HAR systems for older people. However, not only if it focuses on older people, some points could be improved. For example, it does not consider only wearables but also smartphones in the same mapping. In addition, it includes articles from 2010 that could be considered old in technology. For example, the most used algorithms do not include any deep learning model, which has significantly been explored in recent years.

In the same year, a systematic evaluation was also published by [Le 2020]. It evaluated several deep learning models for HAR from wearable sensors. Convolutional Neural Network (CNN), DeepConvLSTM - a combination of CNN and Long Short Term Memory (LSTM), and SensCapsNet, a Capsule Neural Network for wearable sensor-based HAR, were implemented and evaluated on three benchmark datasets. This work explores HAR, but it does by evaluating three models, which is insufficient to understand the area.

Also, in 2020, [Chang 2020] systematically studied Unsupervised Domain Adaptation for Robust Human-Activity Recognition. They study the problem of wearing diversity which pertains to the placement of the wearable sensor on the human body, and demonstrates that even state-of-the-art deep learning models are not robust against these factors. The core contribution lies in presenting a first-of-its-kind in-depth study of unsupervised domain adaptation (UDA) algorithms in the context of wearing diversity. They discuss the problem of placement of wearable devices in the body, but placement is just one of many aspects to be considered in daily physical activity recognition.

The last result from Scopus is the work of [Cerón 2018], 2018. They perform a systematic review of Human Activity Recognition (HAR) approaches supported on Indoor Localization (IL) and vice versa, describing the methods they have used, the accuracy they have obtained, and whether they have been directed towards the AAL domain or not. Because their work focuses on the relationship between HAR and IL, it does not provide a general description of the area of ADL detection.

After analyzing those results, a systematic mapping of the area of daily physical activity recognition could help understand a general idea of it so that it could be used to improve the life of wearable users. Therefore, in the following sections, it is possible to understand how the mapping is done and the results of it.

3. Method

The systematic mapping process has been done according to [Petersen 2008] and [Clapton 2009], and its results were scanned and presented by following the PRISMA protocol. The following subsections explain each process.

3.1. Research questions

Since this is a systematic mapping study, its primary objective is to understand the research area comprehensively. In order to achieve this, the study needs to address several fundamental questions that provide a clear direction and framework for the overview of current research regarding daily physical activity recognition techniques. Therefore, the following set of questions can serve as a summary of the main objectives of the mapping study:

1. What are the techniques most frequently used in daily physical activity recognition?
2. What data is frequently used in the recognition?
    a. Which are the most commonly used sensors?
    b. Where are the sensors typically positioned?
    c. Is the raw sensor's data used, or is any processing applied?
    d. Which datasets are being used?
3. Which and how many activities are recognized?
4. Are the computational capabilities of the wearables taken into consideration? Mainly, are the recognition methods lightweight?

The first question aims to identify the primary methods or algorithms used to recognize daily physical activities using wearable technology. The second one aims to identify how the data is applied to those systems, which includes understanding which data is needed, how it is passed to the techniques, and where they can be found. The third question aims to understand what has been recognized. At last, what the literature review shows about using lightweight methods.

3.2. Search methodology

In this section, the search methodology is explained. The search was conducted by creating a search string applied to the Scopus search, as shown next:

TITLE-ABS-KEY ("Human Activity Recognition" OR "Human Activity Decoding")

AND TITLE-ABS-KEY ("Neural Network" OR "Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Deep Learning")

AND PUBYEAR AFT 2019

AND (LIMIT-TO (LANGUAGE , "English") OR LIMIT-TO (LANGUAGE , "Portuguese"))

AND (LIMIT-TO (PUBSTAGE , "final"))

AND TITLE-ABS-KEY ("Wearable Sensor")

OR CONFNAME ("Wearable")

In the first condition, it is checked for all works that include the phrases "Human Activity Recognition" or "Human Activity Decoding" in the title, abstract, or keywords. Then it is looked for the ones that use AI, so the phrases "Neural Network," "Artificial Intelligence," "AI," "Machine Learning," or "Deep Learning" are expected in the result. This work has considered what was done in 2020 and after since it was considered three years an acceptable margin for state of the art in technology. Because the languages the authors are familiar with are Portuguese and English, they were also a constraint. Moreover, most academic works are written in English [Rao 2019], especially in technology. Therefore, it was also considered only the ones at the final publication stage and considered the usage of wearables. By experimentation, it was found that some works did not mention wearables in their title, abstract, or keywords, including "wearable" in their conference names as the only indication, so that was also included in the research string.

3.3. Inclusion/Exclusion criteria

After applying the search string, the results must be checked to see if they are relevant to answer the research questions. For that, the inclusion/exclusion criteria are applied. The ones used in this work are:

- It must only use commercially available wearables (or sensors that simulate one). As mentioned before, the following wearables are considered: smartwatches, smartbands, wristbands, earbuds, and smartglasses;
- It must be able to function even if only one wearable device is available;
- Must be able to recognize daily physical activities, e.g., sweeping the house, going up and down the stairs, running, and walking;
- Must be able to detect at least two different activities;
- It must not be a short paper. In this case, the works with four or fewer pages are discarded based on the premise that the available information needs to be more detailed;
- Must be submitted after 2019. It was considered three years an acceptable margin for understanding what is being done with state of the art in technology, including the emergence of new types of technology, such as blood oxygen sensors;
- Must be written in Portuguese or English, the languages that are familiar to the authors;

3.4. Selection Process

In the selection process, the criteria are applied to the results of the string search. It can be divided into three stages:

1. Firstly, papers with at most four pages are discarded, following the criteria that it must not be a short paper;
2. The title and abstract are checked for each result to see if it is according to the criteria. At this stage, even if some criteria cannot be checked, it is moved to the next stage. That is done to avoid removing a work that some information is only found in another section;

3. Each result from the previous stage was checked to see if it matched all the criteria.

3.5. Online Visualizer

After the results are obtained, they are analyzed to answer the research questions. In the next section, it is possible to see the selected works. To better visualize the data, an online platform will be made by compiling the data into JSON files and, by using GitHub sites[2], HTML, and google charts[3], provide a tool for searching datasets based on one or more specific activities or searching the works based on the techniques that a researcher is looking for. Finally, there will also be an option to see interactive and customizable results graphs.

3.6. Threats to validity

Since the primary author has mainly conducted the mapping process, a few regards should be considered. They can be summarized in the following points: selection and interpretation bias and human error. The bias has been minimized as best as possible: the primary author discussed the topics of any ongoing work that he did not feel 100% sure of and followed the inclusion/exclusion criteria as strictly as possible. As to human error, the authors tried to minimize it by structuring the resulting data well and reviewing the parts most prone to error.

4. Results and discussion

The search string on Scopus was conducted on December 6, 2022. As shown in Figure 1, It returned 395 results[4]. After applying the first selection process, 35 results were eliminated. Five results were also discarded at this stage since they were entire conferences or workshops, and their papers were already listed. After the second selection process, only 188 results remained. Finally, after the last one, 44 results remained.

Of those 44, some articles propose configurations and scenarios incompatible with the defined criteria, in addition to at least one compatible. In these cases, only the part of the technique compatible with the defined criteria was considered in this research.

All the results, techniques, datasets, and sensors used can be seen in Table 1 and are detailed in the following subsections, which try to map the area of daily physical activity recognition. To answer the first research question, all the techniques used for recognition are analyzed. To answer the second and third ones, the types of preprocessing, feature extraction, sensors, and datasets frequently used in this kind of application are examined, and the most found activities are studied. Finally, the last

[2] Github sites is available at: https://pages.github.com/

[3] Google charts provides interactive charts for browsers and mobile devices. It is available at: https://developers.google.com/chart

[4] All the results can be found at: https://github.com/vhlk/Systematic-Mapping-Activities-Wearables/blob/main/data/search_articles.csv

question is acknowledged by investigating if the state of the art considers lightweight algorithms.

The online Visualizer is also presented at the end of the results, discussing how some data can be interactively visualized and searched.

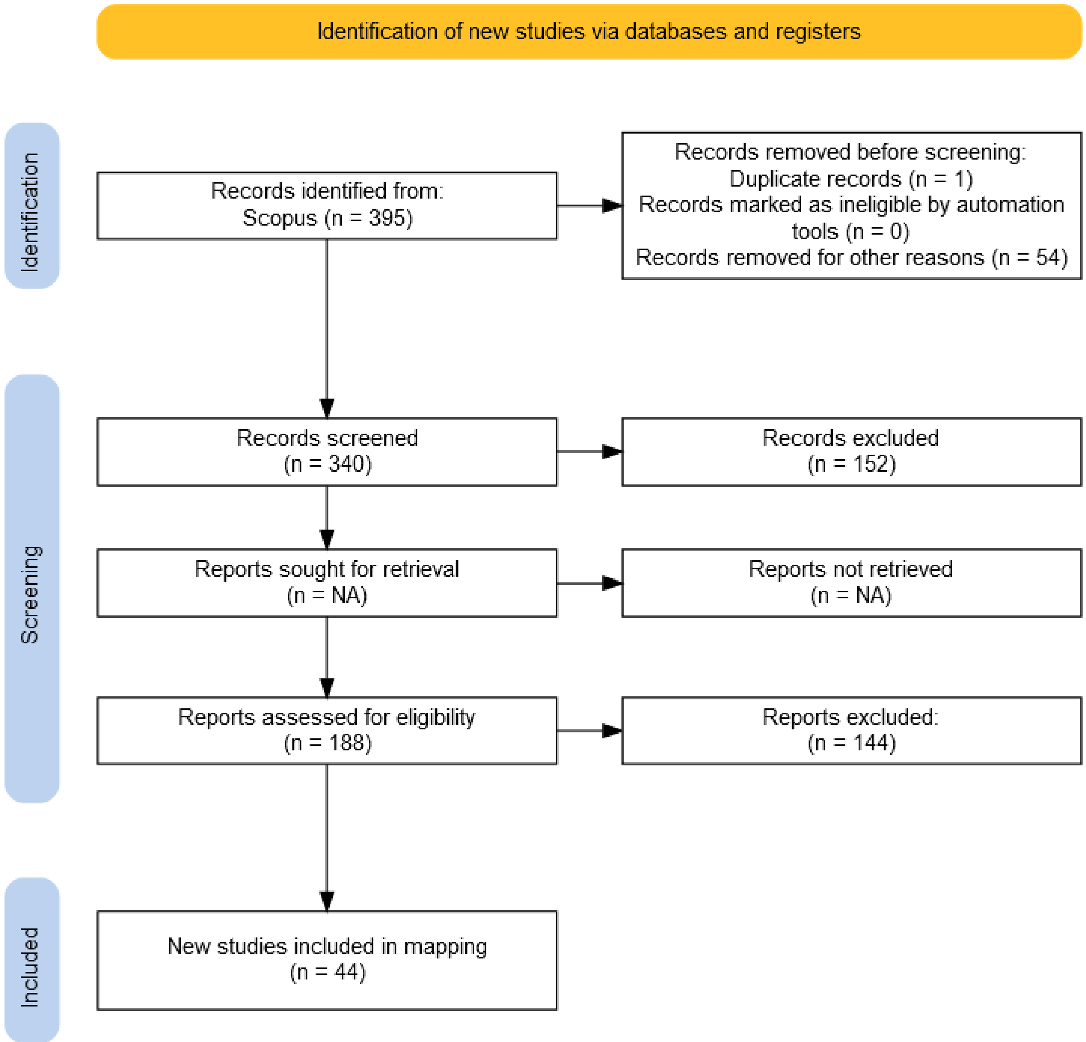

Figure 1. PRISMA flow diagram[5] of this work systematic mapping.

Table 1. Results and its techniques, datasets, sensors used, and year.

Title	Authors	Techniques used	Datasets	Sensors used	Year
A Deep Learning Architecture for Human Activity Recognition Using PPG and Inertial Sensor Dataset	Bondugula R.K.; Sivangi K.B.; Udgata S.K.	CNN	Dataset from PPG wireless sensor for activity	PPG; ACC	2022

[5] PRISM flow datagram was created with Shiny App [Haddaway 2022]

			monitoring		
Hierarchical Deep Learning Model With Inertial And Physiological Sensors Fusion For Wearable-based Human Activity Recognition	Hwang D.Y.; Ng P.C.; Yu Y.; Wang Y.; Spachos P.; Hatzinakos D.; Plataniotis K.N.	CNN; LSTM	PPG-DaLiA	ACC, PPG; EDA	2022
Hierarchical Human Activity Recognition Based on Smartwatch Sensors Using Branch Convolutional Neural Networks	Hnoohom N.; Maitrichit N.; Mekruksavanich S.; Jitpattanakul A.	CNN	WISDM	ACC; GYRO	2022
DANA: Dimension-Adaptive Neural Architecture for Multivariate Sensor Data	Malekzadeh M.; Clegg R.; Cavallaro A.; Haddadi H.	CNN; LSTM	UTwente	ACC, GYRO; MAG	2021
Improving Human Activity Recognition using ML and Wearable Sensors	Mubibya G.S.; Almhana J.	LDA; QDA; KNN; DT; RF	PAMAP2	Temperature; ACC; GYRO; MAG	2022
Human activity recognition by wearable sensors in the smart home control problem	Nebogatikov I.Y.; Soloviev I.P.	MLP; KNN; RF; Naive Bayes; AdaBoost; SVM	An Open Dataset for Human Activity Analysis	HR; ACC	2021
Human activity recognition based on hybrid learning algorithm for wearable sensor data	Athota R.K.; Sumathi D.	CNN; LSTM; GRU	WISDM	GYRO; ACC	2022
Deep Learning Approach for Complex Activity Recognition using Heterogeneous Sensors from Wearable Device	Hnoohom N.; Jitpattanakul A.; You I.; Mekruksavanich S.	LSTM	WISDM	GYRO; ACC	2021
Human activity recognition by combining external features with accelerometer sensor data using deep learning network model	Varshney N.; Bakariya B.; Kushwaha A.K.S.; Khare M.	CNN; LSTM	Recognition of Daily Human Activity Using an Artificial Neural Network and Smartwatch	ACC	2022
ResNet-SE: Channel Attention-Based Deep Residual Network for Complex Activity Recognition Using Wrist-Worn Wearable Sensors	Mekruksavanich S.; Jitpattanakul A.; Sitthithakerngkiet K.; Youplao P.; Yupapin P.	CNN	WISDM; UT-Smoke; UTwente	GYRO; ACC	2022
An Integrated ARMA-Based Deep Autoencoder and GRU Classifier System for Enhanced Recognition	Rivera P.; Valarezo E.; Kim T.-S.	GRU	Opportunity	ACC; GYRO; MAG	2021

of Daily Hand Activities					
Complex Human Activity Recognition Using a Local Weighted Approach	Asuroglu T.	RF	PAAL ADL Accelerometry dataset	ACC	2022
Deep convolutional neural network with rnns for complex activity recognition using wrist-worn wearable sensor data	Mekruksavanich S.; Jitpattanakul A.	CNN; GRU	UTwente	ACC; GYR; MAG	2021
A multi-sensor deep learning approach for complex daily living activity recognition	Woodward K.; Kanjo E.; Taylor K.; Hunt J.A.	CNN; LSTM	own dataset	ACC	2022
Validation of human activity recognition using a convolutional neural network on accelerometer and gyroscope data	Hysenllari E.; Ottenbacher J.; McLennan D.	CNN	own dataset	ACC;GYRO	2022
NoFED-Net: Nonlinear Fuzzy Ensemble of Deep Neural Networks for Human Activity Recognition	Ghosal S.; Sarkar M.; Sarkar R.	CNN; LSTM	WHARF	ACC	2022
Deep learning based human activity recognition (HAR) using wearable sensor data	Gupta S.	CNN; GRU	WISDM	ACC; GYRO	2021
Exploring Artificial Neural Networks Efficiency in Tiny Wearable Devices for Human Activity Recognition	Lattanzi E.; Donati M.; Freschi V.	CNN; MLP	RWHAR	ACC; GYRO	2022
Simultaneous Recognition Algorithm of Human Activity and Phone Position Based on Multi-sensor Data Fusion	Ai D.; Hao R.; Feng C.; Li Y.; Liu Y.	LSTM	RWHAR	ACC; GYRO	2022
Comparison Study of Inertial Sensor Signal Combination for Human Activity Recognition based on Convolutional Neural Networks	Nazari F.; Mohajer N.; Nahavandi D.; Khosravi A.; Nahavandi S.	CNN	PAMAP2	ACC; GYRO	2022
Deep Learning Approaches for Unobtrusive Human Activity Recognition using Insole-based and Smartwatch Sensors	Hnoohom N.; Maitrichit N.; Mekruksavanich S.; Jitpattanakul A.	CNN	19NonSens	ACC; GYRO	2022
Highly-accurate binary tiny neural network for low-power human activity recognition	De Vita A.; Pau D.; Di Benedetto L.; Rubino A.; Pétrot F.; Licciardo G.D.	CNN	PAMAP2	ACC; GYRO	2021

Deep ConvLSTM with Self-Attention for Human Activity Decoding Using Wearable Sensors	Singh S.P.; Sharma M.K.; Lay-Ekuakille A.; Gangwar D.; Gupta S.	CNN; LSTM	WHARF	ACC	2021
Heterogeneous Recognition of Human Activity with CNN and RNN-based Networks using Smartphone and Smartwatch Sensors	Mekruksavanich S.; Jantawong P.; Hnoohom N.; Jitpattanakul A.	CNN; LSTM; GRU	HHAR	ACC; GYRO	2022
Human activity recognition based on smartphone and wearable sensors using multiscale DCNN ensemble	Sena J.; Barreto J.; Caetano C.; Cramer G.; Schwartz W.R.	CNN	WHARF; UTD-MHAD1	ACC; GYRO	2021
A machine learning approach for human activity recognition	Papoutsis A.; Botilias G.; Karvelis P.; Stylios C.	LSTM	RWHAR; own dataset	ACC; GYRO	2020
ADLs Detection with a Wrist-Worn Accelerometer in Uncontrolled Conditions	Fioretti S.; Olivastrelli M.; Poli A.; Spinsante S.; Strazza A.	KNN; DT; RF; Naive Bayes; SVM	own dataset	ACC	2021
A lean and performant hierarchical model for human activity recognition using body-mounted sensors	Debache I.; Jeantet L.; Chevallier D.; Bergouignan A.; Sueur C.	KNN; SVM; LR; GB	DaLiAc	ACC; GYRO	2020
SensCapsNet: Deep Neural Network for Non-Obtrusive Sensing Based Human Activity Recognition	Pham C.; Nguyen-Thai S.; Tran-Quang H.; Tran S.; Vu H.; Tran T.-H.; Le T.-L.	CNN	19NonSens (own dataset)	ACC; GYRO	2020
Feature Engineering for Human Activity Recognition	Atalaa B.A.; Ziedan I.; Alenany A.; Helmi A.	RF	WHARF	ACC	2021
Human Activity Recognition Using Elliptical and Archimedean R-Vine Copulas with Multimodal Data	Kulkarni S.; Shreyas R.; Rk R.; Harshith M.; Srikanth S.; Gurugopinath S.	MLP	PESHAR (own dataset)	ACC; GYRO	2021
Human Activity Recognition Using Wearable Sensors: Review, Challenges, Evaluation Benchmark	Abdel-Salam R.; Mostafa R.; Hadhood M.	MLP	UTD-MHAD1; WHARF	ACC; GYRO	2021
Accurate human activity recognition with multi-task learning	Li Y.; Zhang S.; Zhu B.; Wang W.	CNN	RWHAR	ACC	2020

Characterizing Peaks in Acceleration Signals-Application to Physical Activity Detection Using Wearable Sensors	Abbas M.; Jeannes R.L.B.	SVM	own dataset	ACC	2020
Deep Neural Networks for Time Series Classification in Human Activity Recognition	Joshi S.; Abdelfattah E.	CNN; LSTM	WISDM	ACC; GYRO	2021
Smart system for recognizing daily human activities based on wrist IMU sensors	Ayman A.; Attalah O.; Shaban H.	DT; RF; SVM	Handy; PAMAP2	MAG; ACC; GYRO	2020
Deep Human Activity Recognition with Localisation of Wearable Sensors	Lawal I.A.; Bano S.	CNN	RWHAR	ACC; GYRO	2020
Improving Deep Learning for HAR with Shallow LSTMs	Bock M.; Hölzemann A.; Moeller M.; Van Laerhoven K.	CNN; LSTM	RWHAR; HHAR	ACC	2020
Comparative Analysis of Different Approaches to Human Activity Recognition Based on Accelerometer Signals	Gomaa W.	RF; SVM; Histogram Based Measures; Kernel Density Estimate; Estimations Using Discrete Distributions	Dataset for ADL Recognition with Wrist-worn Accelerometer Data Set	ACC	2021
Recognition of human activities for wellness management using a smartphone and a smartwatch: A boosting approach	Tarafdar P.; Bose I.	AdaBoost; XgBoost; Boosted C5.0	extrasensory	ACC; Compass	2021
A deep learning approach for human activities recognition from multimodal sensing devices	Ihianle I.K.; Nwajana A.O.; Ebenuwa S.H.; Otuka R.I.; Owa K.; Orisatoki M.O.	CNN; LSTM	WISDM	ACC; GYRO	2020
A Comparison of Wearable Sensor Configuration Methods for Human Activity Recognition Using CNN	Tong L.; Lin Q.; Qin C.; Peng L.	CNN	Daily and Sports Activities	ACC; GYRO; MAG	2021
CNN-Based Deep Learning Network for Human Activity Recognition During Physical Exercise from Accelerometer and Photoplethysmographic Sensors	Mekruksavanich S.; Jitpattanakul A.	CNN	PPG Dataset	ACC; PPG	2022

Classification of Physical Exercise Activity from ECG, PPG and IMU Sensors using Deep Residual Network	Mekruksavanich S.; Jantawong P.; Hnoohom N.; Jitpattanakul A.	CNN	Wrist PPG	PPG; ECG; ACC; GYRO; MAG	2022

4.1. Techniques

This subsection aims to understand what are the techniques that have been applied in the area of physical exercise detection. Two main types of techniques were found: those that use classical machine learning (10) methods and those that use neural networks (34). They are shown next.

4.1.1. Classical Machine Learning

From the papers included, ten works presented at least one type of Classical Machine Learning technique. Most of them (70%) used multiple machine learning techniques so that it could be verified which one could achieve better results for this specific task. Random Forest has been the most used of the many options employed, as seen in Figure 2, which shows all algorithms used more than once. Other commonly used include Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Decision Trees (DT), Naive Bayes (NB), and AdaBoost. Used only once were: Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Linear Regression (LR), Gradient Boosting (GB), XgBoost, Boosted C5.0, Histogram Based Measures, Kernel Density Estimation, and Estimations Using Discrete Distributions. It is worth mentioning that GB, XgBoost, and Boosted C5.0 all used Decision Trees as their weak prediction model.

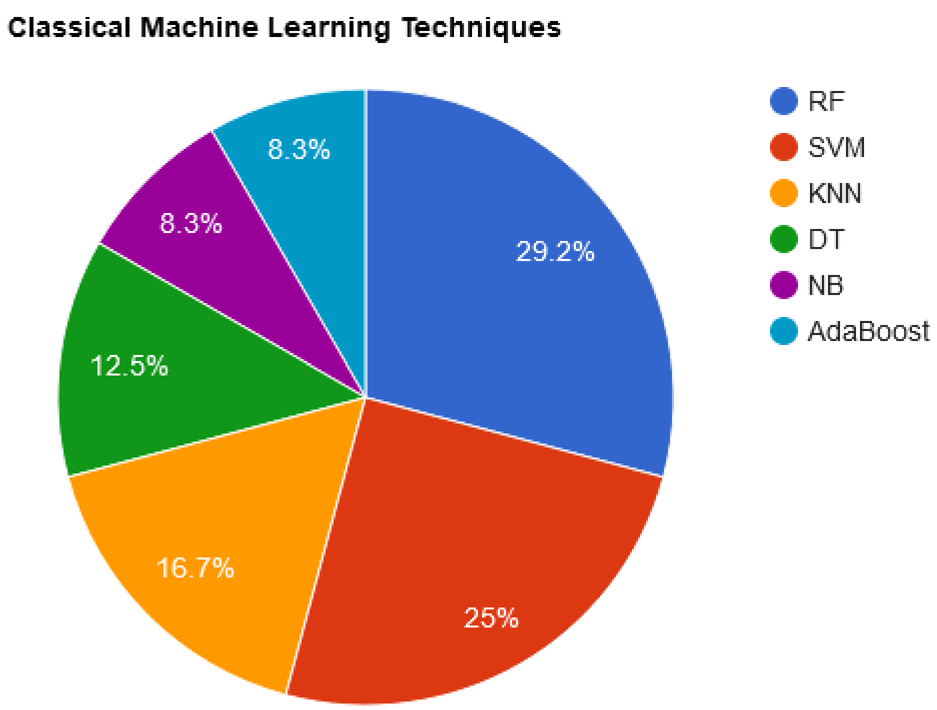

Figure 2. Most used Classical Machine Learning techniques. Only the techniques used more than once are shown.

4.1.2 Deep Learning

Most (approximately 77%) of the results showed the usage of Deep Learning (DL) models. Some of them included special algorithms, i.e., Convolutional Neural Networks (CNN), Recurrent Neural Networks (namely, Long Short-Term Memory, LSTM, and Gated Recurrent Units, GRU), and others are composed of only neurons, which in this work are called MLP (Multilayer Perceptron). The most used algorithm is CNN, corresponding to approximately 82% of all works that use Deep Learning. One of the reasons for its popularity is the ability to extract local features from the data, sometimes used in association with an RNN (Recurrent Neural Network) to replace feature engineering and data preprocessing, which would need some domain expertise [Dua 2021]. Of the 34, 4 (approximately 12%) were MLPs, not using any special algorithm, as seen in Figure 3.

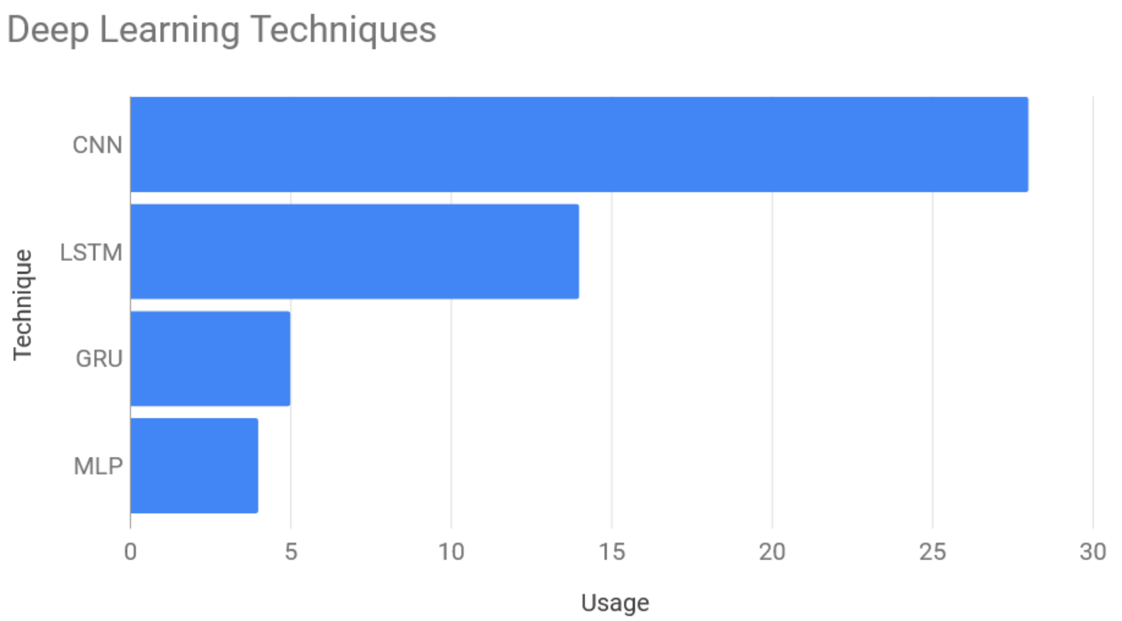

Figure 3. Deep Learning techniques.

When comparing the usage of Classical Machine Learning and Deep Learning, it is possible to see a preference for the latter in recent years. However, when analyzing the number of works, there is also an indication of decreasing works using the Classical Machine Learning approach (Figure 4), while the other seems to gain popularity (Figure 5). One reason could be that it is still being refined, and its results are constantly improving. Another reason could be related to the need for data processing, as discussed later and in more detail next.

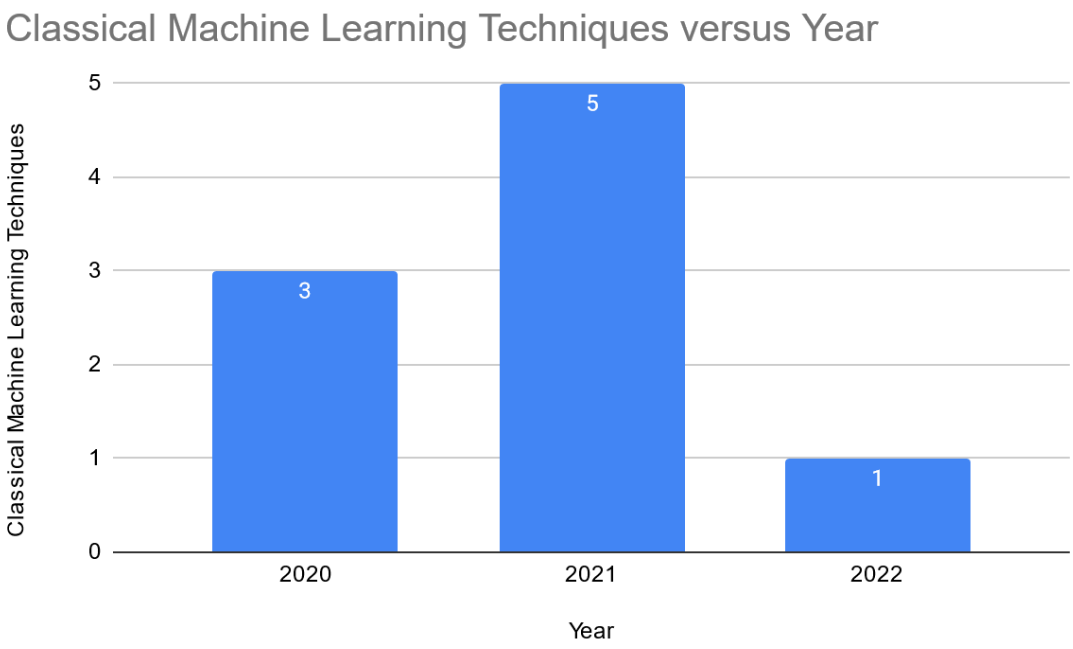

Figure 4. Classical Learning techniques each year.

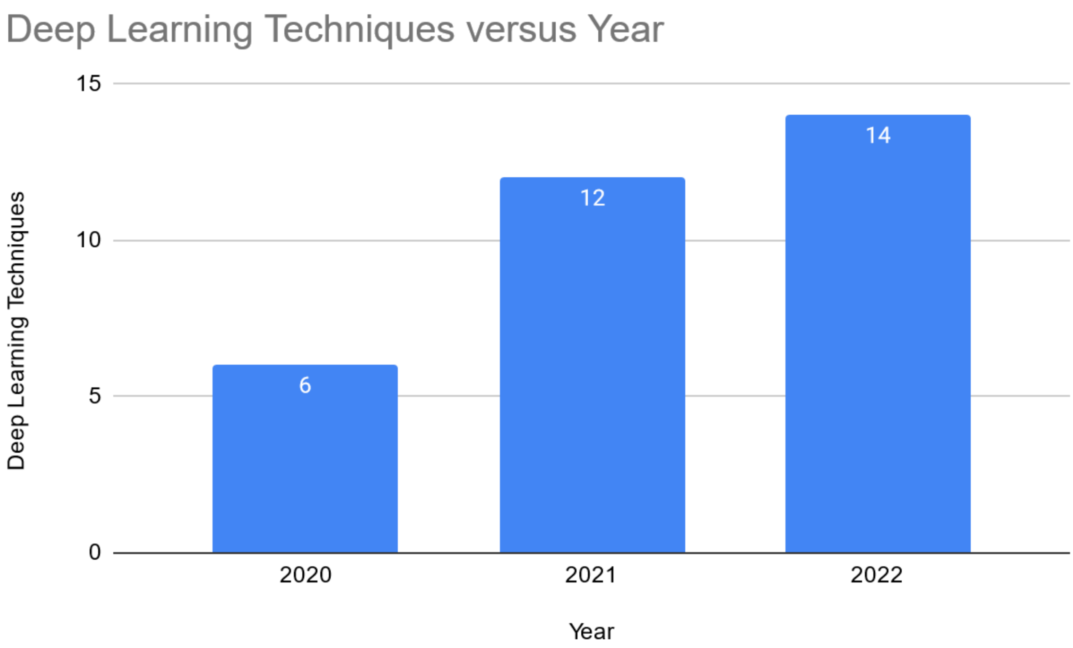

Figure 5. Deep Learning techniques each year.

4.2. Preprocessing

From the results, 38 (or approximately 86%) of the works used some kind of preprocessing. Of the 38, 29 are used in DL models (approximately 85% of DL models) and 9 in Classical Machine Learning models (90% of them). This result is not enough to suggest that one model uses more preprocessing than the other.

The most currently found type of preprocessing is the sliding window technique, as seen in Figure 6. It involves using a fixed-length window that moves or slides over the data, allowing analysis on each window and capturing temporal features and patterns. It is used in 34 works, approximately 77%. It is used in 27 of the 34 DL models (approximately 79%) and 7 of the 10 Classical Machine Learning (70%), which is insufficient to suggest a preference for using it in any of the two models. Nineteen used a fixed overlap, ranging from 20 to 75 percent. Out of those, 12 (approximately 63%) used a 50% overlap, as seen in Figure 7.

The second most applied preprocessing is the normalization of the input data, which is done in approximately 32% of the cases. Normalization aims to bring the data into a consistent range that allows for more effective analysis and modeling. It can be used because many machine learning algorithms are sensitive to the scale of the input features. Other techniques include noise reduction, removal or grouping of classes, signal downsampling, class balancing, and removal or inference of missing values.

As expected, the most used combination is the sliding window with some other types of preprocessing. The combinations are with normalization, with 13 occurrences; noise reduction, with ten instances; downsampling, and removal or grouping of classes, with three events each; removal or inference of missing values, with two occurrences; and class balancing, with one occurrence.

Downsampling had only three occurrences, but all of them also used normalization. In addition, normalization was also applied in approximately half of the times that were used: noise reduction (6 out of 11 occurrences), balancing (1 out of 2 events), and missing values (1 out of 2 times).

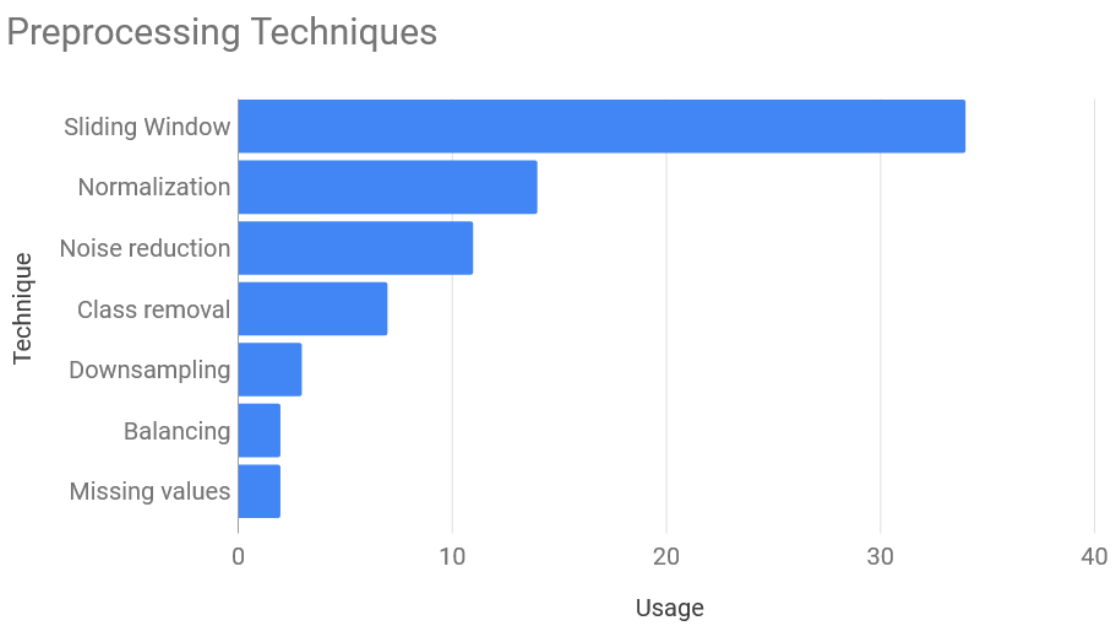

Figure 6. Most used preprocessing techniques.

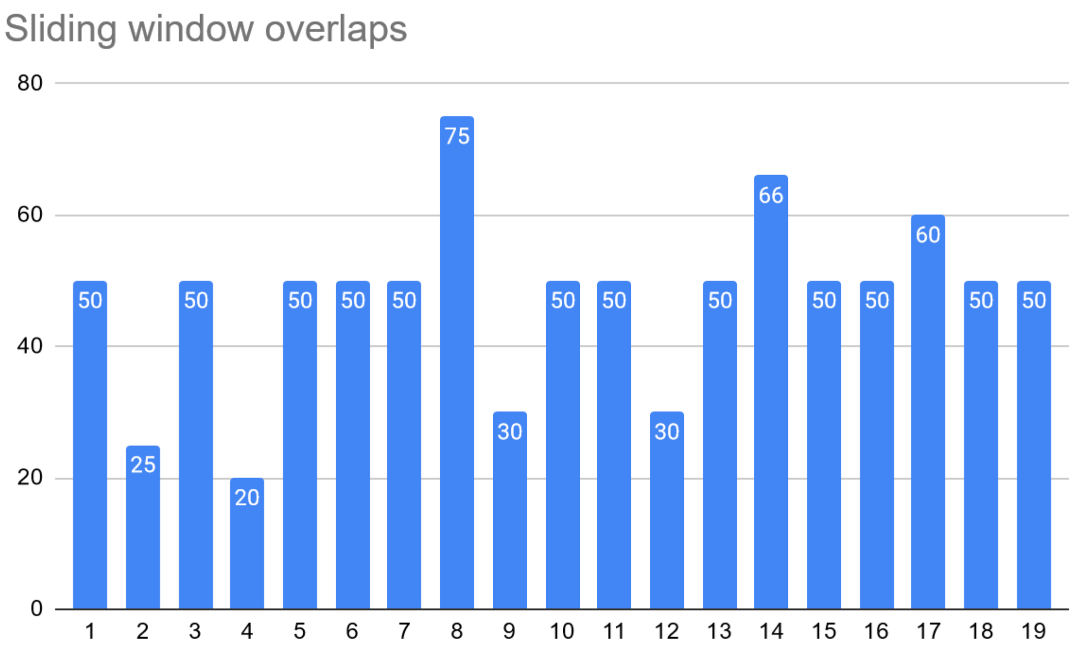

Figure 7. Fixed sliding window overlaps.

4.3. Feature extraction

Feature extraction was used in 14 of the 44 works (approximately 32%). Out of those 14, 6 were applied to DL models (representing approximately 18% of them) and 8 of the Classical Machine Learning methods (80%). Feature extraction is significantly more used in Classical Machine Learning methods than DL, confirming what was discussed in subsection 4.1.

There were three main groups of feature extraction used. The most usually applied (approximately 27%) was the extraction of statistical data from the time and frequency domain, as seen in Figure 8. These types of extraction include several features, e.g., mean, standard deviation, energy, skewness, entropy, spectral centroid, spectral power, and many others. There were also three that extracted data components, for example, separating accelerometer signals into dynamic and gravitational components, as done in [Debache 2020]. Finally, one also used a Gaussian mixture model to model the data distribution.

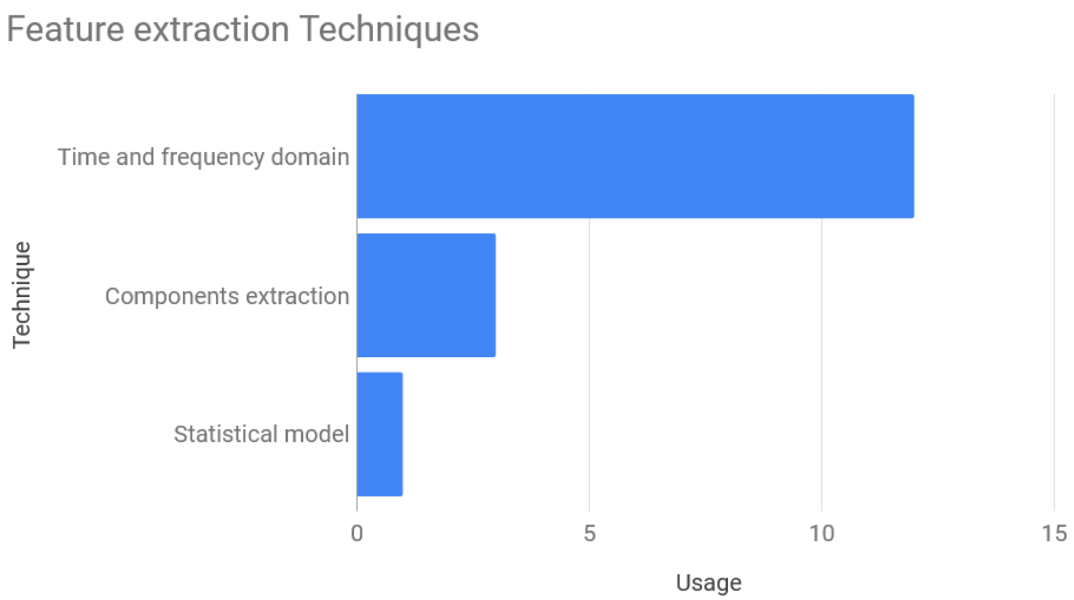

Figure 8. Usage of types of feature extraction.

4.4. Wearable and sensors

There is a visible preference for using the accelerometer, which has low cost and power consumption and can measure the acceleration in the three orthogonal axes [Shakya 2018]. All 44 authors used the accelerometer. In the second place, gyroscopes are used, with approximately 61% of usage in all works. The other sensors found are, in order of usage: magnetometer (nearly 16% usage) and photoplethysmograph (about 9% usage). Electrodermal activity, heart rate, compass, electrocardiograph, and temperature were used in one method each. The results can be seen in Figure 9.

It is possible to see that the assumption that blood oxygen sensors would be relevant in the studies was not validated. It could be for two reasons: its usage does not reflect significant changes in the recognition, or it is an option not very explored. The latter could be because the presence of this sensor is relatively new, or it is more frequently found only on high-end devices, restricting its usage.

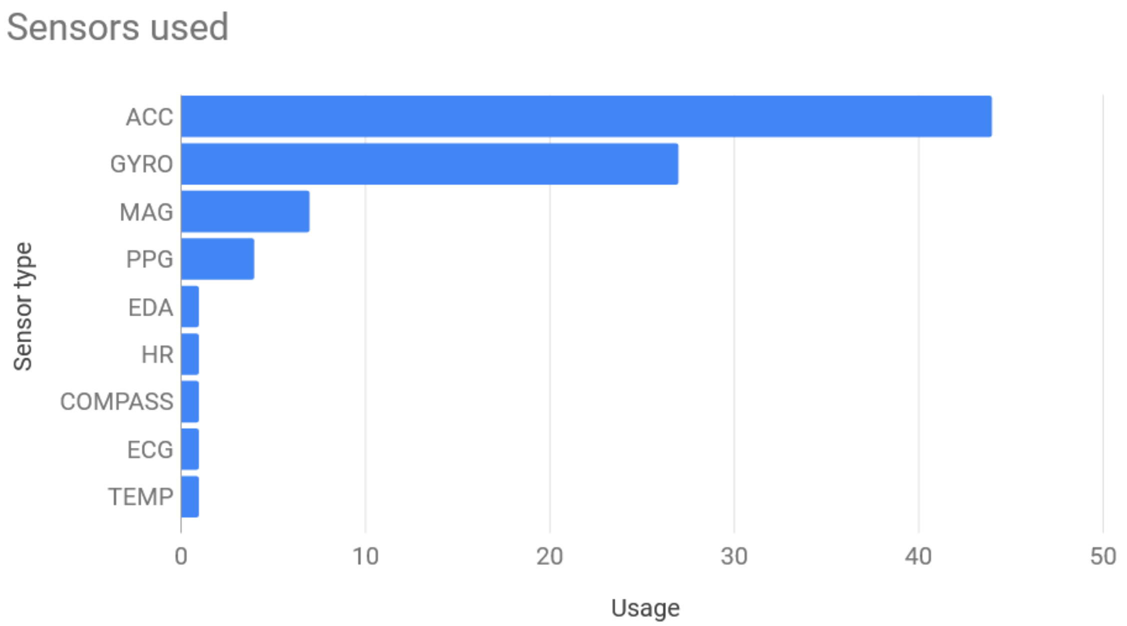

Figure 9. Usage of sensors.

4.5. Position

All the results used a wearable (or a wearable sensor) on the wrist. One work has also used one dataset that considers smartwatch usage for retrieving heart rate and a smartglass for retrieving the accelerometer data [Nebogatikov 2021]. This distribution could be due to the restriction of eligible wearables, which were all commonly available in the market.

4.6. Datasets and recognized activities

There were many datasets employed for this type of application. Most authors used datasets available online, but approximately 14% created their own for their work. To the best of this work's authors' knowledge, they are not publicly available. The most used are described next, and the percentage of usage of the datasets with more than one utilization can be seen in Figure 10.

The most used was the "WISDM Smartphone and Smartwatch Activity and Biometrics Dataset Data Set"[6] [Weiss 2019], which recorded gyroscope and accelerometer data of 18 activities from 51 subjects.

The second most used was the "RealWorld Dataset"[7] [Sztyler 2016], which covers acceleration, GPS, gyroscope, light, magnetic field, and sound level data of the activities climbing stairs down and up, jumping, lying, standing, sitting, running/jogging, and walking of fifteen subjects. For each activity, it was recorded the

[6] WISDM dataset homepage: https://archive.ics.uci.edu/ml/datasets/WISDM+Smartphone+and+Smartwatch+Activity+and+Biometrics+Dataset+

[7] RealWorld dataset homepage: https://www.uni-mannheim.de/dws/research/projects/activity-recognition/dataset/dataset-realworld/

acceleration of the chest, forearm, head, shin, thigh, upper arm, and waist. Each subject performed each activity for roughly 10 minutes except for jumping due to the physical exertion (~1.7 minutes).

"Wearable Human Activity Recognition Folder (WHARF)"[8] [Bruno 2014] is the third most used dataset. It is a collection of labeled accelerometer data recordings obtained by a single wrist-worn tri-axial accelerometer. It consists of over 1000 recordings of 17 volunteers doing 14 activities.

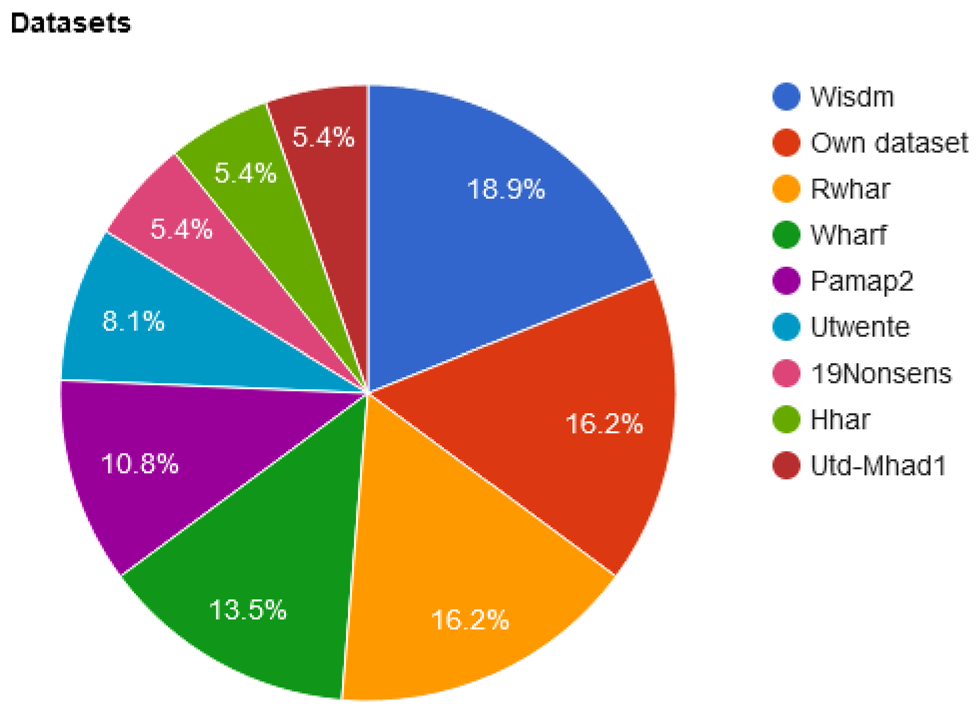

Figure 10. Datasets used in activity recognition. Only datasets used more than once are shown.

It is possible to access the list of all datasets and activities found at the online platform vhlk.github.io/Systematic-Mapping-Activities-Wearables. Figure 11 illustrates the interface where searching for activities by writing in the text box is possible. While typing, it suggests all the available activities that match what is being typed. After choosing the activity, there is the option to add it to the search list, which comprises all the added activities. Next to the add button is the option to search for the activities added to the search list and a button to enable or disable the cleaned activities. By default, this option is enabled, providing activities grouped from the various datasets. By disabling it, activities that mean the same but differ in how it was written (plural, infinite, or other variations of the same word) or synonyms will not be considered the same activity.

[8] WHARF dataset homepage: https://github.com/fulviomas/WHARF

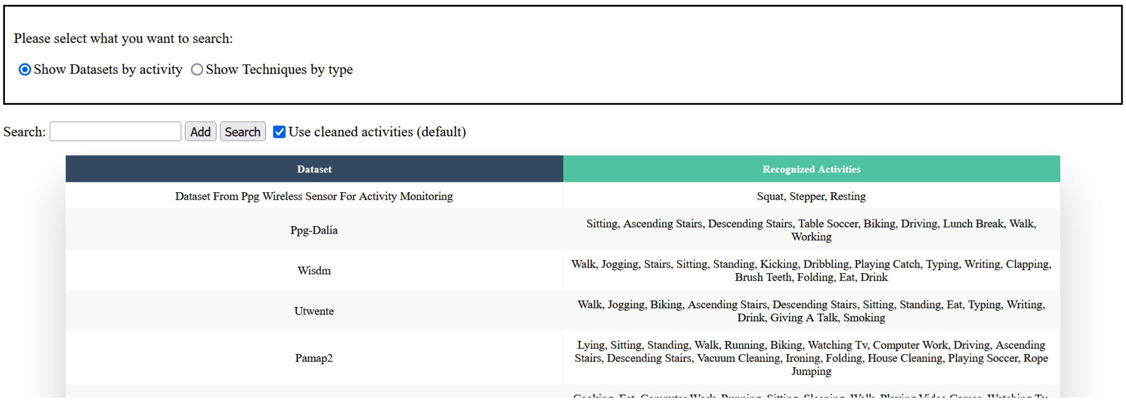

Figure 11. List of datasets and their activities at vhlk.github.io/Systematic-Mapping-Activities-Wearables/.

Additionally, the most common activities present in the datasets were also computed. In order of appearance, the datasets' top 9 most provided activities are: walking, sitting, standing, ascending and descending stairs, biking, eating, drinking, and running, as shown in Figure 13. After cleaning the labels, i.e., trying to match different writing of the same activities from different datasets, there were 116 activities. The results suggest that could be enough data to be used in daily physical activities[9].

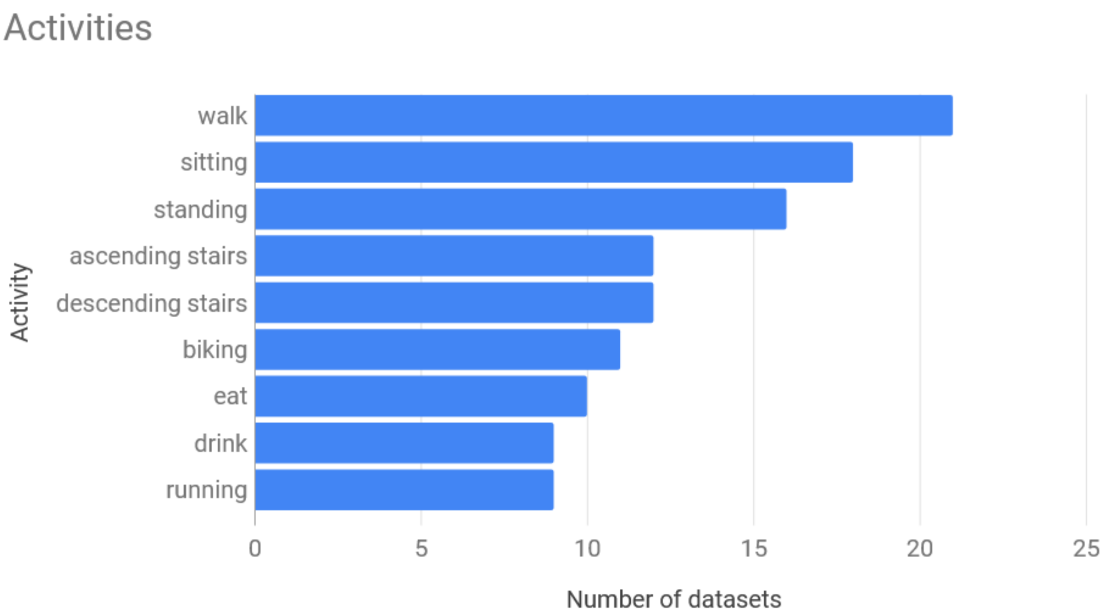

Figure 13. Top 9 activities detected.

It has also been observed how many activities are usually recognized. For example, in Figure 14, it is possible to see that the most common is 18 activities being used, but the range varies from 3 to 24. Increasing the number of activities could lead to

[9] The list of all activities is available at: https://github.com/vhlk/Systematic-Mapping-Activities-Wearables/blob/main/data/List_cleaned_activites.txt

an increase in the complexity of the method used. Which activities should be detected by a reasonable recognition system will impact the number of activities needed to be recognized.

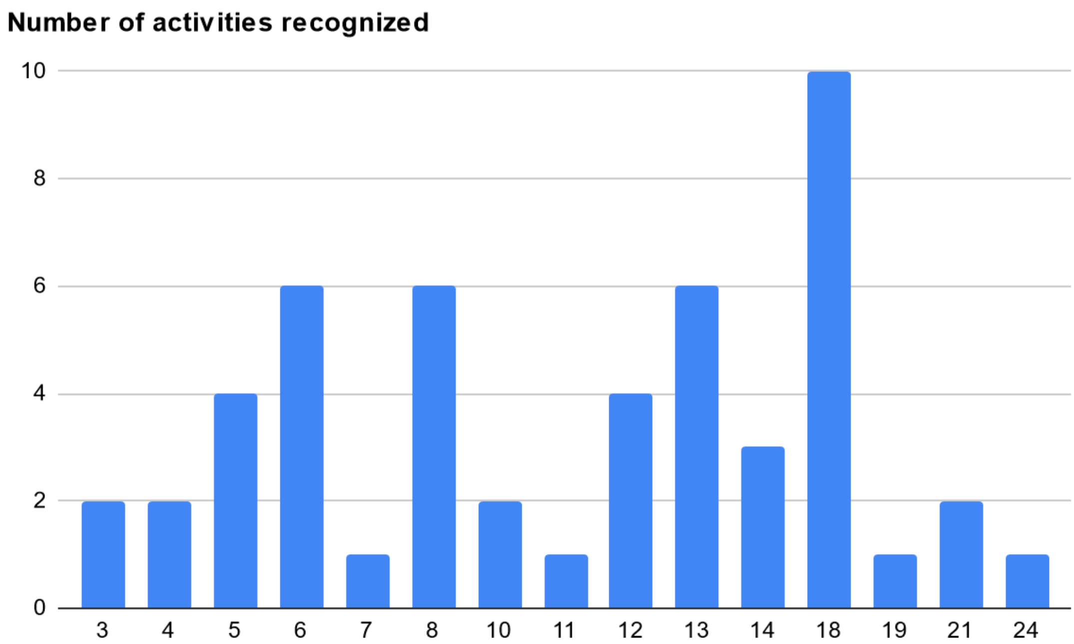

Figure 14. The number of activities recognized.

4.7. Lightweight methods

Most of the proposed solutions did not consider techniques or methods that use fewer resources when needed to run on wearables or mobile devices. Only 3 of them considered ways to achieve it. One of them considered the usage of a standard quantization scheme in Tensorflow Lite[10] [Lattanzi 2022]. One optimized their methods considering the hardware [De Vita 2021], and the last changed their technique and experimented with fewer sensors to consume less power [Abbas 2020].

4.8. Online Visualizer

As the work primarily focuses on providing a starting point for studying techniques that can recognize daily physical activities using wearable devices, the authors have also made available its results online. The platform currently supports an option for searching all datasets according to the activities being searched, as seen in Figure 15, and an option to search all works that have used specific techniques, as shown in Figure 16. Also, almost all the figures shown in this work can be found on the platform, including tweaks to the chart type and max number of items displayed. The platform is hosted at vhlk.github.io/Systematic-Mapping-Activities-Wearables.

[10] Tensorflow Lite is a mobile library for deploying models on mobile, microcontrollers and other edge devices. Its homepage can be found at https://www.tensorflow.org/lite?hl=pt-br.

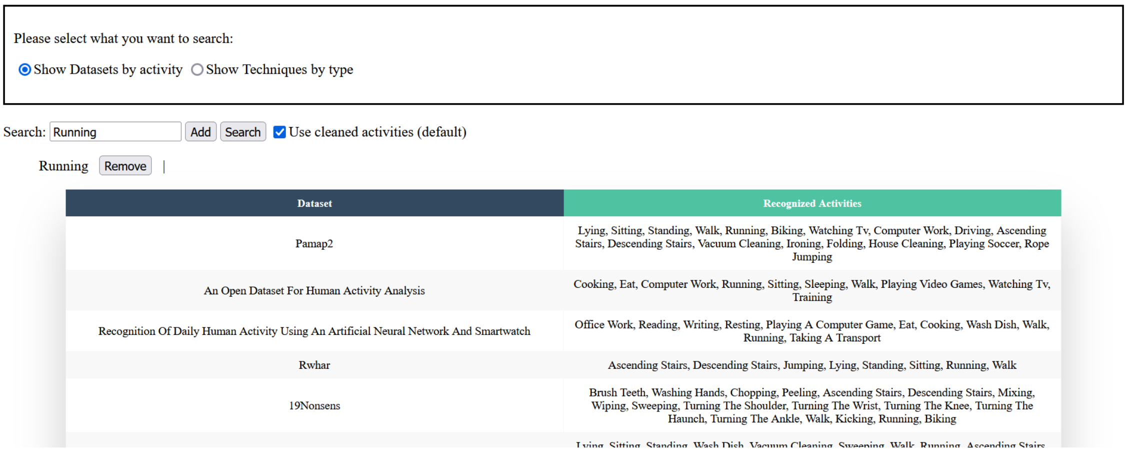

Figure 15. Searching for datasets that detect "Running."

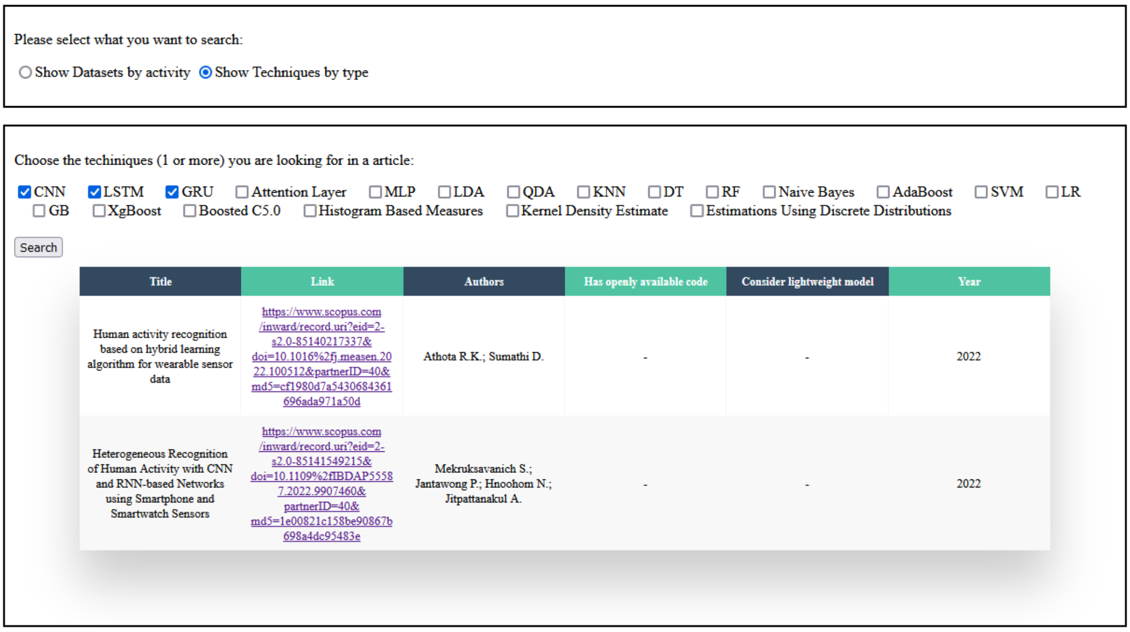

Figure 16. Searching for works that use specific techniques (CNN, LSTM, and GRU).

5. Conclusion

This work presents a systematic mapping that summarizes the area of recognition of daily physical activities using wearable devices. For that, A search string on Scopus was conducted to provide a background for future researchers on daily physical activity recognition using wearables. Its results were processed according to the criteria, resulting in 44 works. After the results, each one was classified according to their usage of primary techniques, preprocessing, feature extraction, sensors, datasets, most found activities, and considerations to lightweight algorithms. A tool for searching datasets based on the activities and searching works based on the techniques used was also developed for better visualization of the data.

The results showed consensus on the usage of the accelerometer sensor, but other types of sensors still need to be explored, for example, blood oxygen saturation. There is also a possibility for future research on efficient and lightweight methods for this type of application. Furthermore, there is a tendency for more studies to be done using Deep Learning models instead of classical ones. Finally, it also needs to be clarified how preprocessing, and feature extraction usage could impact accuracy and time performance.

By mapping the area, this work intends to facilitate the understanding of it and also discusses some limitations so that new studies can be made. It can also be a starting point for a deeper understanding conducted by a systematic review.

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