A systematic review of non-intrusive human activity recognition in smart homes using deep learning

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ABSTRACT

Smart homes are a viable solution for improving the independence and privacy of elderly and dependent people thanks to IoT sensors. Reliable human activity recognition (HAR) devices are required to enable precise monitoring inside smart homes. Despite various reviews on HAR, there is a lack of comprehensive studies that include a diverse range of approaches, including sensor-based, wearable, ambient, and device-free methods. Considering this research gap, this study aims to systematically review the HAR studies that apply deep learning as their main solution and utilize a non-intrusive approach for activity monitoring. Out of the 2,171 studies in the IEEE Explore database, we carefully selected and thoroughly analyzed 37 studies for our research, following the guidelines provided by the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology. In this paper, we explore various modalities, deep learning approaches, and datasets employed in the context of non-intrusive HAR. This study presents essential data for researchers to employ deep learning techniques for HAR in smart home environments. Additionally, it identifies and highlights the main trends, challenges, and future directions.

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1. INTRODUCTION

The rising demand for human activity recognition (HAR) systems in healthcare institutions is reshaping patient and elderly care. These systems, integrated into smart homes, help relieve the strain on hospitals and nursing homes by providing real-time healthcare support to individuals, allowing them to maintain their independence. This review excludes vision-based approaches because of privacy and user acceptability issues [1]. We will focus on non-intrusive modalities like sensor-based wearables, ambient sensors, or device-free (wireless fidelity (WiFi) and radio-frequency identification (RFID)) for HAR. Besides, sensor-based approaches offer better recognition performance and low computational costs.

Non-intrusive HAR in smart health systems faces numerous challenges in sensor choice, activity type, and deep model selection. Deep learning is effective for HAR in smart homes, as it extracts features using heuristics and human expertise, overcoming the limitations of traditional methods [2]. Deep learning (DL) can work with various network types and overcomes limitations in machine learning. Deep learning models execute feature extraction and model-building simultaneously, learning relevant features from raw data. They excel in complex activity recognition tasks due to their adaptability and generalization capabilities [3]. Deep learning models like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory networks (LSTMs) are essential for HAR tasks like image and video recognition. Hybrid models combine various algorithms, capturing spatial and temporal features, making them suitable for sensor data processing. CNNs perform automatic feature learning and extract higher features from deep layers, while LSTMs excel in time-series data, resulting in better performance and high accuracy [2]. Researchers have developed various HAR models for different applications: elderly, children, and babies monitoring, safety, sleep monitoring, development, crowd surveillance, healthcare, lifestyle patterns, exercise, gait analysis, abnormal activity recognition, and human activity prediction in smart homes and other fields [4].

While significant advancement has been achieved in the field of non-intrusive HAR using deep learning techniques in smart homes, there is a necessity for a systematic review that consolidates and synthesizes the existing literature. Previous reviews have explored aspects of HAR or deep learning in isolation. Thus, there is a lack of holistic research that mainly focuses on the trends, challenges, and open issues in non-intrusive HAR using deep learning in intelligent homes. This review paper responds to this gap by systematically examining the current literature and identifying research gaps; it also attempts to provide a valuable resource for researchers and developers working in the field of HAR, enabling them to discover current HAR modalities, deep learning approaches, benchmark datasets, the latest trends, and identify the gaps and discover future directions to advance the research.

2. METHOD

2.1. The review protocol-PRISMA

The preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology led the current study as a framework for conducting systematic reviews and meta-analyses [5]. To guarantee that our work satisfied the requirement of a high-quality systematic review, we followed the 27-item PRISMA review process. The systematic searching strategy consisted of three steps: identification, screening, and eligibility.

2.2. Formulation of research questions

To determine the specific research questions and extract the search string, we applied the PICO model [6]:

- Population (P): elderly and dependent individuals living in smart homes.
- Intervention (I): non-intrusive HAR approaches and methodologies.
- Comparison (Co): comparison of different modalities, deep learning approaches, and datasets used in non-intrusive HAR.
- Outcomes (O): understanding the effectiveness, trends, challenges, and future directions in non-intrusive HAR for smart homes.

To analyze each study, five research questions were formulated:
RQ1: How is the distribution of studies based on publication time?
RQ2: What modalities are used for non-intrusive HAR?
RQ3: What deep learning methods are employed for HAR, and how do they perform?
RQ4: Which datasets are commonly used for non-intrusive HAR?
RQ5: What are the trends, challenges, and future directions for non-intrusive HAR using deep learning?

2.3. Systematic searching strategies

The search process for the systematic review comprised three fundamental steps: identification, screening, and eligibility. Figure 1 provides a comprehensive overview of the entire process through the flow diagram. The subsequent sections will delve into a detailed explanation of the steps mentioned above, shedding light on the intricacies of each stage in the systematic review process.

2.3.1. Identification

In the identification process, our primary goal was to enhance keyword coverage in databases by aligning our keyword selection with the research questions. We meticulously examined each keyword to achieve this, identifying its variations based on synonyms and related terms. This comprehensive approach ensured that our search strategy encompassed a wide range of relevant terms and phrases, ultimately enhancing the depth and breadth of our database search.

However, the main keywords used in this study are HAR, deep learning, sensor, wearable, and device-free. We searched in the IEEE Explore database which provides comprehensive and advanced searching functions. We constructed a full search string using the Boolean operator "AND" and "OR", phrase searching: ((("human activity recognition" OR "HAR" OR "human action recognition" OR "motion recognition") AND ("deep learning" OR "autoencoder" OR "auto-encoder" OR "deep belief network" OR

”convolutional neural network” OR ”convolution neural network” OR ”recurrent neural network” OR ”RNN” OR ”LSTM” OR ”long short term memory” OR ”generative adversarial network” OR ”GAN” OR ”reinforcement learning” OR ”attention” OR ”deep semi-supervised learning” OR ”graph neural network”) AND (“sensor” OR “sensor-based” OR ”ambient” ”wearables” OR “smart home” OR ”smart homes” OR ”assisted living” OR “ambient assisted living” OR ”multi-resident” OR ”multiple residents” OR “device-free” OR “WIFI” OR “RFID”))).

The review focused on original research papers and conference papers published between 2019 and the present. In addition to this, we conducted a meticulous manual search to identify articles relevant to non-intrusive HAR using deep learning. Through this rigorous process, we successfully retrieved a total of 2,171 articles.

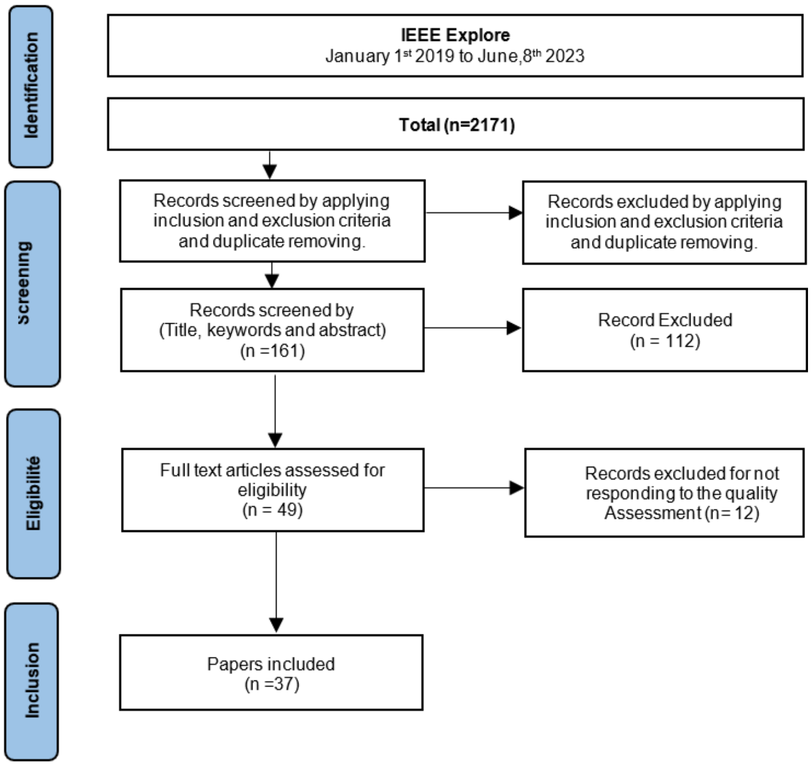

Figure 1. PRISMA flowchart for study selection

2.3.2. Screening

All selected articles identified in the previous stage went through the screening process. We screened papers for our systematic review based on these inclusion and exclusion criteria,

- Inclusion criteria : i) all the studies included the important keywords (deep learning, HAR, non-intrusive, sensor, WIFI, RFID, wearable, ambient, smart home, healthcare, multi-resident); ii) studies in artificial intelligence (AI), convolutional neural nets, recurrent neural nets, deep learning (artificial intelligence), body sensor networks, sensor fusion, health care, and patient monitoring; iii) studies published between January 1st 2019, to June 8th 2023; iv) conference papers and journal articles; and v) open access.
- Exclusion criteria: i) review paper, book chapter; ii) studies are not accessible in full text; iii) studies are not written in English; iv) studies on video-based HAR, image HAR; v) studies before 2018; and vi) methods other than deep learning.

Among the 2,171 papers in the IEEE Explore database, 161 articles were retained after applying the inclusion and exclusion criteria. These articles proceeded to the screening phase, where they were evaluated based on their title, keywords, and abstracts. During the eligibility phase, 49 articles were reviewed in full text. The search results were exported in BibTeX format to be used as input for reference management tools. We utilized JabRef as our reference manager tool, primarily for managing the downloaded references and removing duplicate papers obtained from different search engines. Additionally, JabRef offers the option to automatically download the full text of all added references, saving a significant amount of time.

2.3.3. Eligibility

In the final stage, a comprehensive manual review of the articles was conducted, involving a thorough reading of the full text. This meticulous eligibility process was applied to the articles retrieved from IEEE Explore, ensuring strict adherence to the predetermined criteria. Ultimately, 49 articles met the inclusion criteria and were included in this stage.

2.4. Quality appraisal

The aim of creating a quality assessment (QA) is to assess the overall quality of the selected studies. Therefore, we utilize specific quality criteria to evaluate the strength and the relevance of the studies' findings:

QA1. Does the study align with the research objectives?
QA2. Is the method or approach used in HAR mentioned in the study?
QA3. Is the research methodology clearly articulated and described in the study?
QA4. Is the dataset used in the study described in detail?
QA5. Has the performance of the deep learning model used in the study been explained comprehensively?

In the study, the researchers examined 37 selected studies to assess their credibility by using five QA questions. All authors of the study reviewed and extracted data from each of the 37 studies as reviewers. The authors appraised the QA to decide the articles' content quality. Each reviewer rated the articles into three levels of priority: high, medium, or low [7]. The articles ranked as high were eligible for review in the following process. The articles marked as "low" are excluded. The articles marked as "medium" are discussed by the authors for eligibility. A total of 12 articles that did not respond to the inclusion/exclusion criteria or QA were removed. Finally, 37 articles were reviewed in full text for data extraction concerning these data items: paper, year, aim, modality, DL model, dataset, accuracy, application, limitation, and future work.

3. RESULTS AND DISCUSSION

This section presents the results of our systematic review, addressing the research questions formulated earlier. We selected thirty-seven studies through our systematic review to identify sensor modalities for HAR using deep learning methods. In Table 1 (see in Appendix), we provide a summary of these selected studies, including their identity (ID), publication aim, publication year, the deep learning methods employed, a discussion of the accuracy achieved by each method, the dataset utilized, the application area, study limitations, and future research directions.

3.1. RQ1: how is the distribution of studies based on publication time?

The chosen studies were published within the last 5 years. Figure 2 displays the number of studies published between the years 2019-2022. However, the graph does not include data for the year 2023, as the research for that specific year is still in progress. Overall, four articles were published in 2019. Nineteen articles were published in 2020, five in 2021, and eight in 2022. Based on the results, we observe that numerous studies have been published in the last five years. Consequently, the deep learning method is a popular approach to improving the HAR in a smart environment.

3.2. RQ2: what modalities are used for non-intrusive HAR?

In addressing our research question and drawing insights from the gathered data in selected articles, several noteworthy observations. Figure 3 illustrates a prevalent trend wherein a majority of the papers adopt the sensor-based approach or the wearable approach, few studies are conducted using the device-free approach such as radar, WIFI, channel state information (CSI), or radio frequency identification (RFID), the researchers need to investigate this area of the research area. Yu *et al.* [8] adopts a hybrid modality approach by combining various types of sensors to recognize activities. By integrating various sensor types, they aim to enhance the accuracy and overall performance of HAR systems.

Based on the data collected from Table 1 which can be found in the Appendix, we have made several observations regarding the modalities used for HAR,

- Sensors can be embedded into devices like smartphones and smartwatches, which contain different types of sensors (accelerometer (Acc), gyroscope (Gyr), magnetometer (Mag), and global positioning system (GPS)) and are used widely by HAR researchers [9], [10]. In a study conducted by Ribeiro and Santos [11], they have used the inertial measurement unit (IMU), which measures the values of Acc, Gyr, Mag, and other sensors. Its advantage is the low cost and high accuracy, and it can be mounted to different body parts [12].
- The use of wearables is inconvenient to the subjects, and thus, smartphones are more desirable. But it only captures simple activities.

- The current advances in biosensors and tattoo sensors can be used for human activity recognition. These types of wearable sensors are non-invasive and can be used for real-time monitoring. Thus, a need to create miniaturized sensor-based devices for remote healthcare monitoring.
- Lately, another good option is a device-free HAR. The recent advancements in RFID technology are witnessed in the internet of things (IoT) solutions, and a few applications have been proposed for activity recognition using device-free RFID technology. In addition, Further attention has to be given to the device-free approach because it provides more privacy and is less intrusive. However, the device-free approach has many challenges, such as the RFID tags capturing only indoor activities and the WiFi can only capture activities within the covered area.
- One of the primary hurdles in the HAR field is the recognition of activities involving multiple residents. Several studies have employed ambient sensors to identify multiple occupants' activities and determine their indoor positions. Another challenge lies in detecting concurrent or complex activities. To address this, Plötz *et al.* [13] employed object sensors capable of detecting composite activities humans perform during their interactions with the environment. Incorporating objects in the recognition process proves crucial in identifying more complex activities. Additionally, Yu *et al.* [8] proposed an alternative approach by adopting a hybrid sensor setup, thereby enhancing the comprehensiveness of the acquired data.
- The sensor placement is crucial to get the correct reading, whether attached or worn by the subject. It depends more on the nature of the activity. If it is a simple or more complex activity, then many sensors are attached to the body to collect comprehensive data. Kulchyk and Etemad [14] investigated the effect of sensor placement on activity recognition. They concluded that the optimal sensor location was on the ankle, especially for activities of daily living (ADL), rather than on the sternum, shoulder, or thigh. Good accuracy can be achieved with at least two sensors located in body parts to get a wide range of motion.

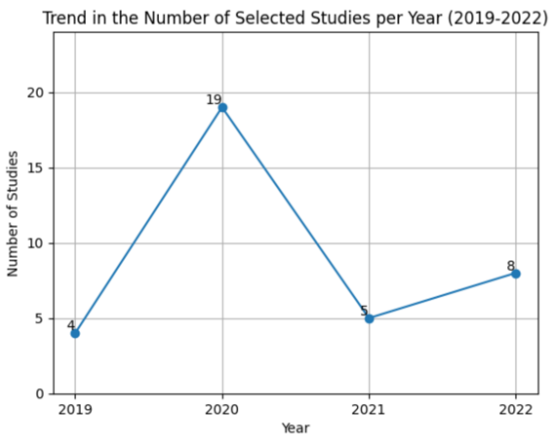

Figure 2. Trend in the number of selected studies per year (2019-2022)

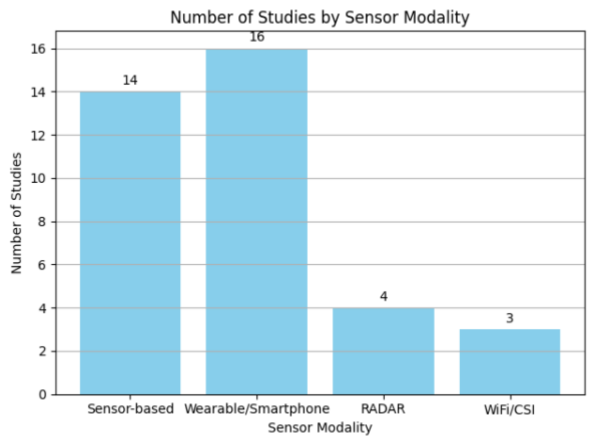

Figure 3. Number of studies by sensor modality

3.3. RQ3: what deep learning methods are employed for HAR, and how do they perform?

3.3.1. Deep learning methods

This section delves into the performance evaluation of deep learning models for HAR. We analyzed the findings from various research papers to gain insights. Figure 4 shows hybrid models emerged as the most popular choice, with 12 papers focusing on them. Following closely behind were CNN and LSTM, with 10 and 6 papers, respectively. Researchers explored a range of deep learning approaches to tackle HAR challenges, including bidirectional long short-term memory (Bi-LSTM), generative adversarial network (GAN), gated recurrent unit (GRU), and more recent advancements like residual network (ResNet) and transfer learning, which showed promising results. Most deep learning approaches have demonstrated exceptional performance, particularly those based on hybrid models. For instance, in a study conducted by Thakur *et al.* [15], a ConvLSTM model was employed for HAR. CNN was utilized to capture spatial information, while LSTM was employed to capture temporal data, resulting in an impressive accuracy of 98%. Similarly, Lu *et al.* [16] adopted a hybrid model combining CNN and GRU, achieving an accuracy of 95% on the PAMAP2 dataset. It should be noted that the performance of these models can vary depending on factors such as the specific dataset used, the preprocessing stage, hardware configurations, and the size of the dataset.

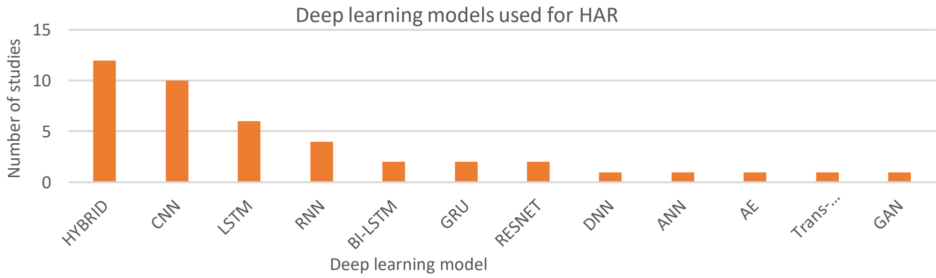

Figure 4. Deep learning models used for HAR

Moreover, RNN leverage the temporal sequencing of sensor readings, considering their time-order relationship. On the other hand, CNN excel in capturing complex features embedded within recurrent patterns [17]. A recent and modern approach using LSTM algorithms stands out (Bi-LSTM, Casc-LSTM, ENs2-LSTM) [18]. Thus, in the HAR problem, the hybrid model can achieve better performance as CNN is capable of extracting features, autoencoders are used for dimensionality reduction and LSTM learns temporal relationships [15].

A trending technique such as transfer learning has shown good results with vision-based HAR models but there is a lack of research on using transfer learning in sensor-based HAR [4] and reinforcement learning needs to be investigated to improve HAR performance and result [18]. Another issue that needs to be investigated is the HAR model for synchronized activities and prediction of future action. There is a lack of research on this topic. Researchers should focus on selecting the suitable optimizer and tuning the right hyperparameters for a better performance of the model. Many challenges are associated with the deep learning model. On one hand overfitting/underfitting, in the case of the limited amount of data, affects the generalization ability. On the other hand, the specialized hardware and memory integration in HAR devices is required to achieve high-performance HAR models, which leads to high costs and limits its use in the real environment [4].

3.3.1. Performance evaluation of the deep learning methods

Before understanding the approach used, it is crucial to assess the performance of the proposed classification model. The effectiveness of a deep learning model can be measured by it is accuracy, sensitivity, specificity, recall, precision, and F-measure. After reviewing 37 research papers, it was noted that most researchers employed accuracy and F-measure as the metrics to assess the proficiency of their models. These performance metrics are essential for assessing machine learning classification models' performance in a given context. Selecting the appropriate metric is a vital step in assessing a dataset. While accuracy proves valuable in a balanced dataset class, it may not be the best fit for imbalanced datasets. Metrics such as precision, recall, f-measure, and specificity may better suit such scenarios. The confusion matrix is frequently used in these cases, presenting a tabular representation of class labels that depict predicted and actual classes along two axes [19]. Table 2 defines all these metrics and their respective formula [12], [19].

Table 2 summarizes the performance metrics, including accuracy, precision, recall, specificity, and F-measure. These metrics are essential for measuring the performance of classification models. To understand these metrics, it is important to know the four key terms used in measuring the performance metrics, namely true positive (tp), true negative (tn), false positive (fp), and false negative (fn) [12], [19].

3.4. RQ4: which datasets are commonly used for non-intrusive HAR?

Based on the data extracted from the selected papers, it is evident that datasets such as warehouse instance segmentation dataset for object manipulation (WISDM), UCI, PAMAP2, and opportunity have gained significant popularity in the field of non-intrusive HAR. The description of these datasets is presented in Table 3. This table provides information regarding the number of subjects, activity types, and sensor types associated with each dataset. Additionally, noteworthy datasets have emerged such as KU-HAR [20], precis HAR [21], fall-up dataset [22], DOMUS [23], CASAS aruba [24], MIT PlaceLab [25], smart environment-Ulster University [26], CASAS-daily life Kyoto [27], and UJAmI SmatLab [28].

Nevertheless, researchers must broaden their investigations by incorporating additional datasets to evaluate their models' performance comprehensively. Specifically, there is a distinct need to explore device-free approaches like WiFI, RFiD, RADAR, and other emerging technologies within non-intrusive HAR datasets. This area of research presents ample opportunities for further exploration and advancement. This is primarily due to the scarcity of publicly available datasets in this particular domain. Notably, Noori *et al.* [29] employed a RADAR approach, and the data used was collected directly by the authors themselves.

Table 2. Performance metrics [19]

Metric	Formula	Definition
Accuracy	$\frac{tp+tn}{tp+tn+fp+fn}$	The ratio of correct predictions and overall predictions
Precision	$\frac{tp}{tp+fp}$	The proportion ratio of accurately predicted positive instances to the total predicted positive instances.
Recall of sensitivity	$\frac{tp}{tp+fn}$	The ratio of correct predictions to the samples in the actual class
Specificity	$\frac{tn}{tn+fp}$	The ratio of actual class 0 to the correctly predicted 0
F1 score/F-measure	$\frac{2(recall * precision)}{recall + precision}$	The weighted average of precision and Recall if the class distribution is uneven

Table 3. Public dataset for sensor-based HAR

Dataset	Type of Activity	subjects	Type of Sensor	REF
OPPORTUNITY	ADL	4	ALL TYPES	[30]–[32]
UCI Smartphone	ADL	30	Acc, Gyr	[17]
PAMAP2	ADL	9	Acc, Gyr, Mg	[33]
USC-HAD	ADL	14	Acc, Gyr	[34]
WISDM	ADL	29	Acc	[35]
DSADS	ADL	8	Acc, Gyr, Mg	[13]
Ambient kitchen	Food preparation	20	Ob	[13]
Darmstadt Daily	Routines ADL	1	Acc	[36]
Actitracker	ADL	36	Acc	[33]
SHO	ADL	10	Acc, Gyr, Mg	[37]
MHEALTH	ADL	10	Acc, Gyr, C	[38]
Daphnet Gait	Gait	10	Acc	[39]
ActiveMiles	ADL	10	Acc	[40]
HASC	ADL	1	Acc	[41]
ActRecTut	Gesture	2	Acc, Gyr	
Berkeley MHAD	Daily Living	12	W, Am	[42]
VanKasteren benchmark	Real-world Home	9	Ob	[43]
SaMO-UJA dataset	Multi-residents-complex-fine-grained Activities	2	Ob, binary, W	[44]
Casas multi-resident	Washington State University-smart apartment	2	AM	[45]

(Acc=accelerometer, Gyr=gyroscope, Mg=magnetometer, Ob=object sensor, AM=ambient, W=wearable).

The data extracted from our systematic review can be found in Table 1 in the Appendix. We have made several observations about HAR datasets:

- The choice of the dataset is crucial to obtain the highest accuracy and achieve the best performance. The most essential dataset features that the researcher needs to investigate, such as (the activities recorded, the choice of sensor modalities, the value of sample rates, the placement of the sensor, the resident information, and the application domain) are essential and must be considered when selecting a potential dataset for HAR problem.
- Despite numerous public datasets, there remains a growing need to create additional public datasets in the field of HAR. Researchers must address these challenges in future studies, including class imbalance, multimodal data, composite activities, heterogeneity, and multi-resident scenarios. Acknowledging and tackling these challenges is imperative to advance the understanding and effectiveness of HAR methodologies.
- A gap in research that needs further investigation is the lack of a dataset for multi-residents in a smart home environment. In addition, the activities in the existing datasets are recorded in a controlled environment, which is not the case in natural human activity; the processing of multi-occupancy datasets needs high computational resources.

3.5. RQ5: what are the trends, challenges, and future directions for non-intrusive HAR using deep learning?

3.5.1. Challenges and open issues

The human activity recognition sensor-based approach faces numerous challenging issues:

- The heterogeneity of sensory data can be with users performing different motion patterns over time. Data distributions of activities are changing over time, and emerging activities may occur. Sensor variation may cause data disturbance with sensors.
- The sensor placement affects the data collected by the sensors. Therefore, it affects the accuracy of the activity. Then, identifying the optimum number and placement of sensors is crucial in HAR systems.

– Feature extraction: the identification of relevant characteristics that differentiate various activities is made possible by feature extraction, which is crucial in recognizing human activity. It is an essential step since it enables the collection of important data required for correctly distinguishing separate activities. The quality and applicability of the features extracted from the sensor data significantly impact how well activity recognition approaches perform.
– Multi-resident: in a smart home environment, multi-resident activity can occur. Hence, designing solutions for handling multi-residents is necessary. The activities performed by the people at home may be parallel when each person performs individually or collaboratively and when they collaborate to achieve the activity, also multi-occupancy datasets require more computational resources and it is difficult to obtain accurate results and performance in the analysis.
– Real-time HAR: a difference between empirical and real-time data can be problematic and needs to be implemented in real-life scenarios.
– Concurrent activities: in reality, the person may not sequentially perform activities. A person may carry out more than one activity simultaneously, that is to say, multi-tasking; the concurrent activity is executed by a single subject, making recognition difficult.
– Device-free dataset: a lack of available public datasets based on wireless RFID technology.
– High computational cost: many researchers rely on high-performance computers (GPU). They should concentrate on creating reliable, portable models that do not require specialist hardware to work in the real world.
– Dataset imbalance: one of the common challenges in HAR is the imbalanced dataset, which can lead to bias in the result and affect the model's ability to predict. Therefore, using evaluation metrics can play a vital role in addressing this problem.

3.5.2. Future directions

Researchers may further investigate the following interesting aspects:

– The importance is to ensure the efficacy and safety of the model by improving the precision, sensitivity, and specificity of wearable sensors.
– The use of the advances of IoT and the miniaturization of the sensors to facilitate their integration with wearable sensors.
– More investigation is needed into Hybrid sensor fusion methods that help improve accuracy and achieve better performance.
– More research should be conducted on action prediction for synchronized activities.
– Other issues, such as data ownership, data sharing, data security, and data interoperability, are among the main concerns of the HAR problem.
– Further improvements are expected in the problems related to imbalanced labels and data volume, feature extraction, and data processing.
– A future area of research that needs to be considered is the creation of public domain datasets for multi-residents that record complex activities and for device-free modality.
– Facing the complications of processing multi-resident datasets, algorithms based on reinforcement learning, and transfer learning have the potential to resolve the problem and are useful in real-time analysis.
– Researchers should explore other techniques to improve experiment results and quality metrics.
– For the problem of high computational cost, researchers should focus on developing a lightweight model that performs well on experimentation and real-life data.
– The need for explainable AI: DL models is called "black boxes". Thus, searching for explainability techniques is crucial to understanding how the model makes decisions.

4. CONCLUSION

This paper presents the findings of a systematic review following the PRISMA methodology, which aimed to provide valuable insights into non-intrusive HAR using deep learning. The analysis involved a meticulous comparison of 37 selected studies, focusing on utilizing deep learning technologies, modalities employed, and datasets. The review encompassed the thorough examination of each study, including its preparation, implementation, and evaluation, offering a comprehensive overview of research conducted between January 2019 and June 2023. It is worth noting that previous research predominantly focused on sensor-based HAR, and this review extends beyond that scope. One of the significant contributions of this study is the presentation of multiple approaches for HAR, including the utilization of sensors, wearables, and device-free methods, all of which prove to be suitable for monitoring the activities of elderly individuals while preserving their privacy. Furthermore, this review explores various deep learning models and their applications in HAR, providing valuable insights into their efficacy and potential. Throughout the review process, the different HAR modalities, datasets, and deep learning models are extensively discussed, shedding light on several gaps in the existing literature. Moreover, emerging trends and challenges are identified, offering researchers valuable focus areas when tackling this topic. In summary, this systematic review is a valuable resource for researchers in non-intrusive HAR using deep learning. By addressing the identified gaps and considering the highlighted trends and challenges, researchers can significantly contribute to understanding and applying deep learning in HAR.

APPENDIX

Table 1. Summary of selected studies (*Continue*…)

Id	Y	Aim	M	Dl	Dataset	Accuracy	Application	Limitation/future work	Ref
S1	2023	Physical sports activities	W	RNN	IMSB, WISDM, ERICA	85.01% 88.46% 93.18%	Gaming Sport Healthcare	- Improving the accuracy - Real-time application - Integration with other technologies	[46]
S2	2023	Multi-sensing data fusion with neuromorphic computing for HAR	IMU, S, R	Hopfield network neurons	Self	98,98%	HAR	Explore the stronger potential of neuromorphic computing of multi-sensing data in HAR.	[8]
S3	2022	HAR Activity prediction Anomaly detection	S	DNN, OCD-AE LSTM	Aruba, Cairo	93%, 76% 90% 54.6%	Elderly monitoring in smart home	- Limited length of sequence used for training the models - Correct the imbalance dataset to improve the DL model	[47]
S4	2022	Multi-view CNN-LSTM architecture for radar-based HAR	R	CNN and LSTM	four datasets	F1score: 74.7%	smartphone security smart-offices	- Generalization capability of the learning methods, with a single radar-sensor - Online continual learning - Framework for the absolute context of the targets and generalize to an unseen environment	[48]
S5	2022	Deep CNN-LSTM with a self-attention model for human activity recognition	S	CNN and LSTM	H-Activity (Self) MHEALTH UCI-HAR	99.93% 98.76% 93.11%	Healthcare sports, and fitness tracking	- Address the problem of class imbalances in the dataset, strengthen our dataset by adding more participants, and adjust the network structure. - A real-time classification of security and health risks affecting the elderly.	[49]
S6	2022	A multichannel CNN-GRU model for HAR	S	CNN and GRU	WISDM UCI-HAR PAMAP2	96.41%, 96.67%, 96.25	HAR	- Process the data more effectively. - Train the model on larger benchmark datasets or Self-collected activity data to verify its generality for sensor-based HAR.	[16]
S7	2022	Channel attention-based deep resnet for complex HAR	W	ResNet	WISDM-HARB, UT-Smoke, UT-Complex	94.91%, 98.75%, 97.73%	HAR	- Optimizing the hyperparameters can decrease model size and computation time, which can improve efficiency. - Incorporating spatial and channel attention mechanisms can enhance the accuracy of convolutional neural networks.	[50]
S8	2022	Multitemporal sampling module for real-time human activity recognition	S	multi-temporal sampling module + CNN	UCI-HAR WISDM OPPORTUNITY PAMAP2	F1 score: 0.94 0.86 0.84 0.75	HAR	- Optimize the trade-off between accuracy and efficiency in sensor devices - Measure the latency and memory of the devices and reflect them in the search process.to improve the accuracy	[51]
S9	2022	HAR based on multichannel convolutional neural network with data augmentation	W	AMC-CNN	WISDM MHEALTH	F1 score: 95.18% 99.86%	HAR	- Reducing the computational complexity and improving the real-time interaction are still - the contents of follow-up research.	[52]
S10	2022	Convolutional autoencoder LSTM for smartphone-based HAR	S SP	ConvAE-LSTM	WISDM, UCI, PAMAP2, OPPORTUNITY	97.76% 98.14% 94.33% 95.69%	HAR	- Investigate the applicability of the proposed method in real life should be analyzed. - Compare the model performance to other recent DL-based methods and Experiment with more available datasets	[15]

Table 1. Summary of selected studies

Id	Y	Aim	M	Dl	Dataset	Accuracy	Application	Limitation/future work	Ref
S11	2021	Design of optimal DL model for HAR	W	BiLSTM	UCI-HAR USC-HAD	Over 93.100%. in the two datasets	HAR	- Security and privacy issues - Time series Data preprocessing challenges - Improve the accuracy of the model	[53]
S12	2021	Hierarchical deep learning-based HAR model (HiHAR)	W	CNN + BiLSTM	UCI HAPT MobiAct	97.98% 96.16%,	Health, abnormal activity security, and fall detection for elderly people	- The proposed model requires a large amount of labeled data for training, and the computational complexity is high - Developing more efficient and lightweight models that can be deployed on resource-constrained devices, and exploring the possibility of using transfer learning to improve the performance of the model on new domains.	[54]
S13	2021	Ultra-wideband radar-based activity recognition using deep learning	S R	LSTM	Self	99.6%.	HAR Elderly Position	- Different sensor fusion strategies might be explored - Perform more complex experiments in real-time environments. Include the heart rate into the system for detecting emergencies.	[29]
S14	2021	Unsupervised domain adaptation in activity recognition: a gan-based approach	S	GAN	HA, HB, and HC PAMAP2 UCI-sport	Accuracy between 40% and 60%.	HAR	- Test shift-GAN on image and text data. - Investigate a more unified network to eliminate the need for the SVM classifier.	[55]
S15	2021	Address the problems of: insufficient training data and biased training data	S	DIM BLS	WISDM HAPT	Overall accuracy 93.6 %	HAR	Online HAR baseline model training	[56]
S16	2020	wearable wireless multi-sensor system for HAR	W	CNN LSTM ConvLSTM	Self, not public dataset	90.8% 90.5% 94%	HAR	- The dataset used is not publicly available - Present public benchmark dataset concerning activity types and sample size.	[57]
S17	2020	passive device-free WiFi CSI based human identity identification approach using RNN (Wihi) for HAR.	WC	RNN	Self	96%	human identity identification HAR	- Multi-target identification, walking path - The testing range - Collect enough, datasets to improve the performance of human identity identification also overcomes these limitations and challenging	[58]
S18	2020	attention-based encoder-decoder framework for multi-sensory time-series analytic of wearable sensor	W	LSTM	Self	99,27%	Squat activities	Deploy a lightweight model on resource limited hardware to improve results and reduce cost.	[59]
S19	2020	investigate the effectiveness of personalization methods for human activity recognition (HAR) using accelerometer signals	S	AdaBoost-HC AdaBoost-CNN	UniMiB-SHAR MobiAct Motion Sense	accuracy increased by about 11% after model personali-zation	HAR	Including the gyroscope in the analysis proving personalization methods on other publicly available datasets	[60]

Table 1. Summary of selected studies

Id	Y	Aim	M	Dl	Dataset	Accuracy	Application	Limitation/future work	Ref
S20	2020	DNN for HAR with wearable sensors: leave-one-subject-out cross-validation for model selection	W	CNN+ LOSOCV 10 fold cross validation+CNN	MHEALTH	85.1% 99.85%	HAR	- Finding the best window size - LOSOCV is time consuming - Evaluate the approach with - Different data sets and improve the accuracy of HAR through personalization.	[61]
S21	2020	Improved loss function for sensor-HAR based on LSTM RNNs	S	LSTM	UCI dataset Opportunity dataset	92.98% 90.36%	HAR	To improve the classification performance of both CNNs and RNNs, it may be beneficial to propose novel loss functions, such as harmonic loss functions. These loss functions could take into account the relative importance of different sequence errors to improved classification accuracy.	[62]
S22	2020	Deep learning multi-channel architecture using a CNN and BLSTM	W	CNN and BLSTM	Phone WISDM Phone+watch	97.91% 96.60% 99.13%	HAR	- Extend the tuning method - Explore better ways to automatically tune and adjust parameters rather than the grid search method	[63]
S23	2020	Using ResNet transfer deep learning methods in person identification according to physical actions	W	RestNet +Transfer deep learning	UCI database	94.21%	Person Identification	Not mentioned	[64]
S24	2020	Deep human activity recognition with localisation of wearable sensors	W	CNN	RWHAR	F1-score of 0.90	HAR Localization	Combining complementary information from both waist and shin data helped in further improving the activity recognition accuracy	[65]
S25	2020	Sensor-based open-set human activity recognition using representation learning with mixup triplets	S	Mixup Triplet with deep metric learning	UCI HAR USC HAD PAMAP2	F1 score: 0.66 0.58 0.67	HAR	Apply the proposed method in more realistic scenario by adding the concept of incremental learning.	[66]
S26	2020	A hybrid network based on dense connection and weighted feature aggregation for HAR	S	ConvLSTM	OPPO UniMiB-SHAR	F1 score: 92.3% 97.3%,	HAR	Verify the robustness and practicality of the model, and test it on other datasets	[67]
S27	2020	Sensor-based HAR using deep stacked multilayered perceptron model	S	Deep Stacked Multilayered Perceptron +ANN	UCI-HHAR HAR-SP	97.3% 99.4%	HAR	Use stacked ensemble learning to achieve higher performance for HAR classification.	[68]
S28	2020	Continuous human activity classification from FMCW radar With Bi-LSTM networks	R	Bi-lstm	Carnegie Mellon MOCAP	90%	HAR	- Apply HAR for multi-residents in the radar field of view Explore techniques for decomposing signatures for classification.	[69]
S29	2020	LSTM-CNN architecture for human activity recognition	SP	LSTM-CNN	UCI, WISDM, OPPORTUNITY	95.78 95.85% 92.63%.	HAR	Not mentioned	[70]

Table 1. Summary of selected studies

Id	Y	Aim	M	Dl	Dataset	Accuracy	Application	Limitation/future work	Ref
S30	2020	Human activity recognition based on gramian angular field and deep convolutional neural network	S	Gramian angular Field (GAF) and deep CNN	WISDM, UCI HAR, OPPO	96.83% 89.48% 97.27%	HAR	To make machine learning models more practical for wearable devices, it is recommended to compress and miniaturize them. This will reduce computation, save hardware resources, and increase equipment standby time.	[71]
S31	2020	Temporal-frequency attention-based human activity recognition using commercial WiFi devices	WC	LSTM	line-of-sight non-line-of sight	96.6% 93%.	HAR	Not mentioned	[72]
S32	2020	Human daily activity recognition performed using wearable inertial sensors combined with deep learning algorithms	W	CNN	University of California (UCI),	93.77%	HAR rehabilitation exercise	Evaluate the amount of rehabilitation exercise for individuals with reduced mobility, such as patients undergoing dialysis.	[73]
S33	2020	Improved Bayesian convolution network for HAR to analyze health care data using wearable IoT device	W	Improved Bayesian Convolution Network (IBCN)	Self	Over 96%	HAR	The system's architecture comprises Wi-Fi and Cloud-based applications, which allows for the seamless addition of new users while enabling updates with the latest training sets.	[74]
S34	2019	WiFi CSI-based HAR using RNN	WC	RNN	Self	More than 95%	HAR	Not mentioned	[75]
S35	2019	Deep SRUs-GRUs based activity recognition system based on wearable body multi-sensors data	W	SRU+GRU	MHEALTH	99.80%	HAR	- Analyze the proposed model on complex and bigger datasets with more complex activities to get a real-time human behavior monitoring system. - investigate the consumption of computational of the model.	[76]
S36	2019	InnoHAR: a deep neural network for complex human activity7 recognition6	W	inception neural network and RNN	OPPO PAMAP2 SP	F1 score: 94.6% 93.5% 94.5%	HAR	- Investigate the kernel size and the connection method - Address the problem of data imbalance in real-life HAR.	[77]
S37	2019	Design and implementation of a convolutional neural network on an edge computing smartphone for HAR	S	CNN	Self	96.4%	HAR	The utilization of the proposed model requires significant computational and energy resources. However, it is useful for creating smart wearables and devices that do not rely on cloud connectivity. This could lead to enhanced user privacy and security.	[78]

S=sensor
W=wearable
R=radar

SP=smartphone
AdaBoost-HC=AdaBoost combined with hand-crafted
SRU=simple recurrent unit

RWHAR=real-world human activity recognition
DIM=deep InfoMax
BLS=based incremental learning

CSI=channel state information
OPPO=opportunity dataset
Self=dataset self-collected

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