The potential of the internet of things for human activity recognition in smart home: overview, challenges, approaches

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ABSTRACT

Human activity recognition (HAR) is a technology that infers current user activities by using the available sensory data network. Research on activity recognition is considered extremely important, particularly when it comes to delivering sensitive services such as healthcare services and live tracking assistance and autonomy. For this purpose, many researchers have proposed a knowledge-driven approach or data-driven reasoning for identification techniques. However, there are multiple limitations associated with these approaches and the resulting models are typically not complete enough to capture all types of human activities. Thus, recent works have suggested combining these techniques through a hybrid model. This paper's goal is to give a brief overview of activity recognition implementation approaches by looking at various sensing technologies used to gather data from internet of things (IoT) gadgets, looking at preprocessing and feature extraction approaches, and then comparing methods used to identify human activities in smart homes, and highlighting their strengths and weaknesses across various fields. Numerous pertinent works were located, and their accomplishments were assessed.

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1. INTRODUCTION

Nowadays, a smart home comes with a wide range of sensors and actuators, which refers to automation tools that can help to detect and measure the physical characteristics of the environment around us. They are capable of measuring light intensity, converting heat into temperature, detecting door openings, detecting temperature and humidity changes in the rooms, as well as operating our home appliances and heating systems. These devices can now be remotely controlled and connected to an increasing number of devices.

Therefore, a smart home must comprehend and recognize human behaviour to offer all of these functions. To achieve this, researchers are working on human activity recognition (HAR) methodologies, involving the observation and assessment of the actions performed by one or more individuals, with the aim of identifying the specific activities being carried out. Two categories [1] sensor-based systems and video-based systems—can be used to categorize the numerous HAR systems [2] as shown in Figure 1.

The HAR system may recognize a person's intentions and actions by tracking his or her activities. Since sensors and cameras are now readily available and fairly priced, it is one of the most popular and difficult study topics right now. In HAR, the term "data collection" refers to the gathering of sensor signals or videos. Datasets are often obtained from sensors such the electromyography, accelerometer, gyroscope, magnetometer, and video or still pictures, making them a fundamental part and the foundation of any HAR system. Activity recognition can be divided into two groups: sensor-based and vision-based.

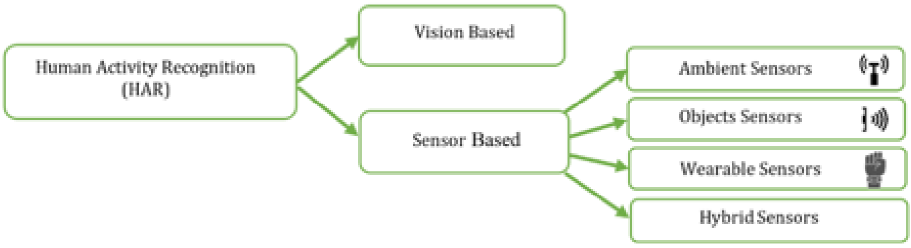

Figure 1. HAR categories

Vision-based HAR is the use of computer vision tools, such as cameras, to monitor changes in the environment and human activity. It has lately become more prominent as a result of its usage across a diverse range of practical applications, like ensuring security and conducting surveillance. To guarantee security in public locations, it is crucial to implement HAR for closed-circuit television (CCTV) systems, which comprise a network of cameras with a central recording hub.

Vision-based HAR research can be divided into red green blue (RGB) data [3] and red green blue-depth (RGB-D) data [4] depending on the type of data employed. Vision-based HAR frameworks utilizing RGB data often exhibit a lower level of accuracy compared to those utilizing RGB-D data, owing to the augmented information and depth channels provided by multi-modal data [3]. Nevertheless, the utilization of RGB data remains prevalent in current HAR frameworks due to challenges such as the complexities of setup (involving intricate configurations for various HAR scenarios), computational demands arising from vast datasets, and elevated expenses.

On the other hand, sensor-based HAR captures daily living activities from sensors [5], and involves following a person's activities using a network of connected devices.Data from the sensors is generated as a time series of state changes or parameter values. Numerous sensors, including accelerometers, magnetometers, noise sensors, electromyography, gyroscopes, and radar, can be positioned on people, on things, or in the environment. As a result, there are three distinct categories into which the sensor-based solutions can be subdivided: wearable [6], sensor on objects [7], and ambient sensor [8].

- Wearable sensor: which is frequently used for HAR systems, can directly record body movement. Accelerometer, magnetometer, and gyroscope are three common wearable sensors that can be easily worn by people or integrated into portable devices like smartphones [9], smart bands, smart watches, or glasses. Then, by comparing the signal differences before and after an activity, human activity can be identified.
- Sensor on objects: the sensors that are affixed to a specific object to track activity around it [10]. While object sensors detect the movement of a specific object to infer human activity, wearable sensors assess human behaviours directly. A smart drinking cup, for instance, may have an accelerometer linked to it to more effectively monitor the user's drinking patterns and alert them when their daily water consumption is insufficient [11]. Another instance of HAR utilizing smart object sensors is the usage of smart doorbells, which typically feature a camera and a microphone and help to detect the presence of a person at a door and to collect data about this person. The person's behaviour, such as knocking, ringing the doorbell, or standing on the doorway, can then be classified using this data by training a machine learning model [12].
- Ambient sensor: radar, pressure sensors, and temperature sensors are some of the ambient sensors that are generally incorporated into a user's smart environment and are used to collect information on how people interact with their surroundings. While object sensors track object movements, ambient sensors record the change in the environment. Guerrero-Ulloa *et al.* [13] Authors propose a system that uses ambient sensors to collect data on the environmental conditions of plants, such as temperature, humidity, and light. This data is then used to control the elements of the plant care system, such as watering, fertilization, and lighting. Ambient sensors have been utilized in several works of literature to identify hand gestures and daily activities [14], [15]. The majority of the work was evaluated in a smart home setting. Additionally, the adoption of appropriate environmental sensors must be carefully planned depending on the activities because they are highly sensitive to changes in the environment.

– Hybrid sensor: for the purpose of improving HAR model robustness and accuracy [16], researchers have increasingly utilized hybrid sensors [17], which signifies HAR applications that combine various types of sensors, like combining ambient and object sensors that can record both the object movements and environment state. These recent works suggest that the adoption of hybrid sensors, which create diverse datasets from numerous sources, can significantly advance HAR research efforts and encourage applications in systems like commercial smart homes [18].

It is evident to record that vision sensors have been widely used immediately [19]. Although privacy concerns have been addressed progressively, residents are more likely to embrace ambient sensors. As a result, the non-vision environmental sensors have emerged as a research focus [20] and they are more commonly accepted since they are regarded as less obtrusive. Sensors are the backbone of smart home technology, providing vital information and acting as the eyes and ears of intelligent systems designed to identify human behavior. The two main approaches to activity recognition are powered by this gathered data: the knowledge-driven approach, which uses human expertise and pre-established rules to interpret sensor data, and the data-driven approach, which uses algorithms to detect patterns among massive amounts of data.

Although several surveys have been conducted utilizing data-driven or knowledge-driven methodology, no specific survey has been conducted that offers a clear comparison of these two approaches. We believe this to be the first article discussing the most recent comparison between knowledge- and data-driven methods for identifying human activity in smart homes. We hope that this work will help provide an overview of the last studies and will suggest potential directions for future research.

This is how the rest of the paper is structured. In section 2, we describe the potential of the IoT for HAR. We discuss the adopted methodology for this review and then we focus on the comparison between the strengths and weaknesses of data-driven and knowledge-driven HAR methods in sections 3 and 4 respectively. Additionally, we present many challenges to identifying human activity in smart homes. A discussion and insights on the review's findings are presented in section 5. Finally, section 6 brings this paper to a close.

2. THE INTERNET OF THINGS FOR HAR

The IoT, often alluded to as IoT, encompasses a network of tangible, real-world objects interconnected through the Internet. These objects communicate with each other by exchanging data collected from sensors and using suitable communication protocols. This emerging technology is gradually becoming a part of our daily life [21]. The technology underlying IoT networking is elucidated in [22] as an improvement of communication protocols for interconnected intelligent objects. This enhancement involves the integration of diverse sensors and actor networks to achieve identification and tracking functionalities. Furthermore, Sultan and Ahmed [23] defines it as a configuration of sensors and actuators embedded within physical objects. These components have the ability to send data across wired networks as well as wirelessly.

Regarding the acquisition of data for remote monitoring and activity recognition, the pivotal components in creating a smart home are IoT sensors and the corresponding sensing technologies. The integration of these sensors through cloud-based databases and networking technologies plays a crucial role, but also it is a difficult technical challenge because it aims for high precision, robustness, and low energy consumption. However, there are many promising techniques to meet this challenge like the adaptation of machine learning algorithms, the use of artificial neural networks, and the specialized equipment [24].

2.1. IoT layer-based perspective for human activity recognition

For the purposes of data collection, sharing, and analysis, IoT applications enable device connectivity and interaction through the Internet. The generated IoT data can go through a number of learning phases for activity recognition [1] using the information obtained from different IoT sensors, as illustrated in Figure 2.

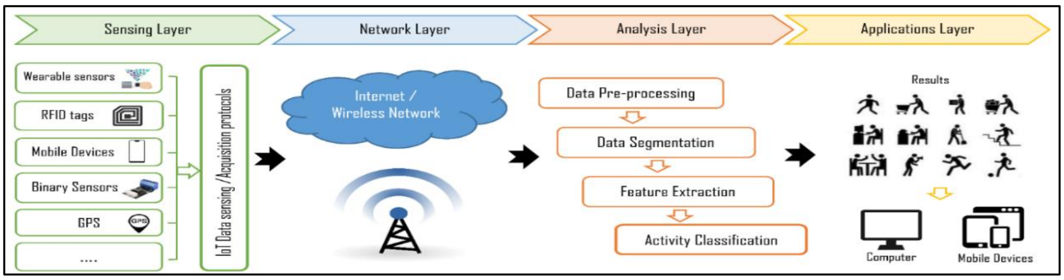

Figure 2. IoT layer-based perspective for HAR

The recent literature on intelligent systems based on the recognition of human activity testifies to the rapidity with which this technology evolves and its transformative impact in various applications [25]. It opens up exciting prospects for improving our quality of life and our safety through a deeper understanding of human activities. The structure of the HAR system consists of four IoT-based layers:

2.1.1. Sensing layer

The sensing layer enables the principal sensing and collecting goals; it is used to identify things and collect data on the environment and its occupants by deploying various sensing devices using a range of approaches, including implanted, wearable, on-appliance, or environmental sensors, and, tags. For instance, in the context of health care, the sensing layer is tasked with keeping track of the users' physical, mental, and emotional well-being. The process of measuring characteristics related to people and their sounds has been made easier in recent years thanks to the progress in small and low-cost wearable sensors. These include inertial sensors (such as gyroscopes, accelerometers, and barometric pressure sensors) as well as physiological sensors (like skin temperature sensors, spirometers, and blood pressure cuffs) [26].

2.1.2. Network layer

The network layer takes on the responsibility of interconnecting all devices within the sensory layer and enabling IoT infrastructures to collect, store, transmit, distribute, and aggregate customized data for activity detection. This layer typically includes a wide variety of ideas and methods, including topologies, architecture, security, privacy, and technologies for communication and location. As a result, it permits the efficient and secure conveyance of data to the appropriate data processing units. Numerous short-range communication protocols have seen widespread adoption, ZigBee is an example.

2.1.3. Analysis layer

The processing layer manages valuable knowledge extracted from the sensor data obtained in the initial layer. It stores and subsequently analyses the signal data received from the network layer. It is responsible for the aggregation, processing, and analysis of sensed information, as well as the subsequent transformation of that information into meaningful knowledge.

Four key data processing stages are involved in activity recognition: data pre-processing, data segmentation, feature extraction, and classification/clustering:

– Data preprocessing: any kind of information gathered from IoT sensing devices must go through preprocessing to facilitate the learning of processing algorithms from relevant data, enabling the refinement of a universal model, especially in the context of recognizing activities within a smart home. The various IoT sensing datasets that have been gathered contain noisy data [27] and they are unstructured as a result of disruptions and varying human actions [28]. Therefore, the major tasks of the preprocessing step prior to the start of feature extraction are the elimination of noise [28], conversion and normalization of data [29], labelling [30], and [31] for transforming the dataset into an appropriate form. So briefly data preprocessing is the process of organizing and cleaning raw data so that it is fit for use in subsequent processes in improving categorization accuracy.
– Data segmentation: is a common approach that refers to one of the crucial aspects of data processing. In actuality, no procedure can deal with the obtained data in a single step. Data must therefore be divided into a collection of segments, known as windows, during the segmentation process. Following that, each segment can be examined independently. There are two segmentation methods described in the literature: static and dynamic [32], [33]. Static segmentation, on the one hand, denotes a predetermined segment size that cannot be altered. Different segment sizes will be employed to evaluate the application. The best-performing size is then selected. In contrast, dynamic segmentation enables the division of the data into a collection of segments of varying sizes. During the application process, each size is dynamically selected.
– Feature extraction: since sensor data is derived from sensor events, it cannot be processed directly until it is included in the feature vector in some way. The features that can be used to express activity in smart homes are numerous, and these qualities may appear in features that portray continuous or discrete values, features that depict temporal sequences of occurrences, or in relation to the content of activities [34]. "Feature extraction" is a crucial step in the activity recognition process because if the features are reliable, any classification technique may be chosen with accuracy. The algorithms must identify a range of activities at the moment they take place as well as the user's state during that time by selecting all of the sensors that make up the circumstance.
– Activity classification: eventually classifies these features into various basic activity patterns. It is possible to infer high-level everyday activities like cooking, eating, or dressing when utilized in combination with user context data (such as an object's state or the user's location). The two primary

machine learning methods of classification and clustering are related respectively to supervised and unsupervised algorithms.

A review of various preprocessing and feature extraction techniques for IoT data from smart homes can be found in [35]. A number of classification algorithms that are utilized in smart homes to identify human activity using the information gathered by the sensors have also been examined. Time limits, data imbalances and noises, and computing complexity. can all have an impact on the ability of sensors to identify human activity from sensor data. According to the authors, time-based labeling of the data gathered by IoT sensors for the purpose of identifying human activity can help to increase accuracy and lower computational complexity.

2.1.4. Application layer

This layer gives users direct intelligent access to a variety of sophisticated services that improve their everyday life and health management. With its remote diagnosis features, medical professionals can evaluate patients from a distance. Features for behavior recognition give the system the ability to track and comprehend user routines and behaviors. It provides surveillance of everyday activities for senior citizens, guaranteeing their safety and well-being. To support overall health, it also integrates smart biological sensing, smart assistance, and self-management tools, measures emergency alarms, and monitors chronic diseases.

3. METHOD

3.1. Selection process

The scoping review method's three basic steps were used to pick a large number of relevant papers for this investigation. The first step is to identify keywords and search for relevant topics using existing databases. We were able to compile the literature for this work using databases such as Google Scholar, IEEE and MDPI by employing a strategy based on a set of keywords. The search string we used for this purpose was: "human activity recognition" and ("data-driven" or "data-based") and ("knowledge-driven" or "knowledge-based") and "smart home," Because of the current study endeavor, 793 papers were successfully collected during the first phase of the systematic review approach.

3.2. Screening process

There are 793 papers in the initial screening round. These publications were evaluated in the second step using inclusion and exclusion criteria that we had established. The primary inclusion criterion, which resulted in the exclusion of 367 data, was the study's five-year period from 2020 to 2024. Since peer-reviewed journal papers provide the most useful information, they satisfy the second condition. The analysis did not include dissertations, book chapters, meeting abstracts, conference proceedings, or book chapters. Moreover, the review contained only English-language papers with full-text accessibility. Based on the specific criteria indicated in Table 1, a total of 269 publications were excluded. So, for the eligibility level, the third level, a total of 97 articles have been prepared. At this stage, every publication was checked to make sure it satisfied the inclusion requirements and fit the goals of the current study. As a result, 32 papers were disqualified because their titles, abstracts, or out-of-field information had nothing to do with the purpose of the study. Finally, 65 items remain available for review.

Table 1. The selection criterion is searching

Criterion	Exclusion	Inclusion
Timeline	<2020	2020-2024
Literature type	Non- journal article	Journal article
Language	Non – English	English
Publication stage	In press	Final
Accessibility	Non – open access	Open access
Peer reviewing	No	Yes

4. HUMAN ACTIVITY RECOGNITION APPROACHES

4.1. The challenges in recognizing human activity in smart homes

In smart environments, accurate activity recognition is essential to support and assist users, especially the elderly and those with cognitive disabilities. In order to perform this mission, Smart homes are outfitted with monitoring tools capable of identifying everyday routines, activities, behavioural patterns, abnormal behaviour [36] and even giving individualized service. They can also be used to keep an eye on environmental changes by deploying sensors on various items and placing them in various locations.

In order to detect the Spatio-temporal states of physical or environmental circumstances, a smart home is outfitted with a number of inexpensive, non-intrusive ambient sensors. Figure 3 illustrates the layout of a smart home and the positions of sensors used for collecting data. Each sensor, for example, passive infrared (PIR) sensors, humidity and temperature sensors, electricity usage sensors, and entryway sensors for doors, among others, is used to track different physical characteristics [37].

PIR sensors are frequently used to monitor tenant movement as an indicator of the occupancy of a particular space in the home. They track the infrared light that objects in their field of view emit and measure it. As a result, they can identify a resident's movement whether they enter or exit the sensor's field of view. While the humidity, temperature, and electricity usage sensors are used to monitor the recorded values for these indicators, the door entrance sensors are utilized to determine if the door is open or closed. These sensors are the most frequently employed for activity daily living monitoring due to privacy, affordability, and ethical issues, as they allow people to live regular lives without feeling constrained by technology [38].

The complex nature of human activity and how it varies from resident to resident makes HAR in smart homes a difficult subject to solve. Each inhabitant has a unique way of life, routine, or set of skills. The enormous variety of daily activities, including the variety and adaptability of the way used to carry them out, necessitate a method that is scalable and must be adaptive. That's why identifying human actions using data from sensors comprises some challenges described:

- Heterogeneous data: typically, each sort of sensor is utilized to provide a certain type of data (i.e humidity, and temperature). In a smart environment, a variety of sensors are often produced, with each one serving a specific purpose (i.e getting an object's status, and identifying user location). As a result, the data provided by this vast array of sensors is heterogeneous.
- Dynamic environment: in an open environment, for example as shown in Figure 3 there is always the possibility of changes, especially with new sensors which arrive or which disappear. So, it's very important to adapt to this dynamicity to avoid having a solution that only applies to one type of architecture or environment.
- Imperfect data: due to hardware limitations on sensor equipment, given data is always subject to some degree of error. Additionally, sensor malfunctions or failures frequently result in lower-quality sensor data. As a result, fixing sensor weaknesses makes it possible to decrease information misinterpretation. One of the primary research questions in scenario identification is how to handle uncertain sensor data. Uncertainty metrics for describing sensor data, such as incompleteness, correctness, timeliness, and dependability, are introduced by specification-based techniques [39].

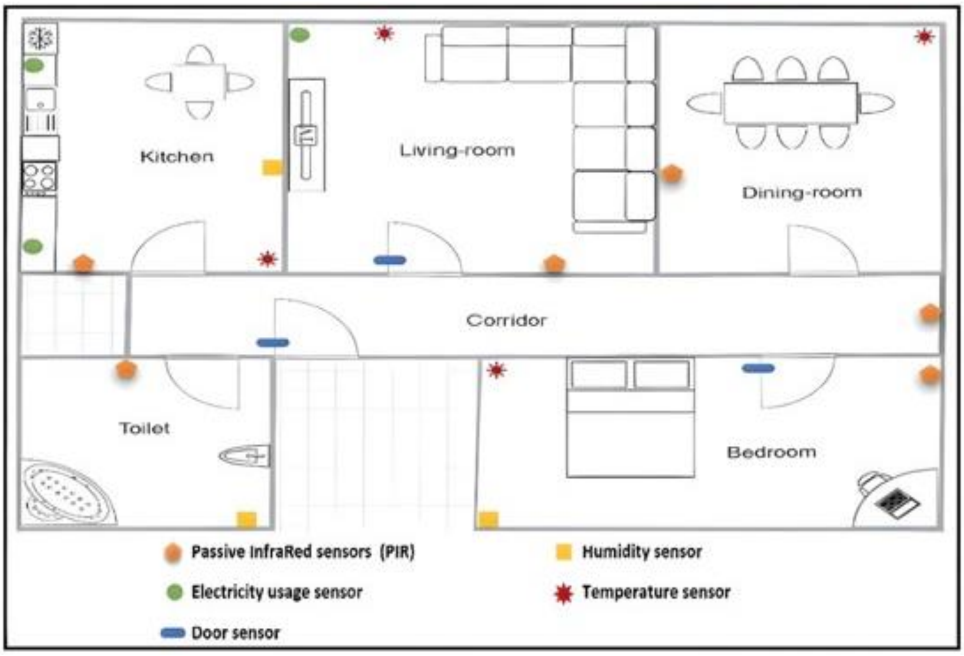

Figure 3. A smart home's floor plan and sensor installation locations employed for activity recognition

- Simultaneous activities: a single user can naturally engage in multiple activities simultaneously [40]. People can listen to music while doing other things, such as shopping or running. It is not required to identify which action began first in this instance because there are concurrent activities where one activity, like running, begins while the other has already begun (e.g., listening to music). It requires a specialized approach to identify these non-sequential behaviours.
- Interleaved activities: in the real world, one activity may be interrupted by another [41]. For instance, an employee is working on an administrative file as a current activity, and then he received a phone call. In this scenario, the first activity is interrupted for the duration of the second activity before the first action is restarted.
- Recognizing multiple residents: even though keeping track of a single resident's daily activities is a challenging task, managing multiple residents is significantly more difficult. In fact, the same actions become more complicated to identify when numerous people living or working together in the same space. On the one hand, a resident may interact with others in a group to carry out shared tasks. In this instance, each resident in the group has the same activity reflected by the sensors' activation. On the other hand, everyone can carry out multiple tasks simultaneously. The sensors for various activities are simultaneously activated as a result. The activity sequences are created by merging and combining these activations. So, a resident's activity could constitute a noise for another's activity. Although various statistical measurements are offered in this field of study, it is still regarded as difficult [42].
- Data streaming: sensor data is provided as a time series or sensor data stream. Hence, this data can be immediately evaluated using an online technique or stored on a computer for further offline processing. Consequently, outcomes that arrive after significant delays might diminish in their effectiveness.

4.2. Human activity recognition approaches in smart homes

For the purpose of identifying human activities within the smart home, there are three major categories into which the methodologies identified in the literature can be categorized: data-driven approaches (DDA), knowledge-driven approaches (KDA), and hybrid approaches (HA). KDA makes use of rule design and expert knowledge. This means it makes use of logical reasoning, modeling, and prior knowledge of the domain. DDA models and detects the action using user-generated data. It is based on machine learning and data mining techniques. The fundamental problem with such methods is that they are not ideal for handling uncertain data. To solve these problems, hybrid techniques that combine the advantages of data-driven and KDA are suitable [43].

4.2.1. Data-based approach

Data-driven methods employing machine learning and data mining approaches develop activity models from existing datasets [44]. They train the activity model, which captures the implicit general rules, using a large amount of labeled data. It can be used to develop more accurate and efficient systems like the example of climate control systems in smart greenhouses [45]. This would optimize crop production, improve product quality, and reduce energy consumption. Data-driven methods, which largely rely on probabilistic and statistical reasoning, contain both supervised and unsupervised learning approaches based on machine learning and deep learning techniques as shown in Figure 4. Actually, the data-driven approach was mostly used in the first investigations [46]:

- Supervised learning algorithms create a model using a labelled training dataset in accordance with a predefined collection of characteristics in order to understand the dependencies and correlations between the targeted prediction output and the input data. It develops rules that determine the likelihood that the label will occur given the input. Following training, the algorithm can categorize fresh unknown data and forecast the output values for novel data using correlations acquired from previous datasets, according to the learned rules. The more examples that are provided, the easier it will be for the algorithm to adapt and handle different inputs. An example of a recent work based on Supervised machine learning algorithms is given in [47].
- Unsupervised learning techniques extract insights directly from the data, without requiring labels. They are the family of machine learning techniques where the data is not labelled. Instead of depending on existing information from the class, they look for and deduce logical relationships between the data. These algorithms use methods to analyse the input dataset in search of patterns, rules, and summaries that assist users in better understanding the data and deriving insightful conclusions. There are numerous unsupervised approaches; some cluster comparable data using distance criteria, while others try to learn these principles on their own. Unsupervised learning has the main benefit of allowing for the discovery of rules and correlations that would otherwise go unrecognized by experts. An example of unsupervised machine learning algorithms is presented in [48].

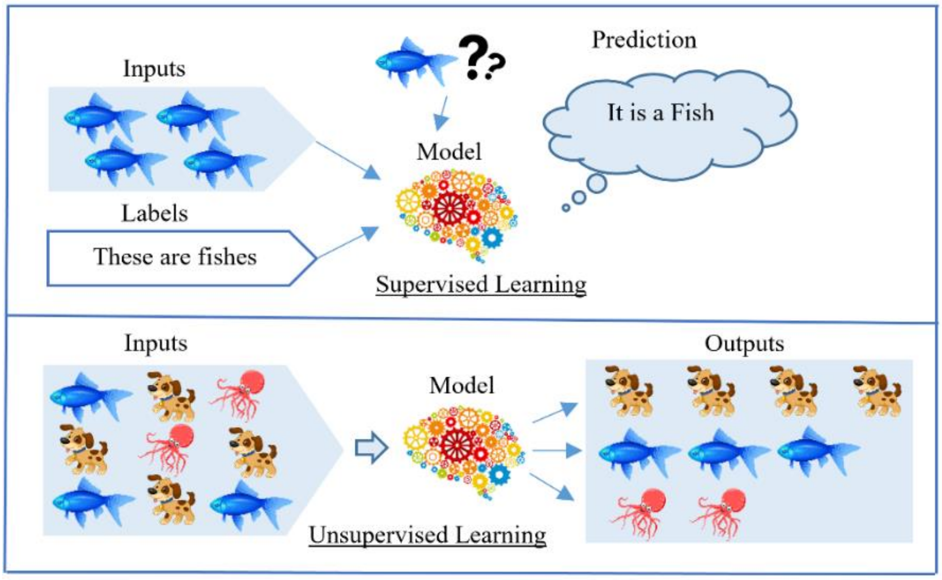

Figure 4. Supervised and unsupervised learning methods

4.2.2. Knowledge-driven approach

Knowledge-driven approach relies on prior knowledge about the real world, which shows that the list of objects and features needed to complete a task is consistently very similar. It incorporates reasoning engines, ontologies, and logic rules to infer appropriate actions from the input of the current sensors. Even if the activity is carried out in various ways in real-world scenarios, the variety in the number and kind of objects involved is limited. For example, the activity "to iron clothes" contains actions involving an iron, an ironing board, a water sprayer, and clothes. However, as people differ in their lifestyles, abilities, and habits they have the potential to carry out an activity in a variety of ways.

The acquisition of the necessary contextual knowledge is the initial step for knowledge-driven systems. Typically, this is accomplished by applying common knowledge engineering approaches [49]. Different strategies can be distinguished depending on the type of knowledge that has been learned. Chen *et al.* [50] demonstrate about activity recognition, several researchers employ logic-based techniques, while others adopt ontology-based techniques. These techniques facilitate a widely accepted and clear representation of activity definitions, which remains independent of algorithmic preferences, fostering portability, reusability, and interoperability.

4.2.3. Comparison

The following Table 2 reviews recent works on smart cities based on a data-driven approach and Knowledge and resumes their advantages and disadvantages according to the presented criteria in section 3. This comparison highlights the continuous debate in the scientific community over the appropriate approaches for diverse applications, from healthcare to smart building management. It is especially relevant in sectors like activity recognition in smart homes.

Data-driven strategies, which are highly regarded for their accuracy and adaptability, perform best in contexts with lots of data. They use machine learning algorithms to examine and forecast data based on patterns found inside. However, they have some significant disadvantages, such as their reliance on large, high-quality data and the possible privacy issues they bring. Furthermore, it can be challenging to understand and put your trust in certain data-driven models, such as those based on deep learning, due to their complexity and black-box nature in crucial applications.

On the other hand, knowledge-driven strategies use pre-established rules and expert insights to provide high interpretability and quick execution. This makes them extremely useful in situations where there is a lack of data or when judgments need to be justified. However, their inflexibility and reliance on thorough, correct domain knowledge might restrict their flexibility and make manual updates necessary to adjust to new data or environmental changes.

Table 2. Strengths and weaknesses of the data-driven and knowledge-driven [51]-[115]

Approach type	Strengths	References	Weaknesses	References
Data-driven	Comprehensive Data Analysis: Facilitates the gathering and examination of enormous volumes of data to gain an understanding of comfort, energy efficiency, and space use in smart buildings.	[51], [54], [60],[72], [83], [102], [111]	Dependence on Data Quality: The quantity and quality of data gathered have a significant impact on performance.	[51], [53], [54], [63], [77], [84], [85], [89], [91], [92], [98], [104]
	Automated Feature Extraction: This technique reduces the need for manual engineering by facilitating autonomous learning and representation. It is particularly useful for HAR.	[52], [53], [63], [67], [75], [76]	Privacy Concerns: Gathering and examining personal information gives rise to privacy concerns.	[51], [56], [73]-[75], [81]-[83], [91], [94], [95], [98], [102], [103], [111], [112]
			Technical Complexity: Specialized tools and knowledge are needed to implement and maintain complicated models.	[51], [61], [64], [73], [81], [83], [87], [100], [109], [113]
	Accuracy and Robustness: Deep AI models trained on massive datasets improve the accuracy and robustness of systems such as wireless sensing.	[53], [61], [86], [89], [99], [105], [108]	Lack of Interpretability: It can be challenging to interpret models, particularly those based on deep learning.	[51], [52], [87], [106]
			Requires Large Amounts of Labeled Training Data: Acquiring a significant amount of labeled data can be expensive and time-consuming	[52]-[56], [63], [65], [81]-[83], [93], [94], [100], [103], [115]
	Flexible and Adaptable Systems: Facilitates the creation of flexible and adaptable systems that are simple to retrain using fresh data.	[53], [55], [65], [66], [79], [81], [84], [98], [102], [103], [105], [110], [113], [114]	Computational Intensity: The training and inference of deep AI models frequently need substantial computational resources, which may restrict the models' applicability.	[53], [65], [76], [105]
	Valuable Insights into Human Activities: they are obtained by using sensor data, which captures variation between datasets for better activity tracking and decision-making.	[51], [54], [57], [65], [69], [70], [87], [91], [96], [101], [106]	Challenges in Managing Heterogeneities among Users and Activities: Managing heterogeneities among users and activities may provide difficulties, particularly in federated learning environments.	[54], [64], [86], [89]
	Privacy in Collaborative Learning: Reduces privacy concerns by aggregating many models without sharing datasets.	[56], [80]	Energy Consumption Concerns: While choosing devices with fewer datasets may result in lower learning accuracy, selecting IoT devices with larger datasets for training may lead to higher energy consumption	[56], [70]
	Predictive Performance Boost: Enhances predictive performance for a variety of uses.	[58], [81], [91], [110],[113]		
			Regulatory and Ethical Challenges: The application of AI in healthcare raises ethical questions and calls for regulatory supervision to guarantee patient safety.	[57], [102]
Knowledge-driven	Expertise Use: Utilizes expertise to inform decisions and forecasts by fusing business rules with expert knowledge; useful in areas with limited data.	[51]-[54], [59], [63], [69], [72] - [75], [78], [80], [84], [87], [90]- [92], [95], [100]-[105], [106], [107], [109], [111], [115]	Limited Adaptability & Dependency on Expert Knowledge: Has trouble adjusting to novel situations or unanticipated events that weren't covered by the guidelines at first. It is highly dependent on the availability and comprehensiveness of experts	[51]-[53], [59], [62]-[64], [72]-[74], [76], [84], [87], [92], [93], [95], [100], [102], [103], [105], [107], [109], [111], [114]
	Interpretability: Models are frequently more comprehensible and transparent, which promotes user adoption.	[52], [53], [63], [75], [78], [88], [103], [106], [108], [109]	Knowledge Representation Difficulties: It can be difficult to appropriately capture and represent dynamic, complicated knowledge.	[51], [63], [71], [89], [91], [92], [95], [101], [113]
	Immediate Implementation: Solutions based on prior knowledge can be implemented immediately, negating the need for protracted learning stages.	[67], [104], [114]	Time-consuming Rule Definition: Manual labor is needed for both feature engineering and rule definition, and essential patterns may be overlooked.	[52], [54], [59], [63], [100], [102], [109], [115]
	Reduced Data Dependency: able to operate with little or no labeled data by using pre-established models and rules	[52], [53], [54], [76], [78], [89], [104]	Accuracy Dependent on Previous Knowledge & on Known Patterns: Previous knowledge, which may not always be current or easily accessible, determines effectiveness.	[51]-[53], [59], [62], [67], [72], [80], [84], [90], [92], [93], [100], [108]
	Support for Decision-Making: Uses professional insights to make more trustworthy and educated decisions; especially useful for IoT and healthcare applications.	[51], [68], [69], [73], [74], [91], [95], [101]	Human Labeling Requirements: The practical implementation of new sensors or deployment adjustments is limited due to the need for human labeling and remapping.	[52], [54], [63], [115]

4.2.4. Hybrid approach

By combining different methodologies, a hybrid approach achieves the "best of both worlds". This approach can provide a formal, semantic, and extendable model capable of dealing with the uncertainty present in sensor data and reasoning rules [116]. Recognizing all types of human activities in home settings might be challenging due to the difficulty in defining complete activity models. A desirable situation model is therefore built on a sound logical framework that includes rules to ensure the consistency and integrity of the knowledge base as well as logical primitives that possess the necessary richness to encompass a diverse range of information, including sensor data, domain expertise, distilled context, and situational knowledge. Hence, by combining data-driven strategies with knowledge-driven models, this challenge can be effectively addressed. Combining the two can result in activity models that are comprehensive and sufficiently enough to include all varieties of human activities. Additionally, these models are also capable of ongoing evolution and can learn to adjust to users' diverse behaviour. Therefore, recent works have been motivated to propose hybrid models. In this survey, we provided numerous HA for HAR which continue to be good choices for processing and assessing sensor data within intelligent environments, influenced by the method of hybridization employed.

In the perspective of combining Knowledge-based and Data-driven approaches, Riboni et al. present a solution named “COSAR” [117], an adept context-aware mobile app that integrates ontologies with machine learning techniques. The machine learning algorithm is first activated to forecast the most expected activities using training data that has been supplied. The results are then refined using an ontological reasoner, which chooses from a set of potential user actions based on the user's location as determined by a localization server. Another hybrid solution is proposed by Riboni *et al.* in [118] called SmartFABER system which is an extension and amelioration of FABER [119]. The objectives of these two frameworks are similar. The system delivers the inferred events and actions to a module tasked with creating feature vectors based on the received events rather than the MLN classifier. The classification of activities is done using a machine-learning module that receives these features. The next step is to apply a suggested technique called Smart Aggregation to infer instances of current activity. Additionally, Riboni *et al.* [120] create an extremely comprehensive ontologic model used the web ontologic language (OWL2), with the eventual aim of connecting this knowledge to Markov logic networks (MLN), facilitating the application of probabilistic reasoning. The system's generality is compromised by their method's requirement for extremely precise activity models.

Gabriele present a novel hybrid strategy using knowledge-based and probabilistic reasoning, he used unsupervised feedback to classify the rules that performed well in the real-world dataset [121]. On the other hand, another hybrid model has been developed in [122] that includes a machine-learning methodology, an ontology, and a log-linear system. This model aims to identify a multi-tiered activity structure with four tiers: complex activity (Level 1), simple activity (Level 2), manipulative gesture (Level 3), and atomic gesture (Level 4). Through the use of a machine learning approach, atomic gestures are detected. Additionally, manipulating gestures, basic activities, and complicated activities are inferred through a probabilistic ontology established by the log-linear and conventional ontological reasoning tasks.

Another hybrid proposal is proposed in [123], MLN are used for activity recognition combining the usage of ontologies with statistical learning methods (MLN). The suggested system makes use of the model-theoretic semantic property inherent in description logic to transform the activity model based on ontology into corresponding first-order rules. This procedure entails creating MLN, where learners grasp weighted first-order rules, enabling probabilistic reasoning within a framework of knowledge representation.

Sukor *et al.* [124] propose an alternate strategy that combines knowledge-driven reasoning with data-driven reasoning to enable activity models to automatically evolve and adapt in response to user specificities. First of all, a knowledge-driven rationale for assuming an initial activity model is described. In order to create a dynamic activity model that learns users' varied actions, the model is then trained using data-driven methodologies. In the same perspective, and in order to overcome the issues with activity modeling, Chen *et al.* [125] propose an ontology-based hybrid strategy that combines data-driven learning capabilities with a knowledge-driven approach. To generate individual activity models using incremental learning, generic activity models that are appropriate for all users are first provided. As a conceptual foundation and technological enablers for Activity Daily Life modeling, classification, and learning, the approach makes use of semantic technologies.

On the other hand, Azkune et al. propose in [49] a novel activity recognition system that merges unsupervised learning approaches with activity models based on knowledge. The most frequent action sequences carried out by a person are first extracted using a domain-specific data mining method previously created by Cook *et al.* in [126]. To determine which activities are being carried out in a particular action sequence, the writers secondly incorporate a knowledge-based activity model into a unique matching method. The method yields an expandable activity recognition system.

More recently, in 2020, Ayari *et al.* [127] showed better performance than baseline models by putting out a hybrid model that combines possibilistic logic with a Multilayer Perceptron (MLP) neural network for emotion-contextual identification in cognitive aid services. Bettini *et al.* [68], by combining semi-supervised learning and probabilistic ontological reasoning, a novel method for activity recognition is proposed. Soft and hard ontological principles are combined to model the interactions between activities and context, and the compatibility of each action with the present context conditions is calculated using a probabilistic ontology. In order to determine the user activity that is most likely to have been conducted, probabilistic semantic reasoning and a machine learning classifier that uses data from inertial sensors are coupled. Huan *et al.* [128] provide a hybrid model that looks at both spatial and temporal information from sensor data to identify human activities. The model includes a convolutional neural network (CNN) and a bidirectional long short-term memory (BLSTM) network.

In order to effectively provide context-aware help, Moulouel *et al.* [43] suggest a hybrid strategy in 2022 that combines probabilistic reasoning and deep learning to anticipate human behaviors in Ambient Intelligence environments. To identify human behavior, Mojarad *et al.* [129] present a hybrid model in 2023 that blends knowledge-driven and data-driven methodologies. This model combines probabilistic answer set programming (PASP) for rules-based reasoning and machine learning with long short-term memory (LSTM). By taking the behavior's context into account, it is intended to comprehend and distinguish between normal and deviant human behaviors.

5. RESULTS AND DISCUSSION

Technology for monitoring smart homes has been utilized to find patterns in daily routines and activities using sensors placed in various locations and on various things, they can also be used to monitor environmental changes. So, to support and assist users, especially the elderly or those with cognitive impairments, precise activity recognition is crucial in smart homes. The contrast between knowledge-driven and data-driven methods for smart home activity recognition shows the potential for accurate activity recognition as well as the unique benefits and drawbacks of each approach, offering insightful information for the development of smart home technologies.

Data-driven strategies use the massive volumes of data produced by smart homes to spot trends and activity. These techniques are especially well-suited to settings where activities and user interactions change over time since they are extremely adaptive and get better as more data becomes available. The process of developing models is streamlined by data-driven models' capacity to autonomously extract features from large, complicated datasets, which eliminates the need for human interaction in feature engineering. Furthermore, these methods frequently attain great degrees of precision, making it possible to identify complex actions and behaviors from the gathered data. However, the caliber and volume of the data that is provided have a significant impact on their efficacy. Due to the hazards associated with gathering and analyzing personal data, which must be reduced by stringent data protection procedures, privacy issues are also very important. Moreover, these models' intricacy and frequently "black box" design can make them tricky to understand, which calls into question their reliability and user acceptability.

On the other hand, knowledge-driven techniques provide high degrees of interpretability and dependability by using preset rules and subject expertise to direct decision-making processes. These techniques can be quickly put into practice and offer instant fixes, even in situations where data may be in little supply. Rule-based systems that are transparent help to foster user trust by providing a clear and comprehensible rationale for decisions. But without manual updates, knowledge-driven systems may find it difficult to adjust to novel or unexpected circumstances, which limits their adaptability. The correctness and completeness of the embedded domain information also limit their effectiveness, with faulty or incomplete knowledge perhaps producing less-than-ideal results. Furthermore, the upkeep of these systems necessitates constant human updates by domain specialists in order to incorporate fresh perspectives or modifications.

The combination of these analyses makes a strong argument for a hybrid strategy that blends the dependability and clarity of knowledge-driven systems with the flexibility and capacity for learning of data-driven approaches. By combining the best features of both approaches, this strategy would provide a more reliable, flexible, and user-friendly solution for activity recognition in smart homes. In order to overcome the shortcomings of each strategy, this hybrid model offers an organized, knowledgeable framework that improves system performance while also taking ethical issues like privacy and transparency into account. Through the combination of domain-specific insights from knowledge-driven frameworks and the computational power of data-driven models, a hybrid approach offers increased efficiency and accuracy while also advancing the creation of socially and ethically acceptable smart home technology.

So, recognizing all types of human activities in domestic settings might be challenging due to the difficulty in defining entire activity models. To effectively tackle the processing and interpretation of sensor data within intelligent environments, both semantic and DDA are necessary. Combining the two can result in activity models that are comprehensive and general enough to include all varieties of human activities. While the learning stage within DDA serves as a means of adapting to novel settings, semantic-based techniques provide a semantic understanding of the incoming sensor data. Additionally, the models can develop continually and learn to adjust to changing user behaviour and dynamic situations.

The new IoT technologies in the activity recognition field promise enormous potential benefits in delivering intelligent services. However, there are still several obstacles in the way of obtaining consistent and efficient performance. Several aspects have been identified in section 3, and they may even present interesting opportunities for future works in this field.

6. CONCLUSION

In this paper, we presented a brief analysis of several sensors and sensing technologies for smart home-based human activity identification. Then, we reviewed and discussed the fundamental approaches to activity recognition designed to accurately anticipate actions via IoT sensor networks and how these strategies hold significance in the context of smart homes, as they empower the intelligent management of household occupants across diverse activities such as home automation, security enhancement, medical assessments, and unobtrusive health monitoring, all in an optimized manner. A comparison of knowledge-driven and data-driven methods for activity recognition is provided, and it can help the field go forward by pointing out the advantages and disadvantages of each approach. This comparison emphasizes the potential of hybrid models while also outlining important areas for further study and development and clarifying the current situation. These models present a well-balanced strategy that could greatly increase the efficacy and user acceptance of smart home technology by combining the flexibility and accuracy of data-driven methods with the openness and dependability of knowledge-driven systems.

Additionally, the debate shows how crucial ethical factors—especially those related to privacy and transparency—are in fostering the development of technologies that protect user data while preserving operational clarity. Combining a variety of expertise could result in more thorough and morally sound answers, according to the report, which promotes multidisciplinary teamwork. This comparison study provides an excellent baseline against which to measure future advancements in smart home technology. It also drives researchers to develop more intelligent, responsible, and user-friendly solutions that address the complex needs of contemporary living environments. Ultimately, we might draw the conclusion that although a tremendous amount of study has been done in this field, there are still many issues and obstacles that need to be resolved.

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