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A review of thermal array sensor-based activity detection in smart spaces using AI

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Abstract

Nowadays, research works into the dynamic and static human activities on Smart spaces abounds. Artificial Intelligence (AI) and low cost non-privacy invasive ambient sensors have made this ubiquitous. This review presents a state-of-the-art analysis, performance evaluation, and future research direction. One of the aims of activity recognition (especially that of humans) systems using thermal sensors and AI is the safety of persons in Smart spaces. In a Smart home, human activity detection systems are put in place to ensure the safety of persons in such an environment. This system should have the ability to monitor issues like fall detection, a common home-related accident. In this work, a review of trends in thermal sensor deployment, an appraisal of the popular datasets, AI algorithms, testbeds, and critical challenges of the recent works was provided to direct the research focus. In addition, a summary of AI models and their performance under various sensor resolutions was presented.

Keywords: Activity detection; Artificial intelligence; Ensemble learning; Smart spaces; Thermal sensor

1. Introduction

The concept of Smart spaces refers to a sensor-based environment supported by intelligent devices. These sensors and intelligent devices allow for the collection of data, its processing, and inferential deductions from the interaction of persons with the environment. It is such, the occupants of the environment are not limited or required to use or wear any gadgets [1]. The fifth-generation (5G) and beyond 5G (B5G) has the advantages of improved connectivity, extremely low latency, increased number of connected devices, and large bandwidth has impacted Smart spaces such as the smart home when artificial intelligence (AI) serves as an enabler [2]. The significance of the supporting technologies defines the unique features of Smart spaces such as timely response to a situation or environmental changes, ease of sensor deployment, the possibility of real-time data collection, and near elimination of wired communication in favor of wireless sensor networking.

Various sectors have utilized the benefits of Smart spaces. The Smart space has found ready acceptance in the health and wellness sector, tourism, and smart homes and factories to mention but a few [3]. In all, the major role involves monitoring activities (for example, humans) in the environment and allowing for response to needs or emergency concerns as the case may be [4]. In addition, monitoring of human, material, and work/building environment can also help in the effective utilization of human and material resources [5] as well as respond to the health needs of people in such a Smart space [6].

Several attempts and approaches have been deployed in recent times to monitor activities in the Smart space [6–8]. This is largely due to advances in sensor technology, ease of deployment, and low cost with reference to sensor type usage. To achieve the purpose of human activity monitoring in smart spaces, researchers have explored the options of vision-based (audio-visual) [6], thermal (ambient) sensing technology [7–9] and wearable technologies (devices such as smart wristbands, watches, etc.) [10]. These three approaches

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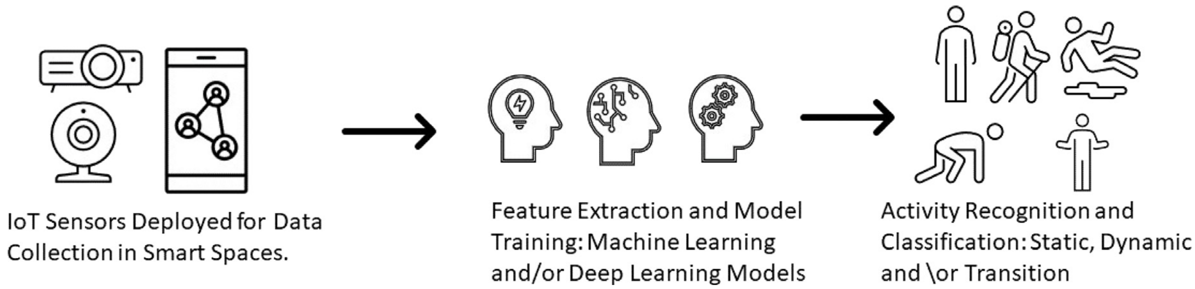

Fig. 1. The basic components of an AI-Based activity detection and classification system show the three sections of IoT deployment, feature extraction, and activities classified.

come with their pros and cons. However, the need to avoid privacy invasion, ensure low-cost implementation, and ease of use without discomfort to users have made the option of ambient sensing attractive in the area of human activity detection and classification [9].

Moreover, thermal (ambient) sensing is considered for the following reasons: it allows for activity detection even in the face of 'no-light condition' the data is easier to analyze with less overhead complexity when compared to image data, and there are several low-cost thermal sensors available from various vendors [9]. Thermal infrared sensors use the radiation emitted from an object to create a temperature difference between an object and a heat absorber. With this, it is possible to compute and create a heat map that forms the bulk of the dataset needed for activity detection at minimum energy consumption, high accuracy, reliability, and low cost [11]. Therefore, it is no wonder that thermal array sensors' adoption and usage in recent times are growing [12].

AI has assisted in enhancing the performance of detection schemes generally, and thermal-based systems in particular. In light of this, several authors have employed both supervised and unsupervised machine learning approaches to make intelligent deductions from schemes. For instance, the authors in [13] employed deep neural networks (DNNs) to ensure effective monitoring of metal production for quality control. This guarantees the inspection of defective metal parts, thus, serving to help curb wastage. Activity recognition involves three components: IoT Deployment in the form of sensors for data collection, the AI model for data wrangling, feature extraction, and activity classification cum detection (identification). Fig. 1 is the summary of the components.

Despite the promising results shown by the low-cost ambient sensors, AI capabilities, and impact of 5G+ for activity monitoring in Smart spaces, there is a limited comprehensive understanding of the trends, opportunities, and challenges faced by researchers in recent times. Most of the existing reviews are general, as they focused on the general concept of AI and sensors for activity recognition. The majority of the existing works focused on the use of AI and mobile and wearable sensors [10] as against the use of thermal sensors, the focus of this review. Inspired by the plethora and diverse research works employing low-cost, thermal (ambient) sensors, AI-assisted activity detection, and classification works, this review seeks to make the following contributions:

1. A short but comprehensive review of works in Thermal-Array Sensor based approach to human activity detection was done
2. Setting the pace for open issues and practical research concerns as it affects the application of artificial intelligence (AI) to human activity detection in smart spaces
3. Investigating the impact the sensor placement, resolution, and test bed design on the quality of dataset as well performance of AI schemes.
4. Exploring further the possible role of AI-enabled thermal sensor-based human activities in smart space scenarios.
5. Provided novel meta-analysis of findings not common to existing reviews on thermal array sensor-based works.

This review is arguably the first attempt to systematically review activity detection in smart spaces using thermal sensors. The organization of this work is: following Section 1 is Section 2 where a detailed review of related review works was presented. In Section 3, the methodology for article selection and meta-analysis is carried out. The various state-of-the-art approaches and their performance evaluation are included in Section 4 detailing the ML, AI, Datasets, and smart space use cases. The paper was concluded in Section 5. Acronyms used in this article are listed in Table 1.

2. Related works

Activity recognition systems in Smart spaces include the detection and classification of human activities. They emphasized real-time, accuracy, and the use of low-cost ambient sensors. In the works of [4], authors developed a simple testbed wherein they collected datasets for smart factories for emergency response based on the classification of abnormal human activities detected. However, they did not explore the use of the recurrent neural network (RNN), and did not attempt to use a public dataset for a fair comparison.

The authors of [7] comprehensively showed the drawbacks of various approaches to human activity detection. In the end, they posited that thermal array sensors (or ambient sensors) are readily used because of the preservation of privacy and no discomfort issues as experienced in multimedia or wearable devices. In [8], the authors used a low-resolution and cost-effective ambient sensor to classify falls and trigger the need for medical attention for the elderly.

Table 1
Acronyms used in the article and their meaning.

Acronyms	Meaning
ACM	Association for Computing Machinery
ADL	Activity of Daily Living
AI	Artificial Intelligence
B5G	Beyond Fifth Generation
BFA	Binary Firefly Algorithm
BPSO	Binary Particle Swarm Optimization
CASAS	Center of Advanced Studies in Adaptive System
CMIM-GA	Conditional Multivariate Mutual Information-Genetic Algorithm
CNN	Convolutional Neural Network
DBN	Deep Belief Network
DNN	Deep Neural Networks
ESP	Espressif Systems Board
FoV	Field of View
GTFS	Game Theory-Based Feature Selection
IET	Institution of Engineering and Technology
IoT	Internet of Things
kNN	k-Nearest Neighbors
LDA	Linear Discriminant Analysis
LSTM	Long Short Term Memory
LIME	Local Interpretable Model-agnostic Explanations
LORE	Local Rule-based Explanations
LoRMiKA	Local Rule-based Model Interpretability with k-optimal Associations
MBACO	Modified Binary Ant Colony Optimization
MDPI	Multidisciplinary Digital Publishing Institute
ML	Machine Learning
MLX	Melexis Sensor
MQTT	Message Queuing Telemetry Transport
NN	Neural Networks
NCC	Nearest Centroid Classifier
OTDR	Object Temperature Detection Range
OCSVM	Once Class Support Vector Machine
PRISMA	Preferred Reporting Items for Systematic Review and Meta-Analyses
QDA	Quadratic Discriminant Analysis
RA	Relief Algorithm
RF	Random Forest
RNN	Recurrent Neural Network
SHAP	SHapley Additive exPlanations
SVM	Support Vector Machines
TRUST	Transparency Relying Upon Statistical
UAV	Unmanned Aerial Vehicles
XAI	Explainable AI
XAIR	Explainable AI for Regression
XGB	Extreme Gradient Boost

A detailed review of sensors, categories, and applications for human activity recognition was done by [14]. Focusing on thermal imaging sensors, they [14] identified that a 16 $\times$ 16 resolution sensor is most appropriate when there is a need to preserve the privacy of the persons in the smart space. Unlike other reviews, they extended the scope of review to include the methodology for measurement within the human activity recognition domain. A similar survey done by [15] emphasized the role of deep learning in enhancing human activity recognition. They submitted that deep learning showed a better performance than traditional machine learning, since deep learning reduces the dependency on human-crafted features.

Furthermore, the authors in [16] extensively reviewed highly cited papers in the areas of fall detection published between 2005 to 2012. Major observations from the review included the issues of real-life implementation, the difficulty of computer vision projects, and the non-uniform approach to the adoption and implementation of ML algorithms. Since the paper focused on wearable devices, they also highlighted the issues associated with poor user acceptance, privacy concerns, smartphone limitations, and ease of use. However, they did not consider the use of thermal sensors, which is a research gap to be filled in this article. Also, the review by [17] detailed various datasets used in human activity recognition. However, the ultimate aim was to dwell on the use of the clustering approach and not on the sensor type or technology for data collection.

Bulling et al. [18] presented a detailed tutorial on human activity recognition using body-worn sensors. The work highlighted the enabling technologies, performance evaluation of AI approaches, and challenges in sensors placement

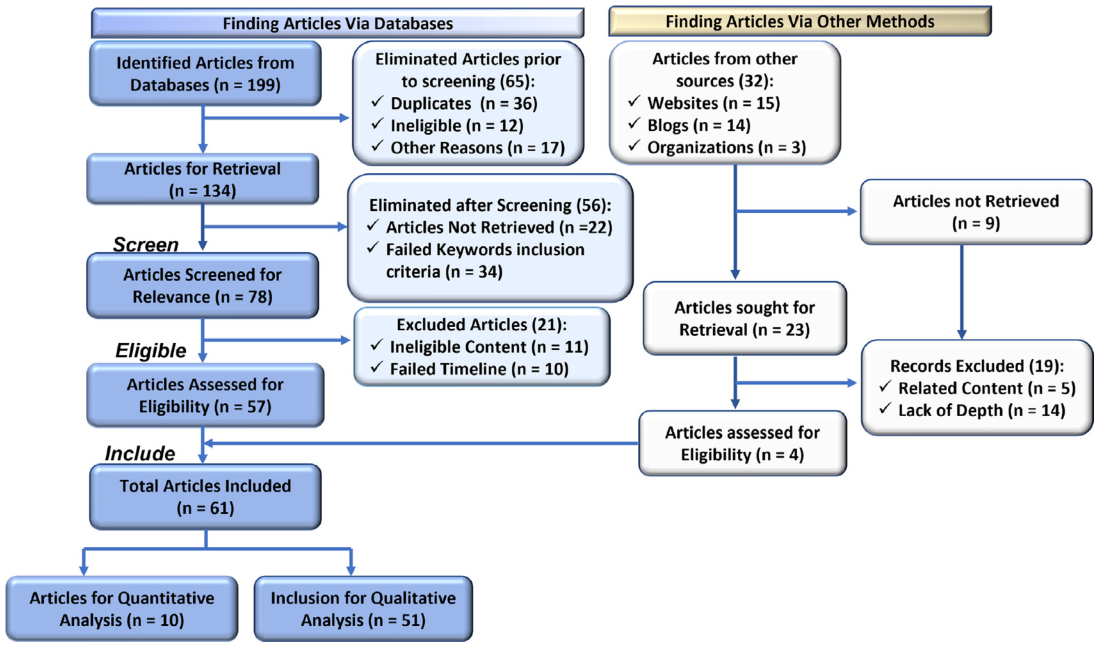

Fig. 2. The flowchart of the PRISMA methodology adopted in this study.

and choice of AI models factoring in trade-offs. The work, however, was based on the use of inertial measurement units.

A review of the adoption of thermal sensors incorporated with unmanned aerial vehicles (UAV) for sensing plants was presented by Awais et al. [19], just as Tran et al. [20] explored the use of the thermal sensor for vision-based systems for autonomous navigation. A common finding in these two works reveals the challenges of effective deployment of thermal sensors such as changes in thermal landmarks through seasonal cycles, infant stage of research of thermal sensors, and difficulty in developing deep learning models for low-resolution thermal sensors to leverage their low cost.

The reviews above showed that quite some work has been done in the area of review of activity detection research. However, a review of sensor category-specific has proven to be more helpful in expanding the frontiers of knowledge in a specific area. Thus, this review is unique in the sense that it is focused on the trends, technology, challenges, and state-of-the-art approaches to the use of AI and thermal array sensors for both static and dynamic activity recognition. Table 2 is a summary of related works and how this review differs from existing works.

3. Review methodology and overview of thermal sensor-based activity detection in smart space

3.1. Methodology and article selection

This review is based on the preferred reporting items for systematic reviews and meta-analyses (PRISMA) [21,22] in compliance with the *prisma statement*, which determines what qualifies as a systematic review. As indicated in Fig. 2, the studies used for this study were obtained from prominent databases and non-database sources. These studies were retrieved from a total of 9 databases, including: *ACM*, *ScienceDirect*, *Springer*, *MDPI*, *IET*, *InderScience*, *PLOS*, *IEEE Xplore*, and *Google*. The databases were searched using keywords like "thermal sensors", "fall detection", "human activity detection", "activity daily living", and non-contact human activity detection" or "thermal sensors" and "Review" or "smart space" and "Review" or "activity detection" and "Review".

In doing this review, the novel 'mentefacto conceptual design' by De Zubiria [23] was leveraged and combined with PRISMA. Here, we summarize the scientific steps taken to select the articles for the review and how they were selected according to [24]. Fig. 3 gives the summary of the flow of the paper from conception to execution as adopted from the works of [24]. The article's inclusion and exclusion criteria for selection included the following:

1. All original articles published in journals and conference proceedings were considered.
2. All studies that reviewed all sensor options, and AI for human activity detection in smart spaces were considered for the qualitative analysis.
3. All studies that actually reviewed the applied thermal sensors and AI human activity detection were considered for quantitative analysis.
4. All articles and website posts must have been written entirely in English.
5. All papers that had access restrictions could not be retrieved and were thus excluded.
6. All studies that are relevant and fall within the reporting years of 2013–2023, representing the last 10 years of growth in thermal sensor adoption for human activity detection in smart spaces [7].

Table 2
Summary of related works showing the unique contribution of this study.

Authors	Thermal sensor type	AI models	Enabling tech	Systematic review	Datasets and tools	Case studies	XAI results	Year
Nwakanma *et al* [4]	✓	✓	✓	×	✓	✓	×	2021
Shelke *et al* [7]	✓	✓	✓	×	✓	✓	×	2019
X. Liu *et al* [8]	✓	✓	✓	×	✓	Fall Detection	×	2018
Fu *et al* [14]	✓	×	✓	✓	✓	✓	×	2020
Wang *et al* [15]	×	✓	✓	✓	✓	✓	×	2019
Raul *et al* [16]	×	×	✓	✓	✓	Fall Detection	×	2013
Colpas *et al* [17]	×	Clustering	✓	✓	×	✓	×	2020
Bulling *et al* [18]	×	✓	✓	✓	✓	✓	×	2014
Awais *et al* [19]	✓	×	✓	×	✓	✓	×	2023
Nguyen *et al* [20]	✓	✓	✓	×	×	✓	×	2021
This review	✓	✓	✓	✓	✓	✓	✓	**2023**

Table 3
Sources of the articles used in this study.

Database source	IEEE Xplore	MDPI	ScienceDirect	Springer	ACM	IET	PLOS	InderScience	Books and Thesis	Others sources	Total
No. of documents	19	13	11	6	2	1	1	1	2	4	61
% Freq.	31.15	21.31	18.03	9.84	3.28	1.64	1.64	1.64	3.28	6.56	100

As illustrated in Fig. 2, At the end of the “key search” and selection based on relevance, a total number of 61 papers were selected from the numerous downloaded spread as articles (49), conference papers (7), white papers and datasheets (2), thesis (1), books (1) and preprint works (1). A total of 134 records were identified after screening for duplicate records, and various other reasons. 22 records were not retrievable, leaving a total of 112 for screening. These records were then screened for relevance. 34 records that failed to meet the keywords requirement were excluded, leaving a total of 78 records. These records were further assessed for eligibility. 17 records were excluded using the predefined inclusion criteria. Ultimately 61 records were used in this review, however, 10 records were used for quantitative analysis (as in Table 2), while 51 records were used for qualitative analysis. Table 3 provides details on the total number of records retrieved from respective databases and sources.

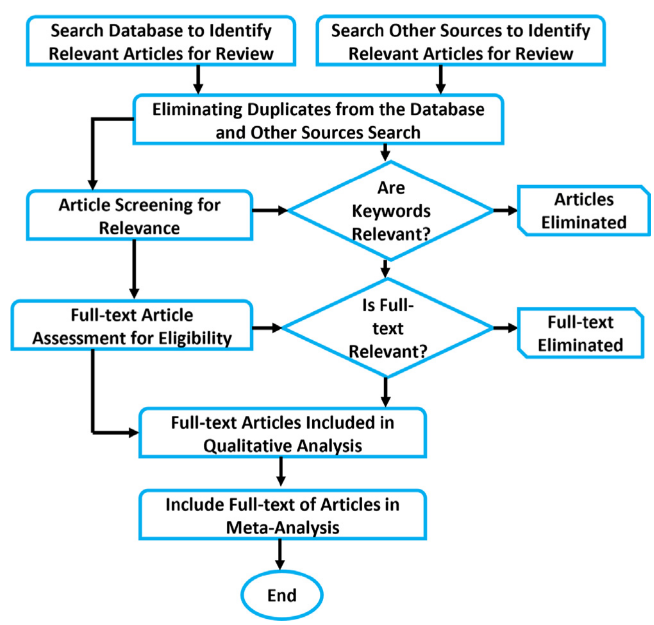

Fig. 3. The flow of the review process followed in selecting and analyzing the relevant articles to this review [23,24].

3.2. System model of thermal sensor-based human activity detection in smart spaces

Fig. 4 shows a typical deployment of thermal sensors orchestrated by machine learning such as random forest for the detection and classification of human activity in a smart space [25]. The thermal sensor has a wavelength range of 8–12 μm [19] making it applicable for non-contact and distance-based sensing. The sensor senses the radiant heat from the human body through long-wavelength infrared. This has been exploited for occupancy detection for smart buildings with AI as an enabler [26] helping to effectively manage energy needs and consumption of buildings.

Thermal sensor does not rely on the environmental lighting conditions and can easily distinguish background temperature from foreground body temperature [27]. To calculate the distance between the thermal sensor and the object (φ), the object dimension (γ), and the FoV (σ) must be known. The distance is then computed using Eq. (1)

$$\varphi = \frac{\gamma}{2 \times tan(\sigma/2)}, \tag{1}$$

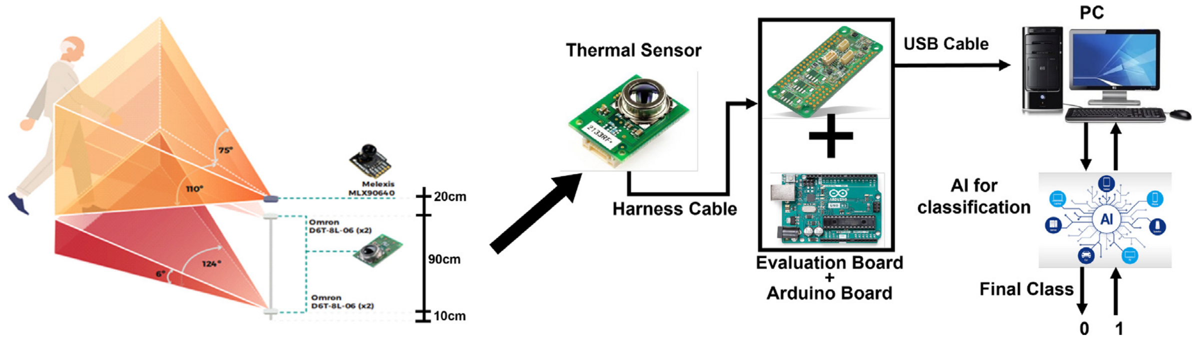

Fig. 4. Thermal sensor and AI deployment for human activity detection and classification case study.

where φ, γ, and σ represent the distance between the thermal sensor and the object, object dimension, and FoV respectively. Also, the FoV (σ) is calculated using Eq. (2)

$$\sigma = 2 * arctan(\frac{\mathbb{N}_{Col/Row} * \mathbb{P}}{2 * \theta}), \tag{2}$$

where $\mathbb{N}_{Col/Row}$ are the number of elements in the column or row, depending if the σ is horizontal or vertical direction should be calculated. The $\mathbb{P}$ is the pitch of the sensitive elements, while the θ is the focal length of the lens.

The goal of activity recognition systems such as the human activity recognition in Fig. 4 is to learn human behaviors which enable the computing systems to proactively assist users based on their requirements [18]. Suppose a user is performing some kinds of activities belonging to a predefined activity set β as in Eq. (3):

$$\beta = \{\beta_i\}_{i=1}^{\eta} \tag{3}$$

where η denotes the number of activity types. There is a sequence of sensor readings α that captures the activity information

$$\alpha = \{\delta_1, \delta_2 \ldots, \delta_t, \ldots \delta_n\} \tag{4}$$

where δ_t denotes the sensor reading at time t.

We need to build a model $\mathcal{F}$ to predict the activity sequence based on the sensor reading α

$$\widehat{\beta} = \left\{\widehat{\beta}_j\right\}_{j=1}^{n} = \mathcal{F}(\alpha), \widehat{\beta} \epsilon \beta \tag{5}$$

while the true activity sequence (ground truth) is denoted as

$$\beta^* = \left\{\beta_j^*\right\}_{j=1}^{n}, \beta_j^* \epsilon \beta \tag{6}$$

where n denotes the length of the sequence and $n \geq \eta$.

The goal of activity recognition is to learn the model $\mathcal{F}$ by minimizing the discrepancy between the predicted activity $\widehat{\beta}$ and the ground truth activity $\beta*$. Typically, a positive loss function $\mathcal{L}$ ($\mathcal{F}$ (α), $\beta*$) is constructed to reflect their discrepancy. $\mathcal{F}$ usually does not directly take α as input, and it usually assumes that there is a projection function Φ that projects the sensor reading data δ_i ϵ α to a d-dimensional feature vector Φ (δ_i) ϵ $\mathbb{R}^d$. To that end, the goal turns to minimizing the loss function $\mathcal{L}$ ($\mathcal{F}$ (Φ (δ_i)), $\beta*$) [15].

Fig. 4 presents a typical case study of the thermal sensor implementation for activity recognition. First, the raw signal inputs are obtained from the thermal sensor. Second, features are manually extracted from those readings based on human knowledge [28], such as the mean, variance, and amplitude in traditional machine learning approaches [29]. Finally, those features serve as inputs to train an AI model to make activity inferences in real activity detection tasks.

4. State-of-the-art approaches and performance evaluation

4.1. AI approaches for thermal sensor-based detection in smart spaces

4.1.1. Machine learning approaches and result evaluation

Common ML algorithms used in addressing activity recognition are: k-Nearest Neighbors (KNN), support vector machines (SVM) [26], regression models, Markov models, Bayesian methods, ensemble classifiers, and fuzzy logic [30]. However, ML is faced with visible challenges such as the need for robust ML with small datasets and under latency constraints, data diversity and the need for data fusion, data distribution at different locations, and diverse data formats. Moreover, excessive demands for handcrafted feature engineering is also a common challenge of ML research generally and sensor-based activity detection, in particular, [31]. Also, traditional ML schemes are not well suited for multi-classification problems. This has led to the adoption of deep learning approaches [32].

4.1.2. Deep learning approaches and result evaluation

The use of conventional machine learning approaches is faced with several limitations. These limitations are due to the over-demand for hand-crafted feature extraction and the inability to meet up the requirement for the need for unsupervised and incremental learning tasks [15]. To solve this problem, researchers have embraced the use of deep learning which is opening the opportunity for automatic high-level feature extraction. The most prominent deep learning model used is the LSTM because of its advantage in using a large volume of time series data to stimulate decision-making from time series data [33]. LSTM is able to learn long-term constraints. It is one of the most accepted recurrent neural networks (RNN) [34]. Also, a deep belief network (DBN) was adopted to improve the detection and classification activities of the elderly in the works of [35]. They employed various means

Table 4
Summary of datasets for activity detection and recognition.

Source	Dataset name	Year	Sensor type used	Activity type	AI model used
[7]	A Fall Detection Dataset	2018	OMRON Thermal Sensor	Dynamic and Static	Feed-Forward NN
[9]	eHomeSeniors	2019	Infrared Thermal Sensor	Several Falls Types	–
[40]	Opportunity Activity Recognition	2013	Switches and Acceleration sensors	ADL, Drill Running	k-NN, NCC, LDA and QDA
[41]	SisFall	2017	Accelerometer, Gyroscope	Falling, ADL	Threshold-Based Classifier,
[42]	CASAS	2020	Ambient Sensor	ADL	SVM, OCSVM, and K-means Cluster

for data collection such as sensors, surveillance systems, and actuators. DBN is a deep learning involving the training of restricted Boltzmann's machines to provide a deep hierarchical representation of the training data [36]. The results of [36] performed better than that of [37]. However, the superior performance was attributed to the data quality and not the learning algorithms.

4.1.3. Ensemble learning methods and result evaluation

Due to the weak, slow, and need for higher accuracy, there is a growing research interest in the use of ensemble techniques. Ensemble techniques involve leveraging two or more base techniques (also known as weak learners) to boost the overall performance of the AI algorithm. This has aided in feature extraction, faster training, and improved accuracy. The authors in [37] proposed an ensemble learning machine to improve the performance of human activity recognition. To achieve their goal, they employed swarm optimization for extreme learning selection. Results show that their proposed idea performed better than conventional ensemble learning algorithms such as Bagging and AdaBoost with an accuracy of 96.7%.

The challenge faced by ensemble learning, however, is the burden on computation time, overhead, and limitation placed on the accuracy in proportion to the number of base classifiers [38]. To address this impasse, authors in [38] proposed a multi-sensor fusion with an ensemble pruning system for the effective recognition performance of wearable activities. Moreover, the authors in [39] adopted three major approaches, stacking, bagging, and blending to enhance the ensemble scheme and give better activity recognition compared to existing solutions.

4.1.4. Datasets used in recent thermal array based activity detection

The datasets commonly adopted for activity detection are listed in Table 4 and explained as follows:

- **eHomeSeniors DataSet:** The dataset used is known as an Infrared Thermal sensor dataset for automatic fall detection research. This dataset is made available by [9]. It was collected using two low-cost ambient sensors: Melexis MLX90640 and Omron D6T-8L-06 infrared thermal sensor. In all, it comprised 15 types of falls and a total of 448 falls. The sensor whose resolution is 32×24 was fixed to a wall at a height of 1.2 m in order to ensure good distribution of the field of view (FoV).
- **Opportunity Activity Recognition DataSet:** This dataset was developed from the object, wearable and ambient sensors. It serves as a benchmark for human activity recognition algorithms. The dataset which was provided by [40] is made of the following ambient sensors: 13 switches and 8 3D acceleration sensors used in addition to other wearable and object sensors to capture various types of runs. Details of the scenarios, assumptions, and on-body placement of the sensors as well as the dataset source can be seen in [43]. However, the limitation is that wearable or on-body sensors come with the discomfort of users, as enumerated by [7–9]. Consequently, the authors in [44] developed a Dezert–Smarandache theory for the fusion of this sensor dataset to enhance activity recognition.
- **Self Data Collection:** Some researchers considered the option of developing their own testbed with which the dataset is collected. Although self-data collection is considered tedious and demanding [15], it is often very reliable and a source of additional datasets to the existing dataset. This is important as it allows for more access to variations of datasets to help the research community. Examples of works with self-data include [4,7].
- **SisFall: A Fall and Movement Dataset:** Falls are attributed to several deaths in the world. This has necessitated the need for several fall detection systems and datasets. The dataset is made of activity daily living (ADL) and fall data captured using about 23 young adults. The author validated their findings using a few data from elderly persons [41]. However, the dataset was not collected using thermal sensors. This further confirmed the earlier position of this paper that quite a few works and datasets are available from the use of thermal sensors. Most of the existing work and datasets are made from wearable devices such as accelerometers, smartphones, and inertial measurement units.
- **CASAS Dataset:** The center of advanced studies in adaptive system (CASAS) dataset was collected by deploying ambient sensors in a three-bedroom apartment while allowing the occupants to engage in diverse activities. The motion sensors were distributed 1 meter apart in the smart space. In all, it contained a total of 5312 sensor events, and erroneous activity datasets [42]. This dataset is widely used for activity recognition and learning in smart spaces [45].
- **Synthetically Generated Dataset:** Data collection, archiving, and processing are one of the major challenges

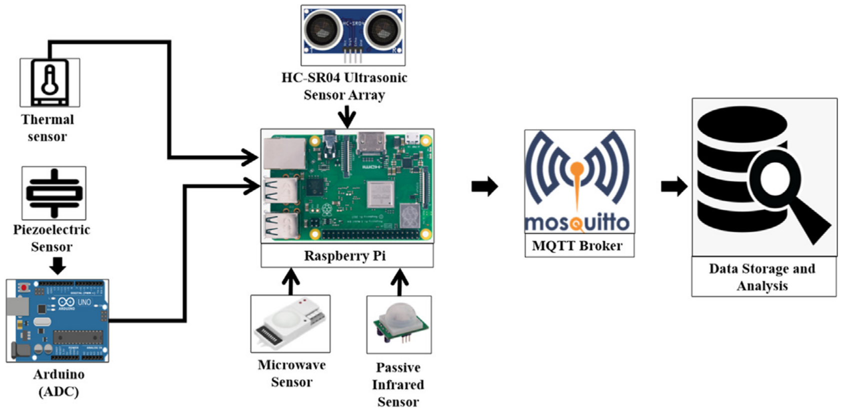

Fig. 5. An overview of the Selected Hardware including the thermal sensor used for data collection.

in AI-based systems. One of the inexpensive ways to compensate for real-world data is by synthetic data generation. Synthetic data generation simply means an artificial way of creating data that is a true representation of the real-world scenario under investigation. It is important to make up for issues like privacy invasion, non-existing data, and the need to save the cost of collecting life data. In a mission-critical application like healthcare, authors in [46] developed and validated a synthetic dataset that is not faced with the challenge of complexity and realism. The result shows that semi-supervised ML algorithms when applied to the dataset gave an appreciable accuracy when compared to the available but limited real-world data.

4.1.5. TestBeds used in recent thermal array based activity detection

This section presents an overview of the testbeds involving thermal sensors in smart spaces.

- **Building Data-Aware and Energy-Efficient Smart Spaces:** Addressing the challenges of energy efficiency, hardware design, data availability, and collection, the authors of [1] developed a testbed for collecting sensor data. They evaluated about six (6) ML algorithms for human activity detection tasks. The testbed avoided audio-visual sensors due to privacy concerns. Instead, thermal sensors and a 2-D positioned grid for localization and detection of human activity was used. To achieve the desired goal of energy efficiency, authors developed algorithms to turn on the sensors when needed. The proposed scheme achieved 30% superior performance in energy consumption when compared to systems without such an algorithm. For activity detection, SVM gave them the best result with 99.95% accuracy.
Table 5 gives a description of the components of the testbed. Note that the Raspberry Pi$_3B$ serves as the cluster for the multiple sensor connections as shown in Fig. 5 [1].

Table 5
Components of the Testbed and description.

Raspberry Pi3B	Cluster node
MLX 90621	Thermal Sensor
SEN 0191	Digital Microwave Sensor
HC-SR04	Ultrasound Range Sensors
Piezoelectric	Vibration data collection
Dropout	0.5
Validation	5-fold cross validation

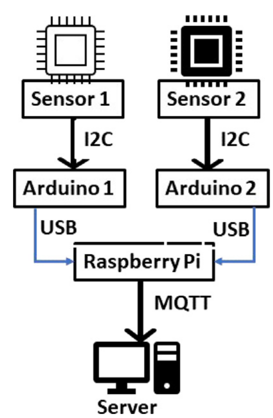

Fig. 6. Two MLX 90621 Sensors connected to the Server for data collection [7].

- **Static and Dynamic Activity Detection Test-bed:** Similarly, the authors in [7] used a low-resolution sensor (4X16) and other non-intrusive thermal sensors to collect data. The data comprised dynamic and static activities in a smart space. They further investigated six ML algorithms. In the case of the static activity, the detection rate was high at an accuracy of 99.96%. The experiment also justified the impact of sensor placement and how data collection was done. The test-bed is similar to the [1] except for the fact that two MLX90621 were used for the data collection as shown in Fig. 6.

- **A Novel Monitoring System for Fall Detection Test-bed:** Similarly, the authors of [8] developed a fall detection and classification system while ensuring a non-intrusive scenario. To this end, they avoided the use of cameras and microphones. The connection of the two sensors is similar to the approach of citesagar19040804. However, they adapted two thermal sensor models D6T-8L-06 by OMRON. This is a 1 × 8 resolution sensor each having a FoV of 62.8°.
- **EhomeSeniors Dataset Test-bed:** In conclusion, authors [9] collected and made their dataset open source for fall detection research. As noted in previous works, they also avoided privacy invasion and took care of the inconveniences of wearable devices. Thus, thermal sensor models D6T-8L-06 and MLX90640 were adopted in addition to their low cost (US$52 and US$49 respectively) and low-resolution advantages.

4.2. Lessons: Factors responsible for the pervasive usage of thermal sensor

- **Need for a Low-cost Implementation:** As activity recognition research develops, researchers seek the need for accurate detection and classification at a low cost. In the work of [36], authors used two low-cost sensors, a gyroscope and an accelerometer to achieve their objective. Similarly, the authors in [1,7–9] used low-cost thermal sensors, OMRON (model: D6T-8L-06) and Melexis (model: MLX90621) to ensure non-privacy invasive, accurate and low-cost implementation of activity recognition systems. The quoted cost of the implementation was as low as US$150. Moreover, it is more expensive to implement a vision-based scheme due to the additional cost of maintaining image and video data.
- **Field of View (FoV):** As observed in Fig. 7, the measurable FoV of the sensor becomes bigger as the distance between the target object increases. The non-contact thermal sensor measures the surface temperature of the objects. The sensor is comprised of a silicon lens optically designed to have specific sensitivity characteristics. Thus, as the distance increases (see area 1 and area 2 in Fig. 7), the temperature measured becomes more of a representation of the background temperature than the temperature of the target object or person. To solve this problem, it is desired that the target object should be sufficiently larger than the FoV area. However, authors in [7,8] proposed mounting of two sensors on a vertical wall perpendicular to increase the FoV. On the other hand, authors in [1] opted for the option of placing the MLX90621 with 4 × 16 resolutions in the middle of the vertical wall in the testbed. This allows for the capturing of two types of data such as standing and sitting on the chair respectively. Increasing the FoV is achieved by mounting multiple thermal sensors placed at an angle of 25° as depicted in Fig. 8. According to [8], the placement of the sensor is also a very factor affecting the FoV. When an obstacle is placed within the FoV of a thermal sensor, it will create a blind spot and inhibit activity detection. This sensor placement proposition is corroborated by Bulling et al. [18].
- **Resolution of Sensors:** Several works have presented the resolutions of sensors used according to their number of elements, object temperature detection range, and FoV characteristics. Below are the common resolution type of thermal sensors [47]:
  - 1 × 1 features a 1-channel sensor chip with a storage temperature range (−20 to 80 °C) while Object Temperature Detection Range (OTDR) is 0 to 50 °C. FoV (X-direction: 58°, Y-direction: 26.5°)
  - 1 × 8 features a single 8-channel array, small size, high accuracy, low noise, and high sensitivity. OTDR (−40 to 80 °C. Authors in [8] used this sensor in their test beds. FoV (X-direction: 54.5°, Y-direction: 5.5°)
  - 4 × 4 features 16 channels in a 4 by 4 arrangement with a 5 to 50 °C OTDR. However, the 4 × 4 also has a higher resolution category for the Omron sensor with higher OTDR of 5 to 200 °C, FoV (X-direction: 44.2°, Y-direction: 45.7°)
  - 4 × 16 is the least resolution and is mostly used to preserve the privacy of users or people in the smart space. Authors in [1] used this sensor resolution in their test bed.
  - 32 × 24 is more suited for safety and convenience applications e.g. fire prevention systems and intelligent surveillance although it exhibits a more superior noise performance and contains 768 FIR pixels. An ambient sensor is integrated to measure the ambient temperature of the chip. It has a −40 °C to 85 °C operational temperature range and can measure object temperatures between −40 °C and 300 °C. It does not need frequent re-calibration, thus ensuring continuous monitoring and lowering system costs. Authors in [9] used this sensor resolution in their test bed.
  - 32 × 32 achieves the highest level of signal-to-noise ratio, temperature range is (−40 to 200 °C). A number of elements (1 to 1024). FoV (X-direction: 90°, Y-direction: 90°)
- **Ease of use:** Thermal sensors need not be placed or attached to the body of the persons to be monitored. In smartphone-based systems, the major disadvantage is the difficulty in allowing the persons under observation to use or move their smartphones as they would have done in real life. Thus, smartphones and other wearable devices do not enjoy the benefit of ease of use by thermal sensors [7–9].
- **Supporting Embedded System and Evaluation Boards:** For functioning, thermal sensors are connected to the sensors evaluation board. There are 3 types of platforms that are applicable to thermal sensors. Evaluations are performed by connecting these sensors to

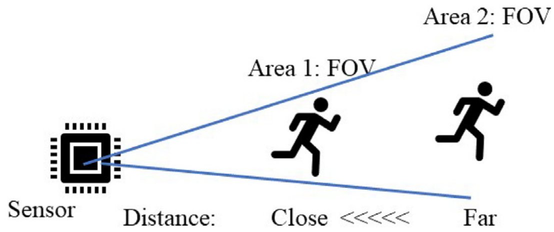

Fig. 7. The effect of distance on the Field of View (FoV) of Thermal sensors which affects the temperature values.

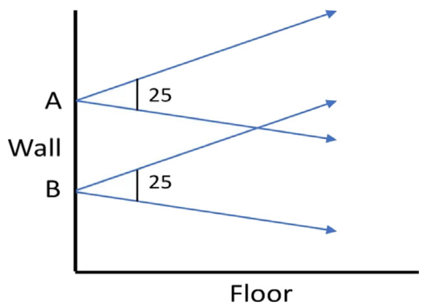

Fig. 8. Increasing the Field of View (FoV) of Thermal sensors by using multiple sensors placed at 25° to the wall [7].

these boards through the harness cable. Types of evaluation boards for the thermal sensor include Raspberry Pi, Arduino, and the Espressif systems board (ESP32 Feather).

- **Non-privacy Invasive:** The non-privacy invasive property of thermal sensors remains the most advantaged and preferred option for detecting mechanisms in industrial applications and smart spaces. Issues of privacy concern are a limitation faced by the use of camera and voice methodology for data collection. The Thermal-array sensor, on the other hand, uses the temperature surface of a body as means of identifying the activities without exposing the personal details of the persons in the smart space [27].

4.3. Performance comparison of selected AI models and impact of sensor resolution on dataset

Table 6 is a summary of works done using the thermal sensor under various resolution scenarios. The results show how the sensor type, sensor resolution, and choice of AI schemes can affect the accuracy of smart space detection implementation.

4.4. Practical concerns and open issues for future generation of smart spaces

1. **Interoperability and Sensor Data Integration:** In the 5G or 5G+ era, it is unanimously agreed that sensors and IoT devices will explode as more and more devices get connected. This implied that in the smart space, there is expected going to be a challenge of sensor vendors integrating their products and the need for sensor data integration to enhance the detection and classification of activities in smart spaces [52]. To manage the data collection and storage complexity, authors in [53] recommended the optimization of sensor locations, events scheduling (especially emergency), reduction or maximization of required nodes, a unified approach or algorithm for data collection, adoption of cloud computing technology to help save battery life of IoT and enhanced or robust algorithms capable of analyzing and comparing large scale data.
2. **Data Fusion:** For effective activity detection, classification, and informed decision based on data from all sensors, information (or data) fusion is critical and a promising research issue. This is a veritable means of making use of large volumes of data from diverse sensors to take decisions that are not possible by limiting oneself to just one or fewer sensor sources [54]. Consequently, the authors in [54] captured the gains, opportunities, and challenges of data fusion in the era of IoT data explosion. One of the challenges of multi-sensor data collection is that of subject-to-subject variability in activity recognition datasets. To solve this problem, authors in [55] developed a multi-sensor fusion technique to recognize 13 activity types. However, they achieved an accuracy of 88.1%, thus, there is room for further research in solving this impasse.
3. **Feature Selection and Combination:** Due to the non-stationary and noisy nature of sensor signals (data), feature selection, discrimination, and the combination is yet another practical concern [56]. To solve this problem, [56] proposed a hybrid of game-theory-based feature selection (GTFS) and binary firefly algorithm (BFA). This performance of the proposal code-named GTFS-BFA shows superior ability over the existing methods such as Relief Algorithm (RA), Binary Particle Swarm Optimization (BPSO), Modified Binary Ant

Table 6
Comparing selected models and how sensor resolution types affect dataset and AI performance.

Sensor resolutions	Source	Model	Accuracy (%)
4 × 4, 4 × 4H, 16 × 12, 32 × 24, 32 × 32	[25]	Modified RF	99.96 Maximum 93 Average
4 × 16	[1]	SVM	99.95
4 × 16	[7]	Default RF	99.96
1 × 8	[8,9]	Bi-LSTM	93
32 × 24	[27]	AdaBoost	98.43
32 × 24	[48]	3D-CNN	98.8
4 × 16	[49]	Default RF	97.5
8 × 8	[50]	SVM	87.5
8 × 8	[51]	LSTM	98.28

Colony Optimization (MBACO), and Conditional Multivariate Mutual Information-Genetic Algorithm (CMIM-GA).

4. **Real-Life Scenarios and Use-cases:** As evident from several works of literature reviewed, the datasets were majorly collected in a simulated environment, synthetic or collected from young people where for instance the fall detection is targeted at old persons. This has placed the issue of the reliability of the detection systems to question if implemented in real life. For example, the authors in [16] noted that in addition to the improper documentation of mechanisms of fall by researchers, the majority of them cannot be a fair representation of the system if older persons are not used to collecting data. Using older persons obviously is challenging and records are low due to the difficulty in subjecting older people to fall [41].
5. **Energy Saving and Long Battery life for remotely placed Sensors:** For an effective activity detection system, there is a need to sustain energy and power for sensors. The most challenged sensors are those in remote locations and thus, several research works abound on energy harvesting, energy sustainability, and context-aware implementations [57].
6. **5G or 5G+ at 28 GHz and its Implication to Activity Detection in Smart Spaces:** Irrespective of the nomenclature, be it 5G, 5G+, or 6G, the consensus is that more and more devices will be connected leading to data explosion and the need for sensor/device integration, vendor-to-vendor agreement, efficient AI algorithms to handle detection and classification of diverse data from heterogeneous devices (sensors) [52]. However, AI is adjudged to add the dual challenge of making the overall system complex and computationally expensive.
7. **Explainable AI (XAI) and Trustworthy AI for activity monitoring in Smart Spaces:** AI models are challenged by the need for transparency, “simulability”, fidelity, and compactness, despite their benefits. The drawback is a result of the systems’ “black-box” design, which enables accurate decision-making but leaves out the justification for the decision being made. This then led to the development of “explainable AI” (XAI). This novel idea enhances the dependability and openness of AI-based systems [58]. The concept of XAI was put up as a means of increasing AI’s transparency and fostering its acceptability in multidisciplinary domains [59]. To this end, different XAI and trustworthiness frameworks are now available such as the SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), Local Rule-based Explanations (LORE), Local Rule-based Model Interpretability with k-optimal Associations (LoRMiKA), Transparency Relying Upon Statistical Theory (TRUST), and Explainable AI for Regression (XAIR) [58–60].

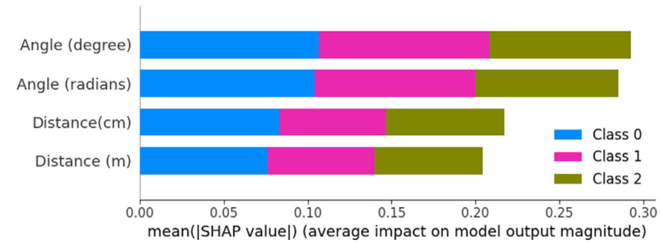

Fig. 9. Explainable Visualization of the Modified Random Forest from [25] using SHAP Values to reinforce the basis for interoperability and how Sensor Angle Placement plays a Major Role in the Deployment of Thermal Sensors. Class 0 = ‘No movement’, Class 1 = ‘Moving Forward’, and Class 2 = ‘Moving backward’.

4.5. Case study: XAI visualization of activity detection based on collected dataset sample

Using the system model in Fig. 4, we deployed the thermal sensor for sample data collection to reflect three activities—‘moving forward’ represented as class 1, ‘moving backward’ represented as class 2, and ‘no movement’ represented as class 0 [25]. The XAI visualization using SHAP values is presented in Fig. 9. The SHAP visualization of the model gives hints about the basis for the classification and offers more explanations beyond the traditional AI metrics of accuracy, recall, precision, etc. The visualization shows how the effect of sensor angle placement and sensor distance to the object affect the interpretability of the activity. The XAI results show that the sensor distance from the object and angle placement is critical to the interpretability of the activity. It also shows that the machine learning model relies more on the angle placement of the sensor to make its prediction when compared to the distance from the object. This is in agreement with the position of [7,61] where they cautioned that for thermal sensors to give the best results, it is a must that the Fov is not obstructed in any way as observed in Fig. 7.

5. Conclusion

This review presents a comprehensive evaluation, appraisal, and open research issues on human activity monitoring and detection in smart spaces using Ambient sensors and AI. Basically, thermal array sensor offers the advantage of being non-privacy invasive, user friendly, and low-cost for the implementation of activity detection systems. In addition, the review provided hints about popular datasets and test beds developed with thermal sensors inclusive. Having established the ubiquitous usage of the thermal sensor, major factors encouraging the usage of the sensor were evaluated. In the end, some practical concerns and open issues were highlighted to direct future research work in the use of thermal sensors for activity recognition, detection, and classification. One of the promising future research directions in activity monitoring is the issue of explainability and trustworthiness of smart space activity monitoring as demonstrated by the case study.

Declaration of competing interest

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

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