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Survey paper

# Deep and transfer learning for building occupancy detection: A review and comparative analysis

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ABSTRACT

The building internet of things (BIoT) is quite a promising concept for curtailing energy consumption, reducing costs, and promoting building transformation. Besides, integrating artificial intelligence (AI) into the BIoT is essential for data analysis and intelligent decision-making. Thus, data-driven approaches to infer occupancy patterns usage are gaining growing interest in BIoT applications. Typically, analyzing big occupancy data gathered by BIoT networks helps significantly identify the causes of wasted energy and recommend corrective actions. Within this context, building occupancy data aids in the improvement of the efficacy of energy management systems, allowing the reduction of energy consumption while maintaining occupant comfort. Occupancy data might be collected using a variety of devices. Among those devices are optical/thermal cameras, smart meters, environmental sensors such as carbon dioxide ($CO_2$), and passive infrared (PIR). Even though the latter methods are less precise, they have generated considerable attention owing to their inexpensive cost and low invasive nature. This article provides an in-depth survey of the strategies used to analyze sensor data and determine occupancy. The article's primary emphasis is on reviewing deep learning (DL), and transfer learning (TL) approaches for occupancy detection. This work investigates occupancy detection methods to develop an efficient system for processing sensor data while providing accurate occupancy information. Moreover, the paper conducted a comparative study of the readily available algorithms for occupancy detection to determine the optimal method in regards to training time and testing accuracy. The main concerns affecting the current occupancy detection system in terms of privacy and precision were thoroughly discussed. For occupancy detection, several directions were provided to avoid or reduce privacy problems by employing forthcoming technologies such as edge devices, Federated learning, and Blockchain-based IoT.

## 1. Introduction

Nowadays, building internet of things (BIoT) and big data analytics provide promising perspectives to enhance building operation and management. BIoT relies on incorporating the internet of things (IoT) concept along with other smart technologies, i.e., machine learning (ML) and artificial intelligence (AI) into the building sector, to support building automation and smart management (Himeur et al., 2021a). Typically, this helps collect different kinds of data produced by either by buildings occupants or/and equipment installed in building environments (Alsalemi et al., 2021).

Besides, a variety of factors influences electricity usage. Building attributes, equipment efficiency, and weather conditions are all physical considerations. On the other hand, end-users cannot readily manage or modify these aspects during building use. The term "occupancy" is used to describe the main level of residents behavior modeling (Rueda et al., 2020). To elaborate, occupancy is a component of behavior that describes the occupants' presence, power usage habits, and interior conditions. In the context of automation systems, identifying presence patterns holds significant importance. This significance stems from its potential to manage electrical devices and techniques like air conditioning, lighting, and ventilation, which may save substantial energy in residential and commercial buildings (Sardianos et al., 2020a, 2021). Additionally, a lot of potential can be offered in enhancing the capabilities of demand-driven systems that utilize true occupancy data to improve the energy-to-comfort trade-off. Not to mention the correlation between occupants' behavior and lifestyle habits to their energy usage (Oikonomou et al., 2009). To highlight the importance of occupancy detection notation, the authors in Leephakpreeda (2005) presented occupancy-based lighting management reduced the system's energy usage by 35% to 75%. Furthermore, according to Jin et al. (2016), by controlling the ventilation operation having the knowledge of occupancy data, this might save up to 55% of the ventilation system demand.

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On another hand, collecting and using occupancy data to enhance the energy-to-comfort trade-off requires powerful ML models that can effectively infer the relevant behavioral information (Elnour et al., 2022a; Himeur et al., 2021b). An extension of ML is DL which employs numerous layers to extract higher-level characteristics from raw input data. By utilizing the backpropagation technique, DL structures determine how a machine's intrinsic parameters should be modified to calculate the subsequent layer representation from the preceding layer. However, the broad utilization of ML, especially DL to monitor the presence of buildings' end-users can be prevented or delayed by various key barriers, among them (i) data scarcity where historical data or real-time records may not be promptly available due to shortages of grid communication infrastructures (Li et al., 2022), (ii) lack of labeled datasets for training ML models (Tariq et al., 2021), (iii) high computing resource requirements of DL models especially when they are trained on a massive range of environmental and energy data (Liu et al., 2021a); (iv) supervised learning can create highly accurate models by training ML models for completing a wide range of tasks using annotated datasets, however, its application on real-world scenario may encounter some issues if actual data deviates or strays from the training sets (Elnour et al., 2022b).

To that end, reducing the volume of training datasets, creating labeled datasets, and decreasing the training time while keeping adequate learning performance are challenging and crucial issues. One solution that can help overcome these problems is transfer learning (TL), which has been recently introduced as a solution to bring numerous advantages to the development process of ML/DL-based systems. TL is a promising ML technique that focuses on transferring knowledge across domains. The concept's inception was inspired by the humans' ability to transfer knowledge between different domains; TL seeks to use information from a corresponding field (also known as the source domain) to enhance learning outcomes or reduce the number of labeled instances needed in the target domain Zhuang et al. (2020). Typically, DL helps to (i) save computing resources and improve efficiency when training new models since the ML/DL models can be pretrained offline on large-scale datasets and then fine-tuned on small datasets (Ahmed et al., 2021); (ii) train ML/DL models on available annotated datasets before validating them on unlabeled datasets, which is of utmost importance, keeping in mind that labeling data is a tough task that takes time and effort and requires the intervention of experts (Zheng et al., 2021); (iii) train ML/DL models using simulated or synthetic data instead of real-world environments (Ko and Park, 2021), (iv) leverage knowledge from existing models instead of starting from scratch each time, and (v) exploit the knowledge acquired from previous tasks for improving generalization about others (Kim et al., 2021).

This article goes through the methodologies for analyzing various data types and determining occupancy information. The primary focus of this paper will be on DL and TL algorithms for occupancy detection. This research looks at occupancy detection algorithms to reach an efficient and accurate system in processing sensor data. In addition, this work will perform a comparative study of the currently available occupancy detection algorithms to determine the best technique regarding training duration and testing accuracy. Consequently, a few suggestions are provided on enhancing various features of the current occupancy detection algorithms. Cloud computing, for example, generates a lot of bandwidth demand, which results in a lot of energy usage. This problem might be solved by moving computing to the network's edge and/or using TL. The use of Federated learning and Blockchain-based IoT are recommended for occupancy detection to improve end-user privacy and security by shifting processing from a centralized to a decentralized fashion. The primary contributions of this paper are as follows:

- Providing, to the best of the authors' knowledge, the first review that explores and summarizes the significance and deployment of DL and TL for occupancy detection.
- Presenting a comprehensible taxonomy to categorize state-of-the-art occupancy detection systems regarding various aspects, e.g., data collection methodology, DL models, TL, platforms for computing, applications, existing concerns, and possible future paths
- Conducting critical analysis and discussion to identify current issues that impede developing reliable occupancy systems, such as data scarcity, lack of open-source toolkits, privacy concerns, and scalability and interoperability.
- Identifying prospective paths that will draw major research and development in the foreseeable future, including edge computing, federated learning, and blockchain, because of their benefits in preserving occupants' privacy and enabling real-time occupancy monitoring.

The reminder of the article is structured as follows: Section 2 discusses the review methodology deployed for the publications selection to be included in the review. Section 3 explains the data gathering component of the article. Section 4 surveys the state-of-the-art DL and TL algorithms for the application of occupancy detection. The findings and the comparative analysis are discussed in Section 5. In Section 6, potential directions are recommend. Finally, concluding remarks are found in Section 7.

## 2. Review methodology

We first conducted a comprehensive literature search in the Scopus, Elsevier, and IEEE databases. All the works that deal with the following aspects were included in this review: occupancy detection, sensors, and data collection, datasets, ML algorithms, statistical models, DL, TL, building type, performance, and limitation. Several combinations of these keywords and their synonyms were adopted when searching. Therefore, research studies introduced between January 2015 and February 2022 were discussed in this framework. This period has been selected to evaluate the more recent and pertinent contributions and also to have a sufficient number of contributions to be studied in this review. Typically, this framework discusses English-written peer-reviewed journal articles, conference proceedings papers, and book chapters. Fig. 2 demonstrates the taxonomy applied in this review to categorize existing studies based on different aspects, including data collection, DL models, TL algorithms, computing platforms, applications, current challenges and future directions.

### 2.1. Study selection

The selection process adopted in this review relies on adhering the specifications of the preferred reporting items for systematic reviews and meta-analyses (PRISMA) (Moher et al., 2009), which is a practical and efficient approach for writing survey studies. Concretely, a search was performed for the last seven years (January 2015–February 2022). This was done to focus solely on the latest trends of DL and TL for occupancy detection while having a sufficient number of studies to be discussed. To eliminate duplicate references, a reference manager software has been utilized, and only the remaining frameworks have then been considered after filtering them by their titles, keywords, and abstracts.

### 2.2. Inclusion/exclusion criteria

All selected frameworks have thoroughly been screened out and carefully read based on the inclusion/exclusion procedure explored in what follows: (i) frameworks considering DL and TL models have been overviewed. Table 1 portrays the search queries conducted in this review; (ii) only studies published from January 2015 to February 2022 have been investigated; only research publications accessible online (i.e., peer-reviewed conference proceedings papers, book chapters, and journal articles) have been included; and (iv) when different frameworks on the same problem have been published by the same authors, the most recent and valuable ones have been analyzed.

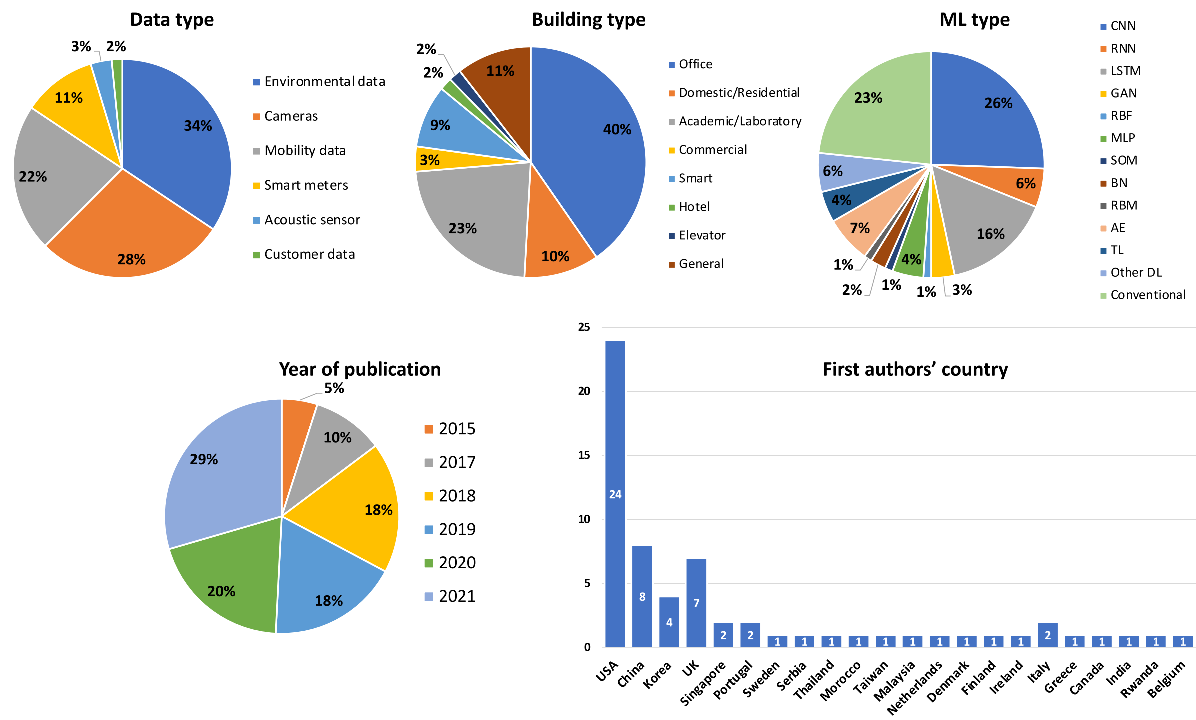


**Fig. 1.** Statistical observations on the included papers.

**Table 1**
Search queries used when conducting the review.

| Parameter | Search query |
|---|---|
| Occupancy | "Building Occupancy" or "Indoor Occupancy Detection" |
| Learning model | "Convolutional Neural Networks" or "Recurrent Neural Networks" or "Long Short Term Memory Networks" or "Multilayer Perceptrons" or " Radial Basis Function Networks" or "Generative Adversarial Networks" or "Self Organizing Maps" or "Deep Belief Networks" or "Autoencoders" or "Restricted Boltzmann Machines" |

### 2.3. Quantitative analysis

Numerous research studies have studied various technologies, sensors, and algorithms to detect occupancy information. A quantitative analysis corresponding to the specifics of referenced studies is presented in this subsection. Typically, we provide the research statistics on the included articles in Fig. 1, in respect to the employment of either DL and TL algorithms, building type, year of publication, and first author's country. In this respect, it is worth noting that environmental data and images are the most used data types to infer occupancy patterns, where 34% and 28% of included studies have been built on them, respectively. It is apparent from the reported results that very little interest is still put towards developing TL-based occupancy solutions (with only 4% of the included papers) although its significant benefits. Typically, 96% of studied frameworks belong to DL-based category. In this context, it is evident that most of the frameworks have been developed based on convolutional neural network (CNN) and multilayer perceptrons (MLP) algorithms, with 26% and 23% of the reported works, respectively. For the publication year, an increasing interest has been noticed, starting from 2018 in the included sample of works. Lastly, statistics of the 1st author's publication are also given. The US, is the country with most publications with twenty four papers followed by china with eight papers.

## 3. Data collection

Based on the reviewed research frameworks, occupancy detection in buildings can be performed using data collected from either the network of sensors (i.e., humidity, temperature, $CO_2$, etc.), mobility sensors (i.e., passive infrared (PIR) sensors collecting mobility data) smart meters (i.e., energy consumption footprints) or cameras (i.e., visual data). Following this classification, this section discusses the main contributions achieved in each category.

### 3.1. Network of sensors

Presence detection is a critical component in smart buildings to optimize the overall energy consumption. However, when designing occupancy detection methods, some challenges arise. One of them is keeping in mind how to protect the occupants' privacy while creating such devices (Sardianos et al., 2020b; Himeur et al., 2020a). An adequate occupancy detection system should be built to prevent inhabitants or their actions from being identified. As a result, non-intrusive methods for detecting occupancy are required; otherwise, existing mechanisms should be improved (Zou et al., 2017; Wang et al., 2021a).

The authors in Abade et al. (2018) presented and evaluated a system for non-intrusive occupancy detection employing sensors collecting data such as noise, temperature, carbon dioxide ($CO_2$), and light intensity. A working system was tested, which included a device to collect and analyze environmental data, as well as an analysis of data patterns across the obtained data using ML techniques to estimate human occupancy in interior spaces.

Additionally, the authors in Adeogun et al. (2019), presented the results on implementing ML methods using sensory data such as temperature, humidity, pressure, $CO_2$, sound, total volatile organic compounds (TVOC), and PaPIRMotion which is based on PIR sensor. The data was gathered from an IoT monitoring system to estimate indoor occupancy information. For binary and multi-class problems, the proposed system could predict room occupancy with an accuracy of up to

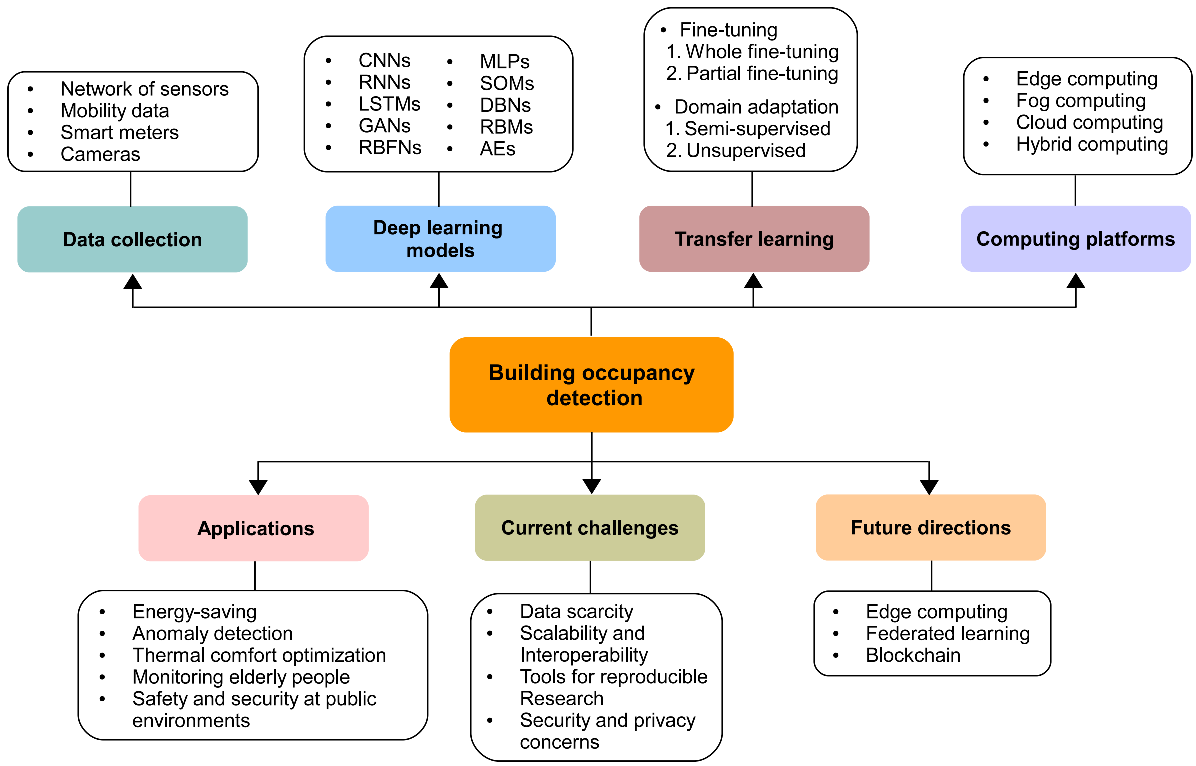


**Fig. 2.** Taxonomy of occupancy detection techniques.

94.6% and 91.5%, respectively. Similarly, the work done in Li et al. (2019) inferred occupancy by fusing data from a network of sensors. In Zemouri et al. (2018), environmental data was employed to detect occupancy. However, the authors claimed they used edge devices in their implementation. Nevertheless, they relied on a cloud provider to supply the packaged code to the IoT devices, which may appear contradictory.

The study in Jeon et al. (2018) tackled the problem in a novel manner. They introduced an occupancy detection system using IoT technologies and on dust concentration change patterns. The extraction technique used by the authors is to create triangle forms, and accordingly their characteristics are utilized to recognize presence in an indoor setting. Data is collected using dust, temperature, and humidity sensors. The system was implemented in a real-live experiment to evaluate the effectiveness. Finally, a qualitative analysis of the experimental outcomes was conducted to compare the system performance against other standard techniques.

Another study performed by the authors in Wu and Wang (2021) concluded that the use of PIR sensors for internal lighting management resulted in a high number of false-negative for stationary occupancy detection, accounting for over 50% of the overall occupancy accuracy. To resolve that issue, they designed a synchronized low-energy electronically chopped PIR (SLEEPIR) sensor that employs a liquid crystal (LC) shutter to reduce the power of the PIR sensor's long-wave infrared output. By incorporating a support vector machine (SVM) classifier, experiments with everyday routines showed a 99.12% of accuracy.

In Abedi and Jazizadeh (2019), the use of doppler radar sensors (DRS) along with infrared thermal array (ITA) sensors demonstrated a high accuracy when using deep neural networks (DNN) algorithms. The DRS and ITA sensors achieved occupancy detection accuracy of 98.9% and 99.96%, respectively.

### 3.2. Mobility data

With the recent success of ML algorithms (i.e., CNN, recurrent neural network (RNN), autoencoders, etc.), the use of big data analytics, and the widespread use of mobile phones, the most modern technologies, including, the IoT, global positioning system (GPS), wireless local-area networks (WLAN), radar sensors, and Bluetooth, have found broad application for the use case of occupancy detection (Ding et al., 2021).

The strategy developed in Demrozi et al. (2021), is based on identifying human-induced changes in Bluetooth low energy (BLE) signals. Comprehensive experiments on five distinct datasets are piloted to determine the approach's efficacy. Several pattern recognition models are used and compared to systems based on IEEE 802.11 (Wi-Fi) standards. In various settings, the occupancy prediction of the developed design reaches an accuracy of 97.97%. When predicting the number of people in a room, on the other hand, the anticipated number of people differs by 0.32 people on average from the actual number.

The study in Wang et al. (2019a) proposed a non-intrusive, unique and accurate method for detecting occupant counts in buildings. The systems used existing Wi-Fi infrastructure without installing additional hardware or sensors. Using Wi-Fi connections count data, the researchers used the random forest (RF) algorithm to estimate occupants count in a room. Similarly, the work in Zhao et al. (2015) utilized GPS and Wi-Fi smartphone connection data to detect occupancy in buildings. Comparably, the study in Liu et al. (2020) proposed an indoor occupancy detection system using a passive Wi-Fi sensor.

### 3.3. Smart meters

Since energy meters are already installed in millions of households and office buildings, energy consumption monitoring has the potential of being an extremely affordable and non-intrusive alternative to manage the end-users occupancy and behavior (Alsalemi et al., 2020). In this respect, data analysis models for human occupation behavior are developed based on the use of sub-metering records from domestic home devices (Himeur et al., 2020b). New statistical and probabilistic methods have been developed and put up for consideration to determine appliance consumption and occupancy (Baek et al., 2021).

For instance, in Vafeiadis et al. (2017), the difficult task of detecting occupants in a domestic setting was addressed using data from smart energy and water meters. Door counter sensor readings were used as ground truth training data for the most common ML algorithms, including boost variants. Based on the results of the simulations, the RF and decision tree (DT) learning approaches outperform the remaining classifiers, with an accuracy moderately higher than 80% and an F-score of approximately 84%, respectively. Similarly, the study in Jin et al. (2017) was performed to predict occupancy patterns from smart meter data accurately and reached an accuracy of around 78%–93% for residential buildings and 90% for office spaces. Additionally, the work done in Feng et al. (2020) utilized advanced metering infrastructure (AMI) data to provide real-time occupancy data for buildings. The researchers developed a DL model which consisted of a CNN and an long short-term memory (LSTM) network. The model forecast occupancy patterns with an accuracy of around 90%. Correspondingly, the authors in Akbar et al. (2015) developed a k nearest neighbor (kNN) approach deployed in smart offices to identify occupancy statues with an efficiency that reached 94%.

The use of load curve data to identify occupancy has been previously explored. On the other hand, such approaches are often based on a time-consuming and complicated model training procedure. To avoid this problem, the authors in Tang et al. (2015) devised a straightforward, non-intrusive occupancy detection method which requires no model training and relies just on load curve data and seamlessly available appliance records. The performance of the approach was evaluated against other supervised classification algorithms and demonstrated acceptable performance.

The work in Pal et al. (2019) introduced the deep learning system for occupancy classification (DeepEOC). The system studies the impact of various feature extraction algorithms. Such algorithms include the principal component analysis (PCA) and SHapley Additive exPlanation (SHAP). For evaluating and comparing the algorithms, three distinct metrics have been considered: Mathew's correlation coefficient, F2-score, and accuracy.

### 3.4. Cameras

Because of their outstanding precision, cameras are also helpful in estimating and detecting building occupancy (Chen et al., 2018). The use of a thermal camera to detect occupancy was explored in Metwaly et al. (2019). The performance of several DL models was investigated on various embedded processors. The developed method reached a prediction accuracy of 98.9% for people counting approximation.

Additionally, the work in Tse et al. (2020) utilizes a camera and Raspberry Pi (RPi) platform to detect occupancy patterns on the network's edge. Specific image processing techniques have enhanced this methodology, allowing it to be adapted and applied in various indoor situations without needing a separate training phase. Occupancy prediction by employing cameras generally yields accurate findings, but it has several drawbacks, including high computing complexity, lighting conditions' influences on the accuracy, and privacy concerns (Chen et al., 2018).

## 4. Overview of existing frameworks

### 4.1. Deep learning models

To derive higher-level interpretations from raw inputs such as pixel data pictures, audio recordings, and text documents, DL, which is a subfield of ML in AI, uses hierarchical architectures such as DNN, CNN, deep belief network (DBN), and graph neural network (GNN). In this section, the various DL methods applied in the context of occupancy detection will be discussed. The general process of identifying occupancy is demonstrated in Fig. 3.

#### 4.1.1. Convolutional Neural Networks (CNNs)

A novel cascade video analysis technique based on a creative fusion of SVM, CNN, and K-means clusters, is proposed in Zou et al. (2017). The system employs a cascade classifier that recognizes the human head and includes a pre-classifier, primary classifier, and clustering analyzer. The experimental findings reveal that occupancy measurement accuracy may reach 95.3%, with a computing cost of just 721 ms. Similarly, in Zou et al. (2018a), daily human activities are recognized using Wi-Fi-enabled IoT devices and a DL framework that includes autoencoders, CNN, and LSTM. Extensive tests are carried out in three typical indoor locations, and the findings show that the proposed framework reached an accuracy of 97.6% for activity identification while eliminating the need for human participation.

Two distinct approaches for processing and fusing data collected from several heat sensors are explored in Arvidsson et al. (2021) with the use of a CNN to forecast occupancy. Tests were conducted to evaluate offered solutions' performance and determine the effect of sensor field view overlap on the prediction outcomes. Equivalently, in Abedi and Jazizadeh (2019), the use of DRS along with ITA sensors demonstrated a high accuracy when using DNN algorithms. The DRS and ITA sensors achieved occupancy detection accuracy of 98.9% and 99.96%, respectively. In Feng et al. (2020), the fusion of CNN and LSTM algorithms was employed to detect binary occupancy patterns from AMI data. The authors obtained 90% accuracy by training the algorithm using actual occupancy data. Likewise, the authors in Saha (2021) presented a few shot learning frameworks for indoor human occupancy identification using very low-quality photos to preserve privacy. This approach supports the use of comparatively simpler CNN architectures. In Sun et al. (2021), indoor human heads are detected using a fully convolutional head detector (FCHD). The research in Mutis et al. (2020) offered a unique strategy for controlling indoor air quality, which incorporates occupancy sensing, motion identification algorithms, and human motion analysis via the analysis of video streams using CNN algorithms. Similarly, the work in Acquaah et al. (2020) employed thermal cameras with AlexNet CNN network to identify occupancy patterns with accuracy up to 98.8%.

The objective of the work in Tien et al. (2021a) was to present a image-based occupancy and appliances usage detection approach for demand-driven control systems to reduce excessive power consumption and improve thermal conditions. In real-time, the approach detects and recognizes many inhabitants, their behaviors, and equipment employed within building spaces. A faster region-based convolutional neural network (R-CNN) was created, then trained, and integrated based on camera data to detect occupancy activities and appliance usage in real-time.

The study in Wang et al. (2021b) presented and modeled an occupancy-aware intelligent dispatching for efficient elevator group control in real-time. The dispatching system estimates elevator capacity using object detection based on CNN and incorporates the model into the optimization of the dispatching by adjusting the prioritized A* search method to deploy the mentioned occupancy detection approach.

The study in Tien et al. (2020a) describes a vision-based DL strategy for detecting and recognizing occupant activity in building areas. Via employing CNN, the model was created to identify occupancy activity using camera footage. Detection accuracy of 80.62% was reached on average. Similarly, a technique for real-time prediction of building occupancy load and an air-conditioning load forecast-based control approach was proposed in Meng et al. (2020), both of which have the potential for improving air quality in public buildings. The system uses a camera to capture visual data from the interior of the building, which is then processed using image processing and DL detection, particularly a CNN model. The study in Tien et al. (2020b) describes the preliminary construction of a data-driven DL framework for identifying occupant behaviors. Additionally, the findings gained from the method's initial test inside building energy simulation are analyzed. A CNN was trained for classification and detection based on images. With an accuracy of 89.39%, the DL model was verified.

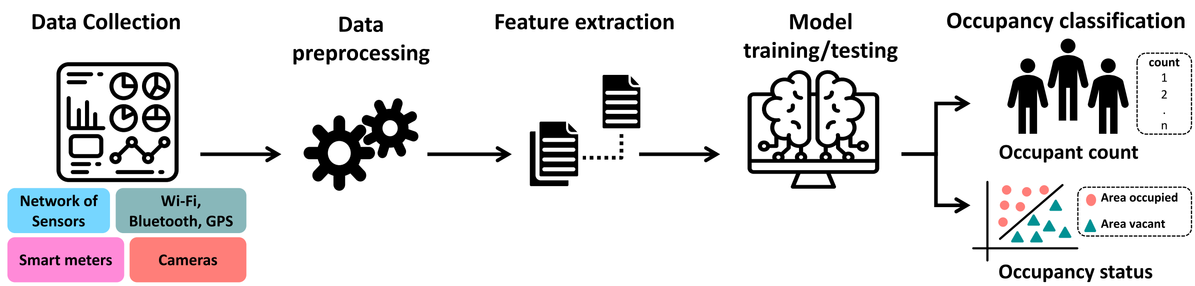


**Fig. 3.** Overview of the process of occupancy detection via ML/DL.

The authors in Callemein et al. (2019) proposed the use of omnidirectional image sensors mounted on intelligent embedded low-resolution cameras to count occupants in office spaces. Because of the dearth of comparable labeled data for training, the authors produced an annotated examples using existing presence detection algorithms. The research in Acquaah et al. (2021) used thermal images to train ML models for occupancy detection to be integrated into heating ventilation and air conditioning (HVAC) control models. Four feature extraction strategies were investigated based on the usage of thermal camera footage, which are: wavelet feature extraction, wavelet scattering, grey-level co-occurrence matrix (GLCM) feature extraction, and feature maps of pre-trained CNN. Typically, two CNN models have been considered, including, the visual geometry group (VGG-16) and deep residual (Resnet-50).

The study in Chen et al. (2020) utilizes the convolutional deep bidirectional LSTM (CDBLSTM) network to identify occupancy from various sensor data with an accuracy of 95.42%. The use of such sensors, with the presence of ventilation, on the other hand, may change the amount of humidity, CO, and $CO_2$ in the home environment, resulting in an incorrect occupancy predication. On another tangent, the study in Kim et al. (2020) detected significant emergency occurrences in single-person homes (SPH) and developed a unique SPH monitoring method based on sound recognition and DL (i.e., using CNN and LSTM).

#### 4.1.2. Recurrent Neural Networks (RNNs)

The research in Wang et al. (2018) makes use of Wi-Fi probe technology to purposefully examine the requests and responses made between the building occupants' access points and network devices. The authors suggested a Markov-based feedback recurrent neural network (M-FRNN) approach for modeling and forecasting presence patterns using collected data. Using support vector regression (SVR) and RNN algorithms, the authors (Zhao et al., 2018) offer a unique technique for detecting a building's occupancy behavior based on temperature and/or likely heat source information. The suggested system in Billah and Campbell (2019) which is based on a limited number of wireless packets, estimates the occupancy of an area using a fast and tiny gated recurrent neural network (FastGRNN) operating on the BLE device, providing energy-efficient real-time analytics.

#### 4.1.3. Long Short Term Memory Networks (LSTMs)

It was suggested in Husnain and Choe (2020) that an occupancy detection system can be built without entirely covering the whole room with sensors. A decision module based on LSTM predicts human presence patterns to cover the sensor's off-range region. It lowers the cost of installing an occupancy detection system. On the same tangent, the authors in Pešić et al. (2019) proposed a technique to detect occupancy centered on the usage of data fusion of Wi-Fi and Bluetooth information and a set of data analytics functions for examining occupancy data across logical and physical boundaries. Lastly, they studied an LSTM neural network (NN) for occupancy forecasting and explained how the same data analytic features could present and anticipate occupancy data. They have achieved an edit distance on real (EDR) signals similarity of 75.45% for workdays.

Another work in Chen et al. (2017) proposed a CDBLSTM method for building occupancy projection using non-intrusive and affordable environmental sensors, including $CO_2$, humidity, temperature, and air pressure. Considering that CNN and LSTM techniques are the two most widely used DL methods for occupancy detection, their respective operating principles are shown in Fig. 4.

Six forecasting models were used in Chang et al. (2021) to analyze the same dataset: gaussian process regression (GPR), RF, least-square support vector regression (LSSVR), back propagation neural networks (BPNN), general regression neural networks (GRNN), and LSTM. The numerical findings demonstrate the superiority of the LSTM network model in accurately estimating the accuracy rate in the hotel compared to other models across three data repositories. The model reached a root mean squared error (RMSE) of 13.31%. The primary objective in Elkhoukhi et al. (2019) is to assess the accuracy of forecasting the number of occupants by applying a steady-state model to $CO_2$ forecasts using contemporary DL techniques, including RNN and LSTM methods.

In Hitimana et al. (2021), Hitimana et al. utilized multivariate time series to predict occupancy patterns in a regression forecasting problem. The empirical evaluation demonstrated that the designed solution effectively collects, processes, and stores environmental data. The acquired data was fed into an LSTM model, which was then compared to various ML techniques to show good performance in the context of the study.

Using a network of PIR sensors in IoT-based lighting systems, the paper in Samani et al. (2020) developed an anomaly detection method using occupancy data with the potential to be applied to building energy efficiency. The next day electricity consumption was predicted using LSTM as the DNN architecture so that the observed reduction in power usage might be leveraged to offer demand response

#### 4.1.4. Generative Adversarial Networks (GANs)

The work done in Zhou et al. (2021) presents a non-intrusive method for comprehensively modeling different occupant activity patterns. The technological innovations are threefold and are centred on the generative adversarial network (GAN) concept and Wi-Fi records. On a similar tangent, human occupation in a confined place may change the radio frequency (RF) spectrum (Liu et al., 2021b). This research proposes a conditional GAN approach to generate human RF fingerprints using the baseline spectrum in the interested region. Additionally, the research in Chen and Jiang (2018) employed a GAN framework for building occupancy modeling utilizing optical camera data.

#### 4.1.5. Radial Basis Function Networks (RBFNs)

This study presents an occupancy prediction model based on a collection of non-intrusive sensors capable of measuring a variety of environmental information (Yang et al., 2012). Sensors data are analyzed to approximate the number of inhabitants in real-time using a radial basis function (RBF) NN.

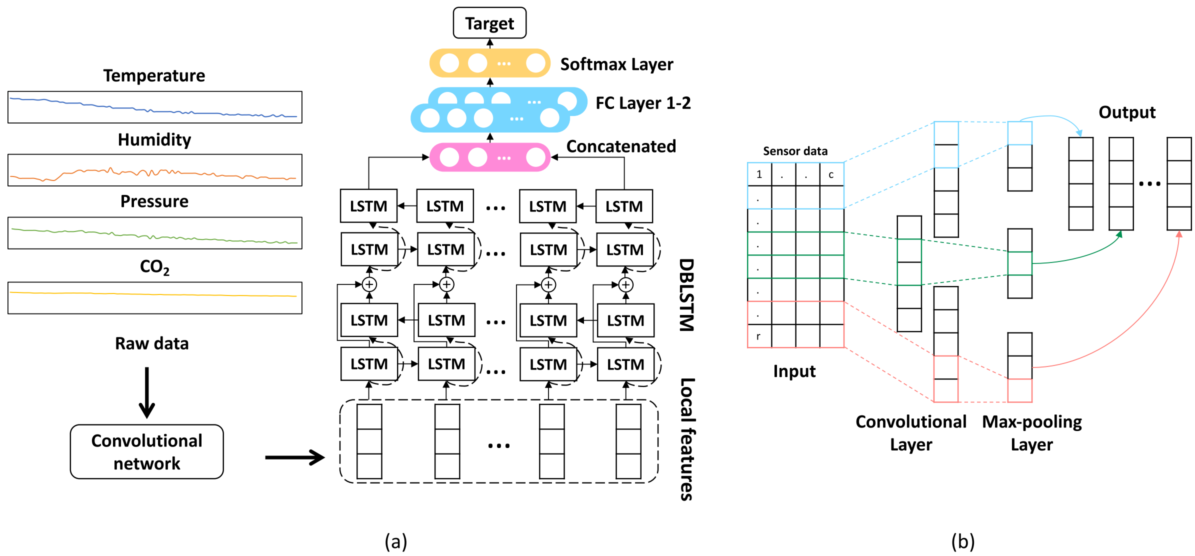


**Fig. 4.** Occupancy detection process using DL showing (a) the high-level procedure and (b) CNN structure (Chen et al., 2017).

#### 4.1.6. Multilayer Perceptrons (MLPs)

The study in Taheri and Razban (2021) established a procedure for managing a campus classroom HVAC system in response to the quantity of $CO_2$ in the surrounding environment. This is archived by predicting the $CO_2$ levels using a MLP network.

In the study performed in Sani et al. (2018), it was determined that the wrapper subset evaluation (WSE) features selection approach is best suited for solving the challenge of forecasting room occupancy relevant to this research and the dataset provided. Date, humidity, light, and $CO_2$ are the best features to utilize out of eight possible features. The given feature set was used, classification results showed that instance-based k (IBk) classifier outperforms MLP and logistic model trees (LMT), with statistically significant differences between their performances. Similarly, the study in Rodrigues et al. (2017) provided a MLP model for estimating classroom occupancy using relative humidity, temperature, and $CO_2$ concentration.

#### 4.1.7. Self Organizing Maps (SOMs)

The authors in Maddalena et al. (2014) presented a camera system with a multi-view property used for people counting. The system uses current advances in multi-view video analysis, incorporating effective components. The 3D self organizing maps (SOM) neural network methodology integrates spatial and temporal templates, and the kNN algorithm estimates the number of people.

#### 4.1.8. Deep Belief Networks (DBNs)

The work done in Dodier et al. (2006) constructed and installed a network of several PIR sensors in two private workplaces and determined occupancy using Bayesian probability analysis methods. The network of sensors which is gathering occupancy data was subjected to a class of graphical probability models known as belief networks.

#### 4.1.9. Restricted Boltzmann Machines (RBMs)

In Khan et al. (2018) real-world verbal and acoustic data is used to develop an acoustic sensing-based occupancy detection and person-counting solution. This helped in emphasizing the importance of incorporating both non-overlapping and overlapping verbal data in a realistic context. The study employed the restricted boltzmann machine (RBM) algorithm.

#### 4.1.10. Autoencoders (AEs)

DL techniques are employed in Liu et al. (2017) to accomplish occupancy detection. The authors developed a sparse auto encoder (AE) to extract features from data and afterwards feed the extracted features to Softmax, Liblinear, and SVM classifiers to determine the status of occupancy for a given room.

DeepSense is a device-free human activity detection technique which is capable of correctly and automatically discriminate typical behaviors using just commodity Wi-Fi-enabled IoT devices, as suggested in Zou et al. (2018b). Additionally, the authors introduced autoencoder long-term recurrent convolutional network (AE-LRCN), a new DL model that uses AE, CNN and LSTM modules to de-noise raw Wi-Fi data to extract representative features.

Device-free occupancy detection is critical for particular IoT applications that do not require the user to carry a receiver. The researchers in Ng and She (2019), Ng et al. (2019) suggested a denoising-contractive autoencoder (DCAE) that could be trained to identify effective feature representations from sparse and noisy feature vectors made up of received signal strength (RSS) data obtained from BLE devices. An occupancy detection approach was designed in the study in Shirsat and Bhole (2021) by employing chaotic whale spider monkey (ChaoWSM) optimization method and a deep-stacked AE for human count identification in buildings. The suggested occupancy detection technique includes preprocessing, extracting and reducing features, detecting occupancy, and counting occupants. The proposed method yielded an accuracy of 94.5%.

The suggested system in Aziz Shah et al. (2020a) is created for future body-centric communication by employing readily available non-wearable components, including an omnidirectional antenna, network interface card and Wi-Fi router. Time-frequency scalograms are extracted from Wi-Fi signals. Then, the occupancy is identified by utilizing an AE NN to categorize the scalogram pictures. The proposed approach has a classification accuracy of 91.1%. Table 2 summarizes existing DL- and TL-based occupancy detection frameworks and compares their characteristics in terms of learning model, sensors/devices used, occupancy resolution, building type, best performance and limitation/advantage of each framework. It is worth noting that occupancy detection systems can be classified into two main categories, i.e., occupancy presence detection and occupant number detection. In this regard, the occupancy resolution column provides information about the nature of the occupancy detection task conducted in each framework, including state measurement, quantity estimation, or activity monitoring (or tracking). It is seen that a significant number of occupancy

**Table 2**
Comparison of occupancy-based solutions using DL.

| Learning model | Sensors/devices used | Occupancy resolution | Building type | Best performance | Limitation/Advantage |
|---|---|---|---|---|---|
| CNN, SVM, and K-means (Zou et al., 2017) | Surveillance camera | Quantity | Office | Accuracy = 95.3% | • Extreme scenarios are not well examined. |
| CNN, LSTM, and AE (Zou et al., 2018a) | Wi-Fi-enabled IoT devices | Activity | Office | Accuracy = 97.6% | • Depends on the availability of Wi-Fi routers. |
| CNN (Arvidsson et al., 2021) | Heat sensor | Quantity | Office | N/A | • 1-System not fully tested with various environmental conditions. 2- Further research on the placement of sensors. |
| CNN (Abedi and Jazizadeh, 2019) | DRS and ITA sensors | State | Office | Accuracy = 99.96% | • Testing conditions are not generalized. |
| CNN and LSTM (Feng et al., 2020) | AMI data from the ECO dataset | State | Residential | Accuracy = 90% | • Lack of research of power consumption behavior of home appliances using AMI data. |
| CNN (Saha, 2021) | Image sensor | State | Residential | Accuracy = 85.84% | • Lower accuracy compared to existing supervised learning benchmarks. |
| CNN (Sun et al., 2021) | Entrance video camera | Quantity | Laboratory | Accuracy = 97.8% | • Privacy concerns. |
| CNN (Mutis et al., 2020) | Surveillance video camera | Quantity and activity | Office | Accuracy = 84% | • 1- Privacy concerns. 2- Low accuracy. |
| CNN and SVM (Acquaah et al., 2020) | Thermal camera | Quantity | Office | Accuracy = 98.8% | • Privacy concerns. |
| R-CNN (Tien et al., 2021a) | Image camera | Activity | Laboratory | Accuracy = 97.09% | • Privacy concerns. |
| CNN (Wang et al., 2021b) | Surveillance video camera | Occupancy density | Elevator | N/A | • Privacy concerns. |
| CNN (Tien et al., 2020a) | Video camera | Activity | Office | Accuracy = 80.62% | • 1- Privacy concerns. 2- Low accuracy. |
| CNN (Meng et al., 2020) | Image camera | Quantity | Office | Accuracy = 70% | • 1- Privacy concerns. 2- Low accuracy. |
| CNN (Tien et al., 2020b) | Video camera | Activity | Office | Accuracy = 89.39% | • Privacy concerns. |
| CNN (Callemein et al., 2019) | Omnidirectional camera | Quantity | Office | Accuracy = 93.9% | • Privacy concerns. |
| CNN and others (Acquaah et al., 2021) | Thermal camera | Quantity | General | Accuracy = 100% | • Privacy concerns. |
| CNN and LSTM (Chen et al., 2020) | $CO_2$, T, AP, H | Quantity (range: 0, low, medium, high) | Office | Accuracy = 95.42% | • Issues with real-life implementation. |
| CNN and LSTM (Kim et al., 2020) | Acoustic sensor | Activity | Residential | Precision = 78% | • Real-life experiments are not performed. |
| CNN (Liu et al., 2020) | Receiver, transmitter devices | State | None | Accuracy = 99.94% | • Relies on the availability of Wi-Fi routers. |
| CNN (Pal et al., 2019) | AMI data from the ECO dataset | State | Residential | Accuracy = 94% | • Training data has bad distribution of two classes. |
| M-FRNN (Wang et al., 2018) | Wi-Fi probe | Quantity | Office | Accuracy = 93.9% | • Relies on the availability of Wi-Fi routers. |
| RNN, and SVR (Zhao et al., 2018) | T, HVAC P | Quantity | Office | Error = 2.64% | • Real-life experiments are not performed. |
| RNN (Billah and Campbell, 2019) | BLE devices | State | General | Accuracy = 95% | • System is environment-specific. |
| LSTM (Husnain and Choe, 2020) | Thermal, PIR sensors | State | Laboratory | Accuracy = 95.62% | • Additional experimental testing is missing. |
| LSTM (Pešić et al., 2019) | BLE devices | State | Smart | EDR = 75.45% | • Testing conditions are not generalized. |
| LSTM, BPNN, GRNN, LSSVR, RF, and GPR (Chang et al., 2021) | Customer rating scores and reviews | Rate | Hotel | RMSE = 13.22% | • Real-life experiments are not performed. |
| LSTM and RNN (Elkhoukhi et al., 2019) | $CO_2$, T, H, P, PIR, camera | State, quantity and activity | Office | Accuracy = 70% | • Lower accuracy compared to existing supervised learning benchmarks. |
| LSTM (Hitimana et al., 2021) | $CO_2$, T, H, L | State | Laboratory | Accuracy = 96.8% | • Noisy parameters affecting the overall accuracy. |
| LSTM (Samani et al., 2020) | PIR | State | Laboratory | Accuracy = 84% | • Lower accuracy compared to existing supervised learning benchmarks. |

(*continued on next page*)

**Table 2** (*continued*).

| Learning model | Sensors/devices used | Occupancy resolution | Building type | Best performance | Limitation/Advantage |
|---|---|---|---|---|---|
| LSTM, DNN, and RF (Wang et al., 2019a) | Wi-Fi access point | Quantity | Office | RMSE = 3.95% | • Relies on the availability of Wi-Fi routers. |
| Learning model | Sensors/devices used | Occupancy resolution | Building type | Best performance | Limitation/Advantage |
| GAN (Zhou et al., 2021) | Wi-Fi devices | Activity | Smart | Activity dependent | • Relies on the availability of Wi-Fi routers. |
| GAN, CNN, and k-NN (Liu et al., 2021b) | Radio frequency signatures | State | Office | Accuracy = 99.94% | • Distance shift between the person and antenna may produce errors. |
| GAN (Chen and Jiang, 2018) | Video camera | Quantity | Laboratory | NRMSE = 14.24% | • Performance could be enhanced. |
| RBF (Yang et al., 2012) | $CO_2$, T, H, L, S, PIR | Quantity | Office | Accuracy = 87.62% | • Sensors utilized in the study were not calibrated. |
| MLP, SVM, AdaBoost, RF, GB, and LR (Taheri and Razban, 2021) | $CO_2$ | Quantity | Laboratory | RMSE = 33.29% | • Real-life experiments are not performed. |
| MLP, LMT, and IBK (Sani et al., 2018) | $CO_2$, T, H, RH, L | State | Office | Accuracy = 99.24% | • Real-life experiments are not performed. |
| MLP (Rodrigues et al., 2017) | $CO_2$, T, RH | Quantity | Laboratory | MSE = 1.99% | • Real-life experiments are not performed. |
| MLP, RF, NB, KNN, SVM, and DT (Wu and Wang, 2021) | PIR | State and activity | Laboratory | Accuracy = 99.12% | • N/A. |
| SOM and k-NN (Maddalena et al., 2014) | Multiple video cameras | Quantity | Office | Precision = 99% | • Lower accuracy results for crowded scenarios. |
| DBN (Dodier et al., 2006) | PIR | Quantity | Commercial | N/A | • Not tested with spaces with large crowd. |
| RBM (Khan et al., 2018) | Microphone and accelerometer sensors | Quantity | Commercial | Activity dependent | • Server based design. |
| AE (Liu et al., 2017) | $CO_2$, T, H, RH, L | State | General | Accuracy = 98.88% | • N/A. |
| AE, CNN, and LSTM (Zou et al., 2018b) | Wi-Fi-enabled IoT devices | Activity | Smart | Accuracy = 97.4% | • Depends on the availability of Wi-Fi routers. |
| AE (Ng and She, 2019; Ng et al., 2019) | BLE devices | Quantity | Laboratory | Accuracy = 90% | • Using cloud processing. |
| AE (Shirsat and Bhole, 2021) | $CO_2$, T, H, RH, L | State | Office | Accuracy = 94.5% | • Real-life experiments are not performed. |
| AE (Aziz Shah et al., 2020a) | Wi-Fi router and omnidirectional antenna | State and activity | Laboratory | Accuracy = 91.1% | • Relies on the availability of Wi-Fi routers. |

$CO_2$: carbon dioxide, T: temperature, H: humidity, HR: humidity ratio, L: light, AP: air pressure, P: power, S: sound, PIR: passive infrared, BLE: Bluetooth low energy, DRS: doppler radar sensor, ITA: infrared thermal array, AMI: advanced metering infrastructure, ECO: electricity consumption and occupancy.

detection frameworks have been conducted in office and laboratory buildings. Also, most studies have been shown to track the occupancy status and quantity of occupants in different kinds of buildings. In contrast, more minor contributions have been devoted to monitoring the activity of building occupants. Regarding the occupancy detection performance, some studies showed low or average performance results; most of them are based on analyzing image data.

#### 4.1.11. DL advantages and drawbacks

Occupancy detection techniques gain significantly from DL; however, there are also some additional constraints. The CNN method is frequently used for image processing but could be less successful with time-series data. Alternatively, time-series data must be transformed into images to utilize the CNN networks' unique architecture. On the other hand, the LSTM and MLP structure are highly likely to be employed in the presence of occupancy-related time-series data (i.e., environmental, mobility, and smart meter data). The autoencoder technique could be useful if data annotation were not available. Models such as GAN, RBFN, SOM, DBN, and RBM are not widely studied or adopted for occupancy detection applications. Real-time model generalization and implementation were lacking from a substantial portion of the papers reviewed. The fact that the majority of publicly accessible occupancy datasets only include occupancy state resolution and seldom occupancy quantity is a significant drawback discovered while conducting the review.

### 4.2. Transfer learning

Training a DL model from scratch requires extensive computational and memory resources and a vast amount of labeled dataset. In smart buildings, large annotated occupancy datasets are not always available. Moreover, creating large annotated datasets is a labor-intensive and costly operation, and the number of monitored facilities might not be sufficient to create a large dataset. TL has been proposed to close this gap as an alternative to training DL models fully.

By leveraging TL, the knowledge acquired from another domain (e.g., another building or another task) could be transferred for solving a targeted building occupancy detection problem. Typically, TL helps to (i) save computing resources and improve efficiency when training new DL, as the latter can be pre-trained offline on large-scale datasets and then fine-tuned on small datasets; (ii) train DL models on available annotated datasets before validating them on unlabeled

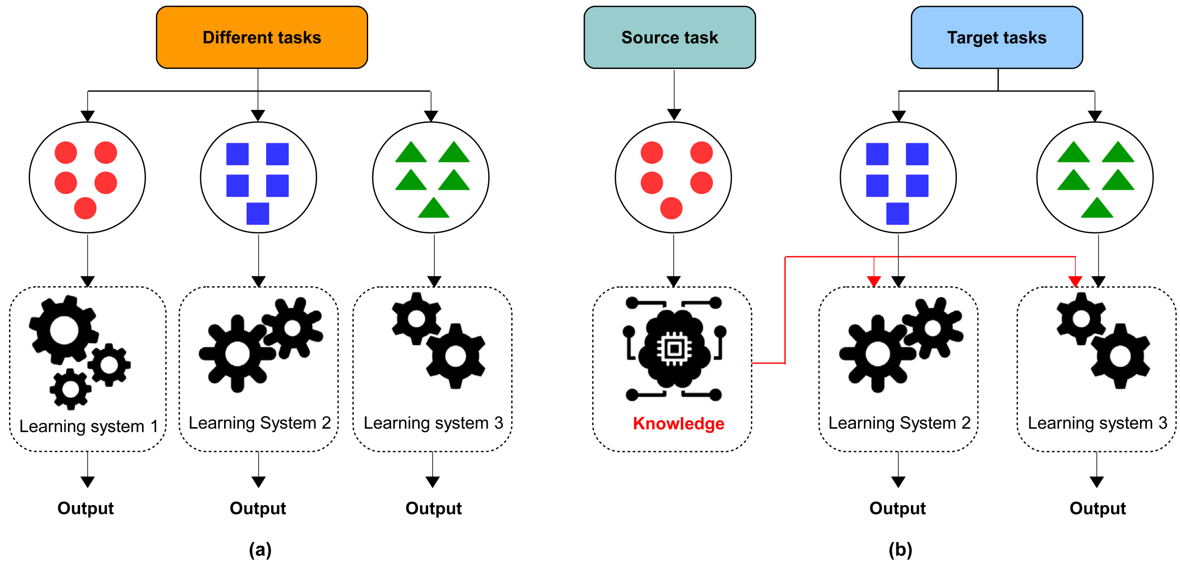


**Fig. 5.** Difference between conventional DL and TL techniques for multiple tasks: (a) conventional ML and (b) TL.

datasets (Che et al., 2021), which is of utmost importance, keeping in mind that labeling data is a challenging task that takes time and effort and requires the intervention of experts; (iii) train DL models using simulated or synthetic data instead of real-world environments (Ko and Park, 2021), and (iv) exploit the knowledge acquired from previous tasks for improving generalization about others (Kim et al., 2021). Fig. 5 illustrates the difference between conventional DL and TL for multiple tasks. Typically, in conventional ML (Fig. 5(a)), the models are deployed to perform multiple classification/learning tasks separately without any interaction between them. In contrast, if transfer learning is considered (Fig. 5(b)), the knowledge learned on a task can be transferred to conduct different but related tasks. This means there is a knowledge sharing between the different tasks.

#### 4.2.1. *Fine-tuning*

The most extensively used TL approach based on DL for occupancy detection is fine-tuning. A pre-trained DL model is often fine-tuned if there is no substantial difference between the source domain (training dataset) and the target domain (test dataset). This is doable by using the target dataset to fine-tune the weights of the whole network, or only fine-tune the weights of the last layers (frequently the fully-connected layers) while freezing the remaining layers.

CNN is commonly used to work with image data, and TL can aid in avoiding the need for training a complex CNN model from scratch, i.e., this help speed up the learning stage an/or deal with limited data. For example, Mosaico et al. (2019) used a pre-trained AlexNet for extracting features from thermal images, estimating the number of occupants. Concretely, they demonstrated that the occupant recognition strategy built on TL could achieve greater performance than conventional models. Environmental sensing data may also be used to detect occupancy. The study in Tien et al. (2021b) analyzes the implementation of a vision-based DL algorithm for detecting occupancy activities in an open-plan office area. The recognition model was first built by establishing and training a CNN to characterize occupancy activities using a TL approach. In a similar manner, the study in Leeraksakiat and Pora (2020) suggests applying TL on an LSTM network to enhance the overall performance. Data from a PIR, $CO_2$, and temperature sensors are gathered every five minutes to be used as the input to the presented network.

The purpose of the work in Khalil et al. (2021) was to apply a TL technique to forecast the occupancy state of an educational facility using environmental sensor data. The suggested approach investigates two DL models, stacked LSTM and deep sequential model (DSM) by (i) training them on a large-scale dataset (two years of historical data), then fine-tuning them on the target datasets (two months of historical data). Weber et al. (2020a) used TL to pre-train and TL with DNN to decrease the quantity of data required for training, enabling it to be deployed for various other rooms without sufficient labeled data. Ultimately, occupant number may be forecasted from past occupant records with a RNN algorithm. Using solely commercial IoT devices, the study developed in Zou et al. (2018c) suggested Wi-Free, a Wi-Fi-based device-free occupancy detection, and crowd counting technique. The authors presented a transfer kernel learning (TKL) classifier to consistently achieve accurate occupancy level prediction throughout environmental and temporal fluctuations. According to test results, Wi-Free achieved an accuracy of 99.1% for occupancy detection and 92.8% for crowd counting in a device-free way while ensuring occupant privacy over temporal variance.

#### 4.2.2. *Domain adaptation (DA)*

Although fine-tuning is fairly simple to use and comprehend, it is less successful when the distributions of the source and target domains diverge. For this case, researchers attempted to include distance measuring in TL into the original networks, a process known as DA. This concept modifies the original network's cost function by including a domain loss to quantify the dispersion of the source and target data.

As it is challenging to record enough ground truth data to train DL models, Weber et al. (2020a,b) proposed a DA occupancy detection scheme based on conducting experiments with data from a $CO_2$ sensors in an office room and additional synthetic data generated using the software. This work investigates reducing the quantity of real-world data required for model training using synthetic data.

Typically, $CO_2$ dynamics under randomized occupant behavior have been simulated. Next, a proof of concept for knowledge transfer from simulated $CO_2$ data is introduced using a CNN with a CDBLSTM. The results obtained in this study have confirmed DA's capability to diminish the required amount of data for model training. Fig. 6 portrays the flowchart of the occupancy detection method based on DA proposed in Weber et al. (2020b).

In Arief-Ang et al. (2017), they presented a $CO_2$ model for domain adaptation human occupancy counter (DA-HOC). When trained model and labeled data are available, the number of persons is accurately predicted by the DA-HOC baseline model. They have created a unique, semi-supervised domain adaption for an occupancy detection model

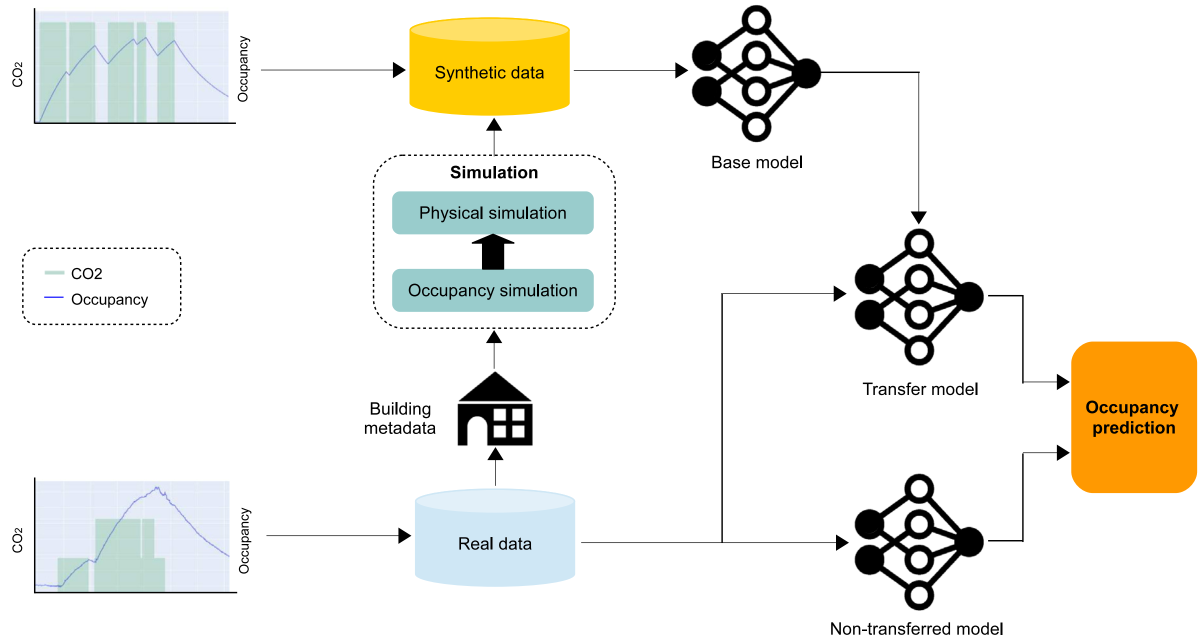


**Fig. 6.** Flowchart of the occupancy detection method based on DA proposed.

**Table 3**
Comparison of occupancy-based solutions using transfer learning.

| Learning mode | Type of TL | Sensor | Occupancy resolution | Building type | Best performance | Limitation/advantage |
|---|---|---|---|---|---|---|
| CNN (Tien et al., 2021b) | Fine-tuning | Cameras | State, quantity and activity | Open office | Accuracy = 98.65% | • High complexity could hinder real-time implementation |
| LSTM (Leeraksakiat and Pora, 2020) | Fine-tuning | PIR sensors | State | Residential | Accuracy = 94.30% | • Security and privacy concerns were not explored, and moderate performance. |
| staked LSTM, and DSM (Khalil et al., 2021) | Fine-tuning | Environmental sensors | State | N/A | Accuracy = 71% | • Moderate performance that needs further improvement. |
| CNN (Mosaico et al., 2019) | Fine-tuning | Thermal cameras | Quantity | Non-residential | MAE = 0.7, RMSE = 1.3 | • Privacy concerns were not discussed. |
| CNN-DBLSTM (Weber et al., 2020a,b) | DA | Environmental sensors | State | Commercial | Accuracy = 93.30% | • Moderate performance and privacy concerns were not addressed. Also, DA between different kinds of buildings was not studied. |
| RNN (Zhang and Ardakanian, 2019) | DA | Environmental sensors | Quantity | Public | RMSE = 4.39 | • Two rooms from the same building were used, which reduces the impact of the DA. Also, the source and target domain share the same feature space. |

that could be deployed in any building/room without sufficient labeled data. A semi-supervised DA model was used to count occupants by Arief-Ang et al. (2018).

The work in Zhang and Ardakanian (2019) seeks to address the limited amount of real-live occupancy training data. This is discoursed by using RNN models to infer occupancy footprints in particular rooms using trend data found via the building management system. Furthermore, by using the DA approach, existing occupancy detection algorithms trained using annotated datasets (i.e., a controlled environment in the source domain) may be transferred to another domain (i.e., the target domain) suffering from label scarcity or unavailability. The model parameters were modified to account for the obvious variations among the two scenarios, and the revised model was used to estimate the number of occupants in the target domain. Table 3 shows a comparison of occupancy-based methods identified in the literature that use transfer learning.

#### 4.2.3. *Cross-building TL (CBTL):*

TL has enabled using the knowledge acquired on occupancy data collected from a building to train ML models on target data from other buildings. This has opened the doors for a new research topic called cross-building TL (CBTL), which relies on improving models' robustness and generalization ability. Thus, this helps transfer the knowledge of ML and DL algorithms by training and testing them on different but related buildings (e.g., households with varying profiles of occupancy, energy consumption, etc.) or entirely different buildings (e.g., households vs. commercial buildings, or office buildings vs. sports venues, etc.) but recorded from the same geographical region. Moreover, CBTL has recently been applied in many other applications of the building sector, such as building energy forecasting (Ribeiro et al., 2018; Fang et al., 2021), energy disaggregation (Yang et al., 2021), fault diagnosis (Liu et al., 2021c,c), thermal comfort control (Park and Park, 2021), etc.

### 4.3. Computing platforms

Due to the computational complexity of DL, different kinds of computing platforms have been utilized in the state-of-the-art to implement scalable occupancy detection framework and equip them with the needed computing resources. Accordingly, based on our investigation, four main computing architectures have been deployed as follows. Edge computing allows data processing on edge of the network which is closer to the users by adopting different kinds of edge platforms, servers, or mobile devices. For instance, smart-plugs, micro-controllers, affordable computing platforms (e.g., Arduino and Raspberry Pi), and multi-core embedded platforms (e.g., Jetson TX1/TX2, Jetson Nano, ODROID, etc.) are the most popular (Alsalemi et al., 2022; Thinh et al., 2021). Fog computing is the processing of data in the intermediate layer, which is placed between the edge and cloud layers (Khalid and Javaid, 2019). Cloud computing enables process occupancy data on the cloud level. Cloud computing can provide various benefits for implementing occupancy detection solutions, such as direct access to data centers with high storage capacities. Although many occupancy detection works rely on cloud computing, using this computing architecture also provides different issues related to privacy threats and communication latency due to transmitting data to remote cloud platforms (Alsalemi et al., 2020). Lastly, in hybrid computing, the data processing and occupancy monitoring stages are implemented on the combination of the previously presented architectures, for example, edge–cloud, edge–fog, or fog–cloud architectures (Talaat et al., 2020).

### 4.4. Applications of occupancy detection

Occupancy sensing plays a significant role in supporting building automation and promoting sustainability and safety in indoor environments. Accordingly, occupancy detection helps (i) endorsing energy saving through optimizing the control HVAC systems, lighting, and other kinds of appliances (Zhang et al., 2022); (ii) track building occupants' behavior, and thus it is an essential element to adjust building system operation and optimize thermal comfort of end-users (Kong et al., 2022); (iii) monitoring elderly homes and hence keeping an eye on their safety (Kaushik et al., 2007); (iv) improving safety and security measures at public buildings from retail and offices to sports venues and hospitality (Azimi and O'Brien, 2022); (v) detecting energy consumption anomalies due to the presence/absence of end-users, e.g., keeping on some appliances, lighting or HVAC systems while a room/building is empty (Himeur et al., 2020c).

## 5. Discussion of key challenges and comparative analysis

### 5.1. Interpretability and generalizability

After achieving convincing performance in many research fields, using ML and DL models has raised different issues. Typically, more research on model interpretability and explainability is needed. New goals have been then set by the AI research community to develop the next generation of ML/DL models that can not only predict systems' outputs with high accuracy but also explain the produced results and enable scientists to interpret the learned models (Himeur et al., 2022a). Typically, DL models continue to be treated mostly as black-box function approximators, which map given inputs to classification outputs. Incorporating these tools into critical processes, such as occupancy detection, behavior monitoring, energy optimization, medical diagnosis, planning and control, etc., necessitates a level of trust associated with their outputs. While statistical assessment is employed to quantify the outputs, the notion of trust relies on providing explanations or visual demonstrations to convince the users (Varlamis et al., 2022a). Put differently, DL models need to produce human-understandable justifications for their outputs, which can lead to insights about the inner workings. Such models are called as interpretable DL algorithms (Du et al., 2019). For occupancy detection, only few studies have been proposed to investigate this important aspect. For instance, Jaworek-Korjakowska et al. (2021) developed an interpretable and explainable DL scheme for seat occupancy detection in a vehicle interior space. To that end, more effort should be devoted to developed explainable and interpretable occupancy detection systems in the near future.

On the other hand, using occupancy detection and prediction models aims to predict the classes of new data collected from new buildings (target domains). This data could significantly differ from the source domain data due to varying building characteristics and operation parameters (e.g., varying profiles of occupancy, use of different equipment and devices, etc.). In this regard, ML and DL models are built on existing data with the aim of extending and generalizing them to new data. Consequently, the generalizability of ML and DL models is of utmost importance when developing robust occupancy detection systems.

Although most conventional ML models have excelled in classifying occupancy patterns (especially with supervised learning), they often fail to generalize, mainly when the target datasets are small (i.e., there is a data scarcity issue) or the target domain data is different than the source domain patterns (Rafiq et al., 2021; Himeur et al., 2020d). By contrast, despite their high computational cost, DL models have revealed excellent generalization and self-learning abilities (not only in occupancy detection but in many other applications). However, it is still seen that the generalizability of occupancy detection models has not been carefully investigated in most existing works. For example, in Chen et al. (2020), the generalization ability of the convolutional deep bidirectional LSTM (CDBLSTM) model used for building occupancy prediction is assessed only by randomly selecting the data for training and testing from the same building. Put differently, more evaluation tests and experiments need to be conducted to check the generalizability of DL models under different occupancy profile scenarios, different buildings with varying operation parameters, etc.

### 5.2. Key challenges

Developing efficient DL-based occupancy detection solutions is impossible without large-scale datasets for training and testing DL models. However, only a few datasets have been proposed in the literature and made public. Among them, the University of California Irvine occupancy detection dataset (UCI-ODDs) (Candanedo, 2016; Candanedo and Feldheim, 2016), electricity consumption and occupancy (ECO) dataset (Kleiminger et al., 2015), and Ecobee donate your data (DYD) dataset (Ecobee, 2022) and the high-fidelity occupancy detection dataset (HF-ODS) (Jacoby et al., 2021). To address this challenge, it is important to produce comprehensive datasets that can meet the requirement of DL models in terms of quantity and annotation. This can help train supervised DL algorithms and facilitate the comparison of their results.

#### 5.2.1. Data scarcity

The lack of annotated data is a persistent issue when developing occupancy detection algorithms in real-world scenarios. In fact, since most of the DL models are supervised they require collecting annotated ground-truth datasets in advance to train these models. However, annotating massive amounts of data is a time-consuming, complex, and expensive task, which experts often perform. To overcome this issue, TL is one option to be further investigated as it helps training DL algorithms on existing large-scale datasets (e.g., synthetic datasets) proposed for similar or different tasks, and then (i) fine-tune them on small real-world dataset (Mosaico et al., 2019), or (ii) perform of domain-adaptation (Weber et al., 2020b). Another option to alleviate the data scarcity problem is by adopting deep semi-supervised learning, in which only few amount of annotated data is used to train DL models.

**Table 4**
Summary of available open-source binary occupancy detection algorithms.

| Algorithm | Building type | Link of the open-source algorithm |
|---|---|---|
| LR, NB, k-NN, DT, RF, GBM, and k-SVM | Office space | https://github.com/LuisM78/Occupancy-Detection-1 |
| NN and RF | Residential/Commercial | https://github.com/sustainable-computing/ODToolkit |
| 1D-CNN | Office space | https://github.com/yaonuma/Occupancy_Detection |
| RF, DNN, MLP | Office space | https://github.com/pcko1/occupancy-detection |
| LR, DT, SVM, RF, and k-NN | Office space | https://github.com/bhargavyagnik/Room-occupancy-predictor |
| k-NN, RF, SVM, and AdaBoost | Office space | https://github.com/mabdullahsoyturk/Occupancy-Detection |
| LR, DT, SVM, RF, and k-NN | Office space | https://github.com/shayanalibhatti/Predicting_room_occupancy_using_logistic_regression |
| SVM, LR, DT, RF | Office space | https://github.com/OmarBouhamed/Occupancy_pred |

LR: logistic regression, NB: naive bayes, k-NN: k-nearest neighbors, DT: decision tree, RF: random forest, GBM: gradient boosting machines, SVM: support vector machines, NN: neural network, DNN: deep neural network, 1D-CNN: one-dimensional convolutional neural network, MLP: multi layer perceptron.

#### *5.2.2. Open-source toolkits to reproduce scientific results*

With the rising number of people counting systems and building occupancy detection solutions, it becomes challenging to compare the results. This is because of the lack of open-source implementation algorithms, open-access test datasets, and consensus on the evaluation metrics. The summary of available open-source occupancy detection algorithms is shown in Table 4. Notably, several of the mentioned open sources for occupancy detection techniques are neither DL nor TL. However, due to the scarcity of open-source occupancy detection techniques, all the widely available ones are included in Table 4. It should also be emphasized that all open-source, publicly accessible occupancy detection methods leverage binary occupancy detection (i.e., occupied/unoccupied).

To that end, designing open-source toolkits to facilitate the development of occupancy detection algorithms has become a priority. In this respect, Zhang et al. (2019) develop ODToolkit,[1] which can (i) import and convert sensor data collected from different building environments into a unique data representation, (ii) enable the implementation of a wide range of ML-based occupancy detection methods, assess the performance of implemented algorithms using the same evaluation metrics in every experiment. Moreover, the ODToolkit has been extended to implement domain-adaptive algorithms for detecting occupancy patterns. Additionally, it helps explore the sensing modalities and precision required to reach a desirable level of accuracy for estimating or predicting occupancy using a fusion of sensors.

#### *5.2.3. Security and privacy concerns*

Detecting building occupancy patterns at the moment in time may represent a threat if this information is leaked as it is strongly correlated with electricity usage. More specifically, the presence time of end-users can be easily inferred from occupancy data, which makes this latter a cause of privacy violation (Shateri et al., 2020). In this regard, Chand et al. (2021) attempt to overcome this issue by predicting occupancy based on the sensor data without a need to breach privacy. Besides, in Aziz Shah et al. (2020b), a privacy-preserving occupancy detection system is introduced, which is based on (i) detecting occupancy using DL-based image analysis, and (ii) encryption collected images with the chaos-based scalogram. Similarly, a secure occupancy detection method is developed in Ahmad et al. (2018), which relies on a video frame encryption paradigm. This framework has been validated against different statistical attacks. Overall, because of the few number of frameworks proposed in the literature to address the security and privacy concerns, it is still challenging to design secure and privacy preserving occupancy detection systems.

#### *5.2.4. Scalability and interoperability*

Considering high sampling sensors and different kinds of data, occupancy detection systems based on DL introduce high computational cost in most real-world scenarios and require significant memory capacities. In this regard, utility companies or end-users considering occupancy detection systems should utilize high-end smart plugs or other hardware platforms with enough storage and practical computing components. Alternatively, the occupancy detection task might be conducted using cloudlet platforms. However, this can significantly increase cloud service costs if the number of users is increased. This is a major problem that impedes widely adopting occupancy detection systems.

To overcome this problem, scalable occupancy detection solutions might be designed using edge devices and servers with embedded high performing Graphics processing units (GPUs). This enables the implementation of (i) low-cost computational processing on the edge (e.g. data collection, processing, resampling, etc.) and (ii) complex DL algorithms on the cloud. Typically, this approach can decrease the cloud service cost (Athanasiadis et al., 2021). From another hand, an essential issue with most occupancy detection solutions is the potential absence of interoperability. Every occupancy detection has a proprietary data protocol, which needs the development and maintenance of different processes and integrations. Additionally, due to the competitiveness between occupancy detection developers, no one is interested to make its data accessible to third parties.

#### *5.2.5. TL limitations*

Although TL significantly benefits occupancy detection algorithms, new issues can be raised. For instance, the problem of negative transfer when encountered in a TL algorithm ends up with a degradation of the classification of prediction performance (or accuracy) of the newly developed model. Specifically, TL can perfectly work if the source and target domains are sufficiently similar. However, if the data used to pretrain the TL model is different enough than the data used to re-train this model (or some of its parts), the performance might be worse than expected. Moreover, measuring the knowledge gained when a TL model is adopted to conduct specific tasks is challenging. The study in Hu et al. (2019) has attempted to analyze the quantization of the TL gain, where four metrics have been introduced to quantify the gain knowledge, i.e., transfer error, transfer loss, transfer ratio, and in-domain ratio. Despite that these measures can overcome some interpretation issues related to the performance results occurring when dealing with various source domains, it is unknown how they will behave in other TL-based methods, especially for building occupancy detection where class sets are different between problems. Further, they can result in non-definite performance if a perfect baseline model is obtained.

On the other hand, one of the challenges that may still impede the advance of TL-based building occupancy detection applications is the wide range of formulations used to describe the mathematical background of developed TL algorithms. For example, while (Hu et al., 2019) promotes the idea of Heterogeneous TL, Fan et al. (2020) opts for statistical investigations of TL-based methodologies, Zhang and Ardakanian (2019), Lin et al. (2021), Zhang and Yan (2020) focus on domain-adaptation TL. Although these frameworks and others included in this review share the same TL idea, they differ in their definition and implementation based on the scenario under consideration. More importantly, different variant terminologies are used, leading to confusion. To alleviate this issue, a unification of TL definitions and background is becoming an emergency. Although the first tentative for unifying TL has been proposed in Patricia and Caputo (2014), this is still not enough to cover the occupancy detection research topic.

[1] https://odtoolkit.github.io/

### 5.3. Physical-based methods

Lu et al. (2022) compiled a list of case studies that investigated estimating the building occupancy based on $CO_2$ sensing. The comparison was based on employing physical-based or statistical methods. Using a physical model has various benefits for predicting occupancy count. Opposite to DL techniques, physical models do not require a substantial amount of training data. They do not need specific building information; they need previous data relating to air exchange rate measurements. Therefore, the dynamic model may be manually built up for rapid use. Physical models are essential since they are general and applicable to various ventilated spaces. It should be noted that the mass-balanced model employed in this application is limited to single-zone space. For the model assumptions to be supported, it is also necessary to verify that the interior air is evenly mixed. Last but not least, the steady-state version of the physical models ignores temperature sensor impacts that could influence the dynamics of the space's air exchange rate (Zuraimi et al., 2017). Statistical models employ a variety of $CO_2$ data to forecast occupancy using either conventional or deep ML approaches. Statistical models frequently exhibit the highest predictive accuracy and computational efficiency. The fact that statistical models are data-driven and are not constrained by the physical characteristics of the building area has the additional benefit of exemplifying durability and data resilience. On the other hand, statistical models require substantial previous knowledge to train and evaluate the data thoroughly. This implies that data derived from sensors cannot be deployed right after installation, and the tested models are restricted to the particular environment from which the model was formed.

### 5.4. Comparative analysis

As it is clear from Table 4, the open-source methods for detecting occupancy are minimal. On the other hand, the found algorithms are all based on the usage of environmental data such as light, temperature, humidity, humidity ratio, and $CO_2$. All in all, not only does there exist a lack of open-source tools for occupancy detection, but they all focus on a sole aspect of inferring occupancy, which is using a network on sensors. Eq. (1) was used to evaluate the effectiveness of the approaches using the straightforward accuracy criterion, which divides the correct predictions by all the projections. Table 5 shows the training time and testing accuracy of the found open-source algorithms; however, the results are considered meaningless since the dataset used is not extensive enough to provide significant results.

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \tag{1}$$

## 6. Potential directions

### 6.1. Edge-based occupancy detection

By entering the era of edge computing, the Internet plays a significant role in collecting data from sensors and distilling relevant information from the sensor data. Therefore, most edge devices are expected to be augmented with AI-powered by DL. However, DL-based techniques require vast amounts of high-quality data for training and are very demanding in terms of power consumption, memory, and computation (Zhang et al., 2020).

Although the development of occupancy detection technologies is gaining popularity in the building energy sector, many challenges remain unresolved and must be addressed to produce reliable and efficient systems. For example, most present energy occupancy detection methods are implemented on cloud servers; however, the increasing use of networking and cloud data centers leads to high bandwidth demand, resulting in increased energy usage (Hannan et al., 2018; Sayed et al., 2021). Furthermore, the development of real-time systems employing cloudlet platforms is hindered by bandwidth limitations, latency issues and internet dependency caused by data transfer to cloud data centers (Cao et al., 2020). The works done in Tse et al. (2020) and Metwaly et al. (2019) demonstrates the usage of edge devices for occupancy detection. Nevertheless, sending and storing confidential and personal information in the cloudlet platforms raises serious privacy and security concerns that were not explored in most existing studies (Raafat et al., 2017).

Typically, in Metwaly et al. (2019), different DL algorithms including feedforward neural networks (FNN), CNN, RNN have been used for room occupancy estimation based on thermal sensors. These DL models have been run on different edge devices, including the STM32F401 and STM32F722 (from the Arm Cortex M4 and M7 families), as they have sufficient resources. Moreover, its performance has been compared with other existing frameworks implemented on other computing boards, i.e., Tmote Sky, Cortex M4, Arduino, Cloud, and GT60 MCU. FNN has considerably improved the state-of-the-art by achieving the best occupancy prediction accuracy of 98.90%.

Besides, in Tse et al. (2020), an edge-based occupancy detection solution is developed to count people in smart campus classrooms using DL. Specifically, cameras and Raspberry Pi platforms have been used to implement a YOLOv3 algorithm and accurately detect occupancy patterns. The performance of this approach has been improved using different image processing strategies (e.g., image cropping), which can also help generalize it to other indoor environments without requiring a specific training process. Similarly, in Monti et al. (2022), Monti et al. introduce an edge-based TL solution for class occupancy detection. In this respect, the YOLOv3-based TL approach is proposed for fine-tuning the YOLOv3 weights using two types of images representing small and large classrooms. Typically, the classical client–server architecture has been shifted to a fat client–thin server architecture, where the occupancy has directly been predicted at the edge.

### 6.2. Federated learning

Occupancy detection using IoT sensors and DL algorithms is becoming ubiquitous and playing a significant role in making sustainable, energy-efficient and more livable buildings. However, inferring relevant occupancy detection information in centralized building energy management systems is frequently affected by a considerable response time delay (Varlamis et al., 2022b). Moreover, monitoring occupancy detection in buildings can raise privacy and security issues, as this sensitive information can be used to track the presence of end-users. Thus, the consequence of such breaches can be harmful to end-users if a malicious person can identify the time when potential victims are vulnerable (Kuang et al., 2021).

To overcome these issues, federated learning has recently been introduced with the aim of (i) enhancing end-users privacy by maintaining training datasets on edge devices without the need for data pool for the model, (ii) continually learning from the collected end-user's data in real-time, (iii) improving hardware efficiency since less complex hardware is used without requiring one complex central server for data analysis, and (iv) performing multi-task processing simultaneously while benefiting from similarities and differences across tasks. On the other hand, since data is recorded on multiple devices in federated learning, the attack surface can be increased (Sater and Hamza, 2021).

### 6.3. Blockchain-based IoT occupancy detection

Although intelligent occupancy detection has various applications in the building sector, it has become a thornier prospect for building end-users. Typically, IoT devices gather massive datasets, which can reveal sensitive information about the owners (Himeur et al., 2022b). Moreover, little attention has been paid to the security and privacy reservation aspects when developing occupancy detection solutions, which raise significant security challenges (Himeur et al., 2022c). Additionally, most existing systems run on centralized cloud platforms

**Table 5**
Comparison of binary occupancy detection algorithms.

| Model | Features | Training time | Testing accuracy |
|---|---|---|---|
| LR | Light and $CO_2$ | 0.42 s | 98.5% |
| NB | Weekend, working hour, light and $CO_2$ | 2.55 ms | 98% |
| k-NN | Light and $CO_2$ | 10.62 s | 97.5% |
| DT | Light and $CO_2$ | 6.38 s | 98.5% |
| RF | Weekend, working hour, light and $CO_2$ | 1198.86 s | 98% |
| GBM | Weekend, working hour, light and $CO_2$ | 67.74 s | 96% |
| SVM | Light and $CO_2$ | 99.00 s | 98.5% |
| 1D-CNN | Light, temperature, humidity, humidity ratio and $CO_2$ | 2.57 s | 98% |
| MLP | Light, temperature, humidity, humidity ratio and $CO_2$ | 1.37 s | 98% |

monitored by major tech companies. Blockchain technology can resolve these issues and others as it enables a peer-to-peer (P2P) connection without the need for a centralized validator (Andoni et al., 2019).

In this respect, more interest should be put towards using blockchain to address the privacy violation of users' data recorded from smart meters while enabling the benefits of big data analytics (Yilmaz et al., 2021). While this research topic is in its infancy, blockchain promises various benefits for occupancy detection systems, e.g., privacy protection of users' data without compromising the accuracy of occupancy detection and building operational efficiency preservation without using authoritative intermediaries. Recently, two studies have been reported in Yilmaz et al. (2021), Fernández-Caramés et al. (2020) to explore the use of blockchain in IoT-based occupancy detection systems.

In Yilmaz et al. (2021), the authors develop a counter-attack for IoT occupancy detection systems by integrating blockchain and LSTM models into a standardized smart metering framework for preventing leakage of users' personal information. Besides, a blockchain-based IoT solution to monitor and track real-time occupancy is proposed in Fernández-Caramés et al. (2020), which promotes COVID-19 public safety. This framework ensures users' privacy without collecting personal information and integrates a decentralized blockchain-based traceability system, which safeguards the gathered information's immutability, security, and availability.

Overall, despite the significance of blockchain for protecting users' privacy in IoT occupancy detection systems, this topic still needs much more investigation and careful analysis to develop real case studies, experiments, and building demonstrations. On the other hand, one of the main challenges that impede blockchain integration into IoT occupancy detection systems is its scalability and storage capacity, which are still under debate. Typically, because of the widespread use of occupancy detection sensors and cameras, gigabytes of data can be generated in real-time (Reyna et al., 2018). Consequently, this is a severe challenge when integrating this data with blockchain, keeping in mind that some actual implementations of blockchain process only a few transactions per second. Moreover, the cost of integrating the blockchain into the IoT occupancy detection frameworks represents another barrier to its adoption (Uddin et al., 2021).

### 6.4. TL perspectives

Although many TL-based occupancy detection techniques have excelled in transferring the knowledge of ML models from the source domains to different and related target domains, still little information is available regarding to what extent they can be generalized. To fill this gap, it is significant to carry out more investigations about the capability of TL not only with reference to the impact of spatial or geographical changes of building occupancy data and also when different building environments (e.g., sports facilities, commercial buildings, office buildings, households, etc.) and occupants' behaviors are considered simultaneously (Akhauri et al., 2021; Feng et al., 2021).

Moreover, various research directions can be identified to further improve TL and widen its utilization. For example, avoiding negative transfer and measuring the transferability across domains represent two critical challenges that can attract considerable research and development in the near and far future. Despite the few attempts proposed in the literature to overcome the negative transfer problem (Paul et al., 2018; Wang et al., 2019b; Minoofam et al., 2021), the latter still requires much more systematic analyses. Moreover, the interpretability of TL models will be one of the promising research paths to increase end-users' trust and acceptance of the TL technology. Additionally, the applicability and effectiveness of TL need to be theoretically supported by conducting efficient theoretical studies (Zhuang et al., 2020).

Besides, in real-world scenarios, source domain data can contain sensitive information that should be protected. In this context, transferring the knowledge included in the source domain while preserving users' privacy is a fundamental challenge. Future research effort must take this issue into consideration by suggesting to integrate efficient security and privacy preservation mechanisms, e.g., decentralized TL using blockchain (ul Haque et al., 2020; Wang et al., 2021c) and federated TL (Zhang et al., 2021; Maurya et al., 2021). Lastly, it is worth noting that TL strategies can be exploited in a broad range of applications related to occupancy detection, such as building energy optimization, building fault and anomaly detection, and thermal comfort control. This necessitates addressing the knowledge transfer issues in more complex scenarios, where a significant research endeavor can be put in the near future.

## 7. Conclusion

This paper meticulously examines the various methods of determining occupancy in terms of data collection type and algorithms used. As discussed in great detail, occupancy detection systems are primarily based on deploying various environmental sensors (e.g., $CO_2$, temperature, humidity, and light sensors) or other specialized devices (e.g., PIR sensors, smart meters, Wi-Fi/Bluetooth, and cameras). Each technology has its own set of pros and cons. As a result, a medley of numerous ambient and specialized sensors has been explored as a solution to improve occupancy detection performance.

The emphasis was on investigating DL and TL approaches for occupancy detection. While occupancy detection methods benefit significantly from DL, there are also inherent limitations. Although the CNN approach is often employed for image processing, it may not work well with time-series data. As an alternative, to make use of the particular design of the CNN networks, time-series data must be converted into pictures. On the other hand, the LSTM structure is likely to be used when there is time-series data relating to occupancy (i.e., environmental, mobility, and smart meter data). If data annotation was not supplied, the AE method would be advantageous. For occupancy detection applications, models like GAN, RBFN, SOM, DBN, and RBM are not frequently explored or utilized. A sizable fraction of the publications assessed lacked real-time model generalization and implementation. Occupancy detection approaches are compared to each other to achieve an efficient and accurate system for processing sensor data. Training a DL model from scratch necessitates a large amount of computing and memory resources and a substantial amount of an annotated dataset. Using TL, information learned from another domain (e.g., another building) might be applied to address a building occupancy detection problem. A comparison study of the widely accessible occupancy detection algorithms was performed to find the best strategy with the optimal training duration and testing accuracy. The comparison analysis was constrained since it was observed that all the open-source methods utilize the UCI-ODDs dataset.

While there are several existing room occupancy detection systems, only a few address the expanding demands of building engineers for next-generation occupancy detection. In order for buildings and houses to become "smarter" and more adaptable, new sensor technologies must identify, count, and track individuals regardless of movements. Potential directions are recommended to improve certain aspects of the existing occupancy detection techniques. The frequent use of cloud computing, for example, leads to high bandwidth demand, resulting in higher energy consumption. Moving computation to the network's edge could potentially resolve this problem. Federated learning and Blockchain-based IoT occupancy detection are also recommended to increase end-user privacy and security by moving away from centralized to de-centralized processing.

### CRediT authorship contribution statement

**Aya Nabil Sayed:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Yassine Himeur:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Faycal Bensaali:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition, Supervision.

### 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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