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A comprehensive analysis for crowd counting methodologies and algorithms in Internet of Things

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Abstract
The Internet of Things (IoT) provides a collaborative infrastructure to communicate smart devices with cloud-edge healthcare applications, medical devices, wearable biosensors, etc. On the other hand, crowd counting as one of computer vision approaches is an emerging topic to detect any objects with static or dynamic mobility in the IoT environments. Smart crowd counting enables pattern recognition for many intelligent applications such as microbiology, surveillance, healthcare systems, crowdedness estimation, and other environmental case studies. According to complicated capturing systems in the IoT environments, crowd counting methods can influence on performance of object detection in the critical case studies using Artificial Intelligence (AI)-based approaches such as machine learning, deep learning, collaborative learning, fuzzy logic and meta-heuristic algorithms. This paper provides a new comprehensive technical analysis for existing AI-based crowd counting approaches in healthcare and medical systems, biotechnology and IoT environments. Meanwhile, it presents a discussion on the existing case studies with respect to analyzing technical aspects and applied algorithms to enhance pattern prediction factors. Finally, some new innovative efforts and challenges are presented for new research upcoming and open issues.

Keywords Internet of Things (IoT) · Artificial Intelligence · Crowd counting · WiFi sensing · Image processing

1 Introduction

Nowadays, crowd sensing has a significant role in many fields, most notably safety and security [26, 56, 57]. Therefore, with the prosperity of technology such as Internet of Things (IoT) and WiFi environments, crowd counting can be used for observing and monitoring public places such as schools, airports, malls, parks, and buildings. The objects considered by the crowd counting techniques are usually either people or vehicles [18, 58]. As crowd analysis plays an essential role these days, automatic observation becomes more demanding instead of manual systems, which could be unreliable and expensive in most cases.

Crowd counting and density estimation are both addressed as computer vision problems, which are challenging tasks in image processing and video analysis [16, 40]. Crowd counting is a technique that aims to count and recognize targets in various situations. It takes an image or a frame of a video as an input and outputs the number of individuals in it. Despite manual crowd counting, which can be demanding and inaccurate, automatic systems help estimate the crowd density precisely.

There are various crowd counting applications in different fields of safety, health care, disaster activities, people estimation, and forensic search. For safety issues, crowd counting methods used in public places such as airports and gatherings can be used in surveillance videos to analyze crowd behaviors [9, 15, 25]. In health-care applications, crowd counting plays a vital role with patients suffering from cancer and other illnesses, where counting

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some cancerous cells for early-stage diagnosis is important [13, 53]. In disaster management, analyzing the gathering can lead to early detection of overcrowding and better management in different public events such as sports events, concerts, and political rallies. In public design, optimizing the design of new buildings can be utilized by crowd counting methods. In forensic search, in most cases including populated situations, face detection has been enhanced from traditional methods by crowd counting [48].

There are some challenges facing crowd counting techniques including occlusions [2], high cluttering [17], illumination variation [39], and scale variations [19, 60]. For instance, varying object density reduces the accuracy of prediction. On the other hand, intensive occlusion increments the error of prediction. Further, high cluttering can replicate an estimated map's resolution and light illumination can lessen its accuracy. Similarly, scale variation reduces both the re solution of a density map and counting prediction.

Due to various applications, from security to design purposes, crowd counting is an inherently challenging issue to be solved. Many researchers have tried to provide surveys of previous techniques in detail [5, 14, 24]. Unlike the previous literature reviews, this paper presents a new comprehensive analysis and technical discussion on the existing Artificial Intelligence (AI)-based optimization algorithms for crowd counting and monitoring approaches in the IoT environments.

The organization of this paper is shown as follows: Sect. 2 presents a literature review based on existing published works in the fields of crowd sensing and crowdsourcing strategies. Section 3 illustrates a paper selection method based on keywords and technical inclusion aspects. Section 4 shows a technical taxonomy for the proposed crowd counting issue based on AI-based optimization algorithms. Also, each related case study is discussed on the existing subcategories of the technical taxonomy. Section 5 presents a technical analysis on each category and existing applied algorithms and evaluation factors. Section 6 depicts open issues and new research challenges of this issue as well. Finally, Sect. 7 shows conclusion and future work.

2 Related work

This section focuses on reviewing the conducted research studies that addressed crowd counting methods using AI in IoT environments as part of them.

Hassen et al. [20] conducted a review of 61 articles that mainly focused on the crowd counting methods which had been shifted from the heuristic to CNN models these days. The authors reviewed the articles by their results on various datasets. Therefore, they partitioned the used datasets into crowded and sparse ones.

Li et al. [30] presented a review of studies, presented in the past 20 years, concentrated on CNN-based crowd counting models and divided them into seven categories (GAN-based, Context-based, Coarse to Fine, Multi-scale feature fusion, Attention-based, Patch-based and Multi-density map fusion) based on their guiding ideology. In addition, the work of video-based crowd counting and few-shot learning was described. Chrysler et al. [11] proposed a review of articles that focused on crowd counting models, especially CNN models.

The presented review by Ilyas et al. [23] concentrated on articles within which convolutional neural networks were employed for crowd counting and divided them into three main categories (network-based, training-approach-based and image-view-based). A detailed quantitative comparison within each subcategory [in terms of n Mean Absolute Error (nMAE)] and the conclusions based on various datasets was provided such as WE, UCF, STB, and STA. The authors reviewed recent CNN-CC techniques, comprehensively, and then subdivided the image-view-based CNN-CC techniques into aerial-view-based and perspective-view-based.

Nguyen et al. [35] conducted a review of studies that focused on crowd counting using deep learning approaches and categorized them by considering how they address the counting challenges. This review concludes 2 major challenges and their DL solutions, which are density variation and labelled data shortage. Both a coarse counting and divide-and-conquer were identified, which was not comprehensively discussed in the past reviews. On the other work, Sindagi et al. [42] presented a survey of recent CNN-based approaches which rely on hand-crafted representations.

Also, Ryan et al. [41] evaluated crowd counting algorithms under three approaches: holistic, local and histogram. The results show that using local features outperform the equivalent two other approaches. Five public datasets (such as Fudan, PETS 2009, UCSD, Mall and Grand Central datasets) were used for evaluating the performance following a K-fold cross validation protocol. In addition, the image features were categorized into 5 types including shape, size, edges, textures and key points.

In Table 1, some technical comparisons are shown based on the above case studies in the literature review. With respect to this comparison, existing review and survey papers just focused on CNN-based machine learning algorithms or deep learning methods. Also, the existing published papers have categorized crowd counting to image density-based methods. On the other hand, in this paper we categorized crowd counting methodologies into three main classes that will presented in Sect. 3. Also, this

Table 1 Comparison of existing technical points for existing review case studies

Research	Reviewed main case study	Publication period	Technical keywords	Executed literature search
Hassen et al. [20]	CNN-based crowd counting approaches	Not mentioned	"Crowd counting", "crowd estimation", "crowd detection", "people counting", and "computer vision for crowd counting"	ScienceDirect and Scopus
Li et al. [30]	Deep learning-based counting methods	2008–2020	"Crowd counting", "Deep learning", "Conventional Neural Networks"	Not mentioned
Chrysler et al. [11]	CNN-based crowd counting approaches	1995–2019	"Crowd counting", "CNN"	Google Scholar
Ilyas et al. [23]	CNN-based image crowd counting	Not mentioned	"Microscopic images", "Crowd counting", "CNN"	Not mentioned
Nguyen et al. [35]	Single-image crowd counting using Deep Learning	2016–2019	"Crowd counting", "Deep learning"	Not mentioned
Sindagi et al. [42]	CNN-based single image crowd counting	Not mentioned	"Crowd counting", "CNN"	Not mentioned
Ryan et al. [41]	Crowd counting methods with Regression	Not mentioned	"Crowd counting", "Regression"	Not mentioned
Proposed systematic review	Crowd counting methodologies in IoT	2015–2022	"Crowd counting", "People counting", "Machine learning", "deep learning", "artificial intelligence", "meta-heuristic", "Medical system", "Internet of Things", "IoT", "Healthcare", "Smart city	Scopus, Web of Science, Google Scholar, IEEE, ScienceDirect, Springer, Wiley, Sage, Inderscience

review provides all crowd counting case studies in the IoT architectures.

3 Research finding and analysis

This section provides research finding strategy to select relevant titles and technical contents for presenting existing AI-based methodologies for crowd counting method in healthcare systems and IoT environments. First, a comprehensive keyword search is applied to scientific databases. Then each title and content of abstract is checked to near relevant content with AI-based crowd counting methods. In the next refinement selection method, each review or survey paper, technical thesis, book chapter and non-peer reviewed paper is removed from the database. Based on the search procedure in this research from 2015 to the end of August 2022, 212 published papers in the field of crowd counting in the IoT have been recorded in scientific databases. Many papers, in this level, have been refined based on main key aspects of the proposed comprehensive research analysis.

In this way, the important areas of interest in the selected articles are identified. In this regard, based on inclusion and exclusion methods, we selected 30 research studies to analyze statistical and technical aspects of the proposed issue.

After refinement of AI-based crowd counting techniques in IoT, following pattern have been investigated for research selection method:

> "Crowd counting" OR "People counting" AND "Machine learning" OR "deep learning" OR "artificial intelligence" OR "meta-heuristic" AND "IoMT" OR "Internet of Things" OR "IoT" OR "Healthcare" OR "Smart city".

By considering the research gaps and new challenges, the following technical questions will be answered:

- Which crowd counting models have been studied and evaluated in the field of IoT?
- Which AI-based optimization algorithms were applied to evaluation of crowd counting in IoT?
- Which prediction factors and performance evaluation metrics are applied in this issue?
- What are the most common pairs of words in the crowd counting methods using AI-based optimization algorithms?

Based on the above technical questions, the existing selected research papers will be classified into a technical taxonomy and analyzed with respect to technical aspects of crowd counting methods, image processing algorithms, evaluation of prediction factors and new research direction methods.

4 AI-based crowd counting methods in IoT

This section provides the existing AI-based crowd counting methodologies based on computer vision in the IoT environments. Also, a new technical classification is presented to show applied AI-based optimization algorithms to detect object activities and evaluation of each optimization algorithm in each methodology.

Crowd Counting is provided to estimate and detect the number of any objects in a data flow video stream and image. Actually, counting the number of existing objects in each slot of video or an image is a critical challenge according to complex objects, shape and form of image and quality of resources. On the other side, many applications such as healthcare systems, medical and biological systems, urban planning have many challenges to create and gather existing data from their environments to detect targeted objects using the IoT devices [51]. AI-based crowd counting methods particularly provide optimized prediction approaches on object detection according to guaranteeing social privacy and security for smart applications [45]. Figure 1 illustrates a technical categorization of existing crowd counting approaches using AI-based computer vision methodologies in the IoT and healthcare systems. This technical model divides existing crowd counting approaches into three types, including people estimation, object estimation and density estimation. The people estimation approach is considered for counting, localization and behavior detection of people with each defined target using smart devices such as WiFi, IoT environments and mobile applications. On the other hand, Object estimation includes different case studies to detecting and counting existing objects such as garbage, military equipment, micro-organizations, environmental objects such as animals, plants, rocks etc., house and buildings, and any objects that influence on human-life activities. Finally, density estimation refers to existing localization and behavior detection models to monitor the set of object, people or any defined target in the smart environments.

Figure 2 presents a technical taxonomy for existing crowd counting environments. This approach has two main environments for counting and monitoring that include indoor environments and outdoor environments. In the indoor environments, all academic locations such as universities, campus, classrooms, kindergarten, research centers and scientific venues are considered for counting and estimating people. In transportation indoor environments, there are some case studies to detect and monitor people of a metro wagon, taxi or airplane. For counting, estimating and detecting sport, entertainment activities, medical and healthcare centers in indoor environments, there are some AI-based crowds counting approaches to predict people and objects. On the other side, for outdoor environment's, there are different locations such as public locations including parks, zoo, streets, highways, roads, and in military environments, underwater, see and beach, forest and mountains.

4.1 People crowd counting using AI-based methodologies

This subsection illustrates existing AI-based crowd counting approaches for monitoring and detecting human aspects in the IoT environments.

Khan et al. [27] presented an efficient device-free crowd counting system with the use of Transfer Learning (CrossCount), to minimize the vulnerability of channel-state-information-based crowd counting systems to environmental dynamics. The proposed framework categorizes the number of the individuals in a room with the help of the collected channel state information (CSI) data and convolutional neural networks (CNN). The authors evaluate the adaptability of the model's environment under different practical scenarios such as the distance between the transmitter and receiver and line-of-sight/non-line-of-sight

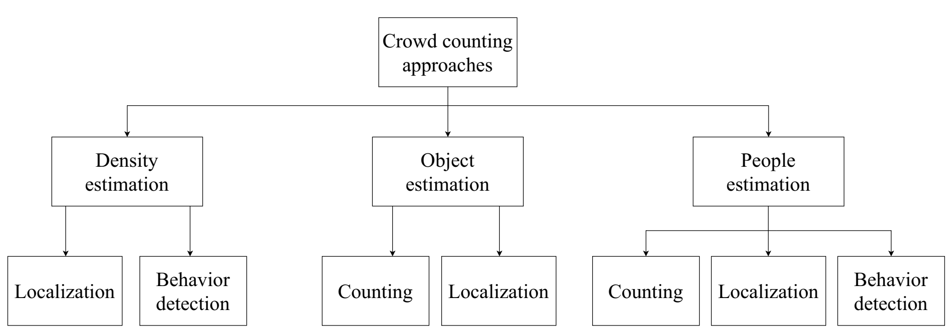


Fig. 1 Existing crowd counting approaches using AI-based computer vision methodologies

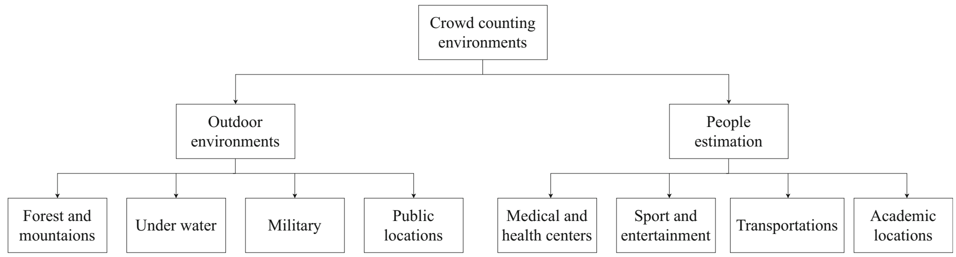


Fig. 2 Existing crowd counting environments to detect targeted objects and people

(LOS/NLOS), antenna selection, number of people, received signal strength indicator (RSSI) threshold and Crowd classification. The experimental results indicate that this model is 4.7% more accurate and 40% lower in training time comparing to conventional CNN models.

Bernaola et al. [7] focused on a device-free seated people counting model in an indoor environment exploiting Ensemble Learning. The model provides a Channel State Information (CSI) to determine which one leads to a higher accuracy. Evaluating transferability of the captured knowledge from ensembles, came to this conclusion that when the model is trained in an exact frequency, its knowledge cannot be transferred among other ones. Through the results, the ensembles fed with raw traces acquire accuracy up to 80%.

Choi et al. [10] proposed an estimation system, called Wi-Cal, which can not only count the crowd but also can estimate the location of the crowd simultaneously by machine learning and WiFi IoT channel state information (CSI) solution. This system is assessed by both deep learning (DL) and machine learning (ML) to extract features that contribute to static state (localization) and dynamic state (moving crowd).

Huang et al. [21] designed an occupancy counting system to be used in energy-efficient buildings. This design accurately counts the number of entries and exits of a building. Both Lattice iCE40-HX1K stick FPGA boards and Raspberry Pi modules were used for making the prototype. The occupancy quantity of a region, was estimated by the prototypes installed at door frames and sent to a Raspberry Pi that supports the data communication between users and the automation system. For better visualization and data processing, an open-source user interface was developed. A 3-month test has been taken from the entry and exit region. The accuracy of 97% has been resulted from the experimental results which leaded to 12% energy reduction. Overall, the presented system had a low cost and an easy usage with a low rate of failure.

Ibrahim et al. [22] presented a device-free crowd counting system based on Recurrent Neural Networks called CROSS-COUNT which leverages the temporal blockage information of a WiFi link to provide accurate results. For decreasing data collection overhead, the authors proposed a technique for class balancing and training data augmentation. Also, the presented system achieved higher accuracy than the current state-of-art counting models based on radio frequency signals (RF) because the blockage pattern has been classified using a Long Short-Term Memory (LSTM) network. The CROSS-COUNT experiments have been taken in cluttered and clear WiFi testbeds and the results show that the model can count the exact number of people 59% of the time, and also, it would have an accuracy of 100% within 2 persons.

Kianoush et al. [29] proposed a target counting method with respect to physical layer and channel activities in the space-frequency domain.

Metwaly et al. and his colleagues [34] proposed an embedded algorithm for crowd counting based on a thermal sensor with high accuracy. The authors designed various deep learning models for estimating the number of people in a room with the use of thermal images. Then, they analyzed the thermal images by implementing these models on Arm Cortex M4 and M7 microcontrollers. The experimental results show that the thermal imaging technique is promising for crowd counting among other models, such as the ones based on RGB cameras. Experimenting on an extended dataset, and studying the impact of the camera distance on the subjects, could be done in future works.

In this study, presented by Padmashini et al. [36], three alternative people detection algorithms were tested against a Deep-Neural-Networks-based (DNN-based) people counting method. In terms of accuracy and precision, the deep neural network outperforms the other three conventional and traditional techniques. These algorithms have been tested under different conditions such as fluctuating density flow of people and presence of occlusion.

The use of WiFi signals for device-free people counting in IoT contexts has been thoroughly studied from several research perspectives. The contributions of machine learning models to this topic have been described by Sobron et al. [43] with a clear focus. The authors presented a comprehensive review of various features and ML models which were employed for recognizing human activity in IoT environments, with the focus on tracking and counting the crowd. They also proposed an open dataset coined as EHUCOUNT with wireless signals captured over diverse physical IoT environments. Then, they extract an experimental benchmark from the EHUCOUNT dataset with 11 different ML models and 374 features.

Tsou et al. [49] designed a device for counting individuals with a passive infra-red sensor (PIR) array detecting the passing situations and generating data records with higher discriminability. In order to identify the passing situations, the authors applied machine learning (ML) classification methods such as Decision Tree, Naïve Bayes, the RBM+LR and the Convolutional Neural Network (CNN) on the collected data records. The experimental results show that the CNN achieves higher accuracy and robustness than other methods.

Wang et al. and his colleagues [50], have provided a system for respiration tracking using Channel State Information of commercial WiFi devices for counting and recognizing human subjects without any prior knowledge of the crowd. They have used sub-carrier (SC) combination method to enhance signals, iterative dynamic programming (IDP) and estimate crowd number to leverage traces for recognition. They have made use of a pair of commodity WiFi devices for their experiment and all the data are collected in an on-campus lab and a car for over two months. The authors developed a breathing rate trace tracking system which can count people as well as recognition. As they mentioned in the article, the advantage of this system compared to similar systems is the ability to identify the number of people by the breathing trace, with a high percentage of accuracy and low error.

Zhang et al. [59] suggested a counting scheme based on WiFi CSI (Channel State Information) and a deep learning network for counting the number of people in a queue. They used amplitude and phase information for identifying the number of people, MIMO (multiple-input and multiple-output) technology with two transmitter antennas and three receiver antennas, novel Fresnel zone model, DL and convolutional neural network to achieve the desired result. The authors proposed a scheme to count queuing people based on Fresnel zone diversity. This article has only expressed a scheme that hasn't been implemented, therefore it's not possible to reach a conclusion about the efficiency of the designed system, but have optimized neural networks and used static solutions alongside dynamic ones.

Babu et al. and his colleagues [4], has been proposed a project to provide the real-time count of people in a public area via application or website. They have used Linux platform for development of android application, Application Program Interface (API) for testing and implementation of application, Android Studio as the main working software, Aurdino based IoT device for person counting, ultrasonic sensor and motion sensor and Haar Cascade algorithm for face detection. The authors presented the idea of designing a software that is used to count people present in a public place and recognize their faces. This app would help users to choose a place with less population density by displaying the population density in each public place. Moreover, it helps to reduce crimes with the face recognition, but this software has not been really developed yet.

Tang et al. and his colleagues [46], presented a Passive WiFi Radar (PWR) technique for occupancy detection and people counting. They applied Cross Ambiguity Function (CAF) processing and used Time-Frequency transforms and employed the CLEAN algorithm and a Convolutional Neural Network (CNN). This system only could achieve both occupancy state detection and people counting, up to 4 people, and the environment was not similar enough to the real one. It doesn't require any modifications to the WiFi access point or additional devices, and extracts target reflections through cross-correlation-based processing.

Zeyad et al. [1] provided a people counting system based on computer vision to present information about the number of people in a specified place. They used a regression model to estimate the number of people. They used a method on conventional cameras for the people counting systems. They said this method is the best for these reasons: cost-efficiency, high flexibility, ability to provide accurate distribution information, wide coverage, and high accuracy. They used The University of California (UCSD) and the Peds2 datasets to achieve results. The proposed system can be used for energy efficiency and the detection of local anomalies in applications such as product display and population control.

Yang et al. [54] presented a crowd counting system called the Wi-Count system, which not only could count the number of people passing through a doorway utilized with Commercial Off-The-Self (COTS) WiFi devices, but also could detect the passenger's direction. For this model to detect the bi-directional movements, the pattern of phase difference series of WiFi signals should be analyzed. The authors observed the detailed information on the crowd behavior by applying source separation techniques. The experimental results show the average accuracy on passing direction detection of 95% and the average accuracy on passing people counting of 92%.

According to Table 2, existing characteristics and technical factors for AI-based people counting methods are presented.

4.2 Object crowd counting using AI-based methodologies

This subsection illustrates existing machine learning and deep learning algorithms for counting and localization of different objects in the IoT environments. There are several case studies to detecting and counting existing objects such

Table 2 Existing characteristics and technical factors for AI-based people counting methods

Research	Main case study	AI method	Technical platform	Simulation environment	Evaluation factors
Khan et al. [27]	Efficient device-free crowd counting system	Convolutional neural networks (CNN)	IoT	MATLAB	Accuracy, time
Bernaola et al. [7]	Device-free seated people counting model in an indoor environment	Ensemble learning	IoT	–	Accuracy, transferability
Choi et al. [10]	Device-free crowd counting and localization	Machine learning	IoT	Python	Counting accuracy, localization accuracy
Huang et al. [21]	Accurate people counting system	–	IoT	A node.js server is implemented inside the Raspberry Pi	Accuracy, cost, usage, energy reduction
Ibrahim et al. [22]	Device-free human counting system	Recurrent Neural Network	IoT		Accuracy
Kianoush et al. [29]	Device-free target counting system	Machine learning	IoT		Accuracy
Metwaly et al. [34]	Crowd counting system based on a thermal sensor	Deep learning	IoT		Accuracy, execution time
Padmashini et al. [36]	Vision based algorithm for people counting	Deep Neural Network	IoT	Python	Accuracy, negatives
Sobron et al. [43]	Device-free people counting	Machine learning	IoT		Accuracy
Tsou et al. [49]	A people counting system based on passive infra-red sensors (PIR)	Convolutional neural networks (CNN)	IoT	Python Django	Accuracy, robustness
Wang et al. [50]	A people counting and recognition system		IoT		Accuracy
Zhang et al. [59]	count queuing people based on Fresnel zone diversity	Deep learning networks for static models and Convolutional Neural Network for feature extraction	IoT		Accuracy
Babu et al. [4]	A real-time count of people in a public area	Haar Cascade algorithm, OpenCV algorithm for the face detection	IoT	Python and MATLAB	Accuracy
Tang et al. [46]	An occupancy detection and people counting system	Convolutional neural networks (CNN)	IoT	–	Cost, accuracy, simplicity, sensitiveness
Zeyad et al. [1]	A crowd counting system incorporated with existing CCTV cameras	Regression techniques (machine learning)	IoT	The University of California (UCSD) and the Peds2 datasets	Mean absolute error (MAE) and mean squared error (MSE), accuracy
Yang et al. [54]	A passing people counting system with COTS WiFi	An enhanced signal separation algorithm	IoT		Accuracy

as garbage, military equipment, micro-organizations, environmental objects such as animals, plants, rocks and etc., house and buildings, and etc.

Wang et al. and his colleagues [52] presented a crowd counting system based on both Convolutional Neural Network (CNN) and WiFi Channel State Information (CSI) in an environment based on WiFi. The proposed system uses the information of the CSI as the input of the convolutional neural network to process. Furthermore, the experimental results show a recognition accuracy of 97% in the environment of 6 individuals. This work not only analyzes the influence of distance between the access point (AP) and the personal computer (PC) on recognition accuracy, but also discuss the performance of the Long

Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) beside the CNN.

Yu et al. [55] proposed a real-time 3D visualization system for crowd counting that could display every data through a 3D animation instead of the traditional scheme which was limited in a single shot. This model makes the spatial relationships clear for the users. Despite traditional 2D systems, this 3D system represents a good user experience as well as a comprehensive cognition which could tell crowd collapsing from separate cameras and provide warnings. The experimental results show that although the system's accuracy is good, more efforts can be done for its improvement. Also, optimizing the communication between clouds and sensors could become better.

Liu et al. [33] performed a channel-state-information-based sensor-free crowd counting system with the help of the existing WiFi infrastructure in a low-cost, non-intrusive and precise manner. The proposed framework is treated as a classification process. Also, some features are selected and taken as inputs of some Machine Learning algorithms which the best was Support Vector Machine (SVM). The system works in a precise and beneficial manner because it only utilizes Commercial Off-The-Self (COTS) WiFi infrastructure and a mini computer instead of using extra sensors. The experimental results show the accuracy that the overall accuracy of 87.2%. Exploring the influence of moving speed individuals and number of objects can be further discussed.

Zou et al. [62] have presented a Wifi-based device-free crowd counting and occupancy detection model called WiFree. For measuring the occupancy detection, the authors designed an IoT platform based on OpenWrt in order to directly obtain channel state information measurements in PHY layer from the pervasive IoT device. Then, they sanitized the raw CSI data with a discrete wavelet transform (DWT) de-noising scheme and by measuring the shape similarity between contiguous time series CSI curves, the occupancy detection scheme was built by them. They have also designed an information theory-based feature selection scheme to recognize the most vigorous features for individuals counting. A crowd counting classifier based on transfer kernel learning (TKL) was designed to improve the robustness of the model. Due to the training feature data and the real-time feature data, TKL was able to build an invariant kernel which reduced the difference between the source and the target distributions. The experiments were held in 3 indoor environments with various sizes, and the results conclude the accuracy of 99.1% for occupancy detection and the accuracy of 92.8% for crowd counting.

Brena et al. [8] proposed a novel system for crowd counting using recognition of patterns in the channel state information (CSI) over multiple links. This system had better performance and higher accuracy by using multiple links than using a single one or the average of several links together. For a precise estimation of counting, fewer features were required to be derived from the signal. Thus, the processing time was reduced since the extraction of the features needed less power for computing. The presented method was based on supervised classifiers that rely on data-driven machine learning. The experimental results show the improvement of the prediction accuracy from 44% with a single link to 99% with six links.

Liu et al. [32] presented DeepCount, a novel system which solve multi-objective environmental sensing problems use the deep learning (DL) approach with WiFi signals. DeepCount is the first solution to use neural networks as a crowd counting solution. Preliminary results show that compared to the traditional classification algorithm such as Support Vector Machine (SVM), DeepCount can achieve an average recognition accuracy of 86.4%.

Solmaz et al. and his colleagues [44], presented a machine learning (ML) system to fix the crowd estimation problem. This system transferred the calibration task from cameras to machine learning after a short training with the information collected from the environment using cameras.

Elharrouss et al. [12] provided a neural networks to show the number of a crowd estimated with scale variations, and it is a combination of convolutional layers from VGG-16 and a cascade network. The authors compared their method with another ten methods by ViseDrone2020 and experimental results showed their method was better.

According to Table 3, existing characteristics and technical factors for AI-based object counting methods are presented.

4.3 Density-based crowd counting using AI-based methodologies

This subsection shows applied AI-based optimization algorithms for density estimation in crowd detection and localization approaches.

FreeCount is a device-free method of crowd counting proposed by Zou et al. [61] that relies solely on common WiFi routers to calculate the precise population density of an area. In areas of average size, FreeCount can operate with just two routers. To select the most representative subset of features for crowd counting estimation, we proposed an information theory-based feature selection scheme. The results of the experiment showed that FreeCount is capable of reliably providing crowd counting accuracy of 96% throughout temporal variance. In order to collect the channel state information measurements in the PHY layer directly from Commercial Off-The-Self (COTS) WiFi routers, been created a new OpenWrt-based software for those devices.

Table 3 Existing evaluation factors for AI-based object counting methods

Research	Main case study	AI method	Technical platform	Simulation environment	Evaluation factors
Wang et al. [52]	Crowd counting system	Convolutional neural networks (CNN)	IoT	MATLAB	accuracy, recall
Yu et al. [55]	Real-time 3D visualization system for crowd counting	Machine learning	Visual Internet of Things (V-IoT)	Unity platform with C# programming	Accuracy, real-time, recall
Liu et al. [33]	Sensor-free crowd counting framework for indoor environments	Machine learning (wavelet-based de-noising algorithm, SVM, RF, KNN, DT)	IoT	Matlab and Python	Accuracy
Zou et al. [62]	Device-free occupancy detection and counting model	Transfer kernel learning (TKL)	WiFi-enabled IoT	MATLAB	Accuracy
Brena et al. [8]	Device-free crowd counting system	Machine learning	IoT	MATLAB	Prediction accuracy
Liu et al. [32]	Crowd counting with WiFi	Convolutional neural networks (CNN)	IoT	Matlab, Python 3.6 and Tensorflow	accuracy, precision
Solmaz et al. [44]	A crowd estimation system with Wi-Fi in Smart Cities	Machine learning for calibration by polynomial regression and neural networks	IoT	–	Accuracy
Elharrouss et al. [12]	A scaled cascade network for crowd counting on drone images	Convolutional neural networks (CNN)	IoT	PyTorch	Accuracy, effectiveness

Ptak et al. and his colleagues [37] provided a crowd counting system based on machine learning algorithms. This counting system works by collecting aerial images by an unmanned aerial vehicle (UAV). To take these types of images, they face more challenges than CCTV camera images. The proposed method requires collecting video sequences, so the authors used VisDrone 2020 Crowd Counting challenge dataset. Also, they used the Xavier NX platform which has good computational power. The neural network model uses for the clarity of the input images and needs a more complex neural network model to achieve high clarity. These items are considered on onboard image processing. Some future works include working on a larger variant of VisDrone—the Drone Crowd dataset also, using directly utilizing the temporal information from more frames with 3D convolutions.

Amirgholipour et al. [3] provided a new Pyramid Density-Aware Attention-based network (PDANet) for crowd counting. PDANet presents correct crowd counting with two-scale density maps. They used the sigmoid function to collect density maps and generated a gating mask for making final density maps. Their PDANet has better performance than other advanced methods. In the future, they have two ideas.

According to Table 4, existing characteristics and technical factors for AI-based density estimation on crowd counting methods are presented.

5 Discussion and statistical analysis

This section presents a discussion and technical aspects of the crowd counting issue on the existing AI-based optimization approaches according to presented technical questions in Sect. 3.

- Which crowd counting models have been studied and evaluated in the field of IoT?

To discuss on the above analytical question, Fig. 3 shows an analytical result on existing crowd counting types that have been evaluated using AI-based optimization methods for evaluation of density, counting and localization of people and objects. According to the following results, crowd monitoring and evaluation of people counting using machine learning and deep learning approaches has the highest research analysis with WiFi sensing in the IoT environments. The existing case studies that have been examined for people counting, behavior detection and localization are included people counting in indoor environments, people localization in outdoor environments and

Table 4 Existing technical factors for density estimation on crowd counting methods

Research	Main case study	AI method	Technical platform	Simulation environment	Evaluation factors
Zou et al. [61]	Device-free crowd counting method	Transfer kernel learning (TKL)	IoT	MATLAB	Accuracy
Ptak et al. [37]	A crowd counting and density estimation system	Machine learning	IoT	Segmentation Models PyTorch library	Accuracy
Amirgholipour et al. [3]	A Pyramid Density-Aware Attention-based network (PDANet) for crowd counting	A combination of adaptive machine learning algorithms	IoT	–	Effectiveness

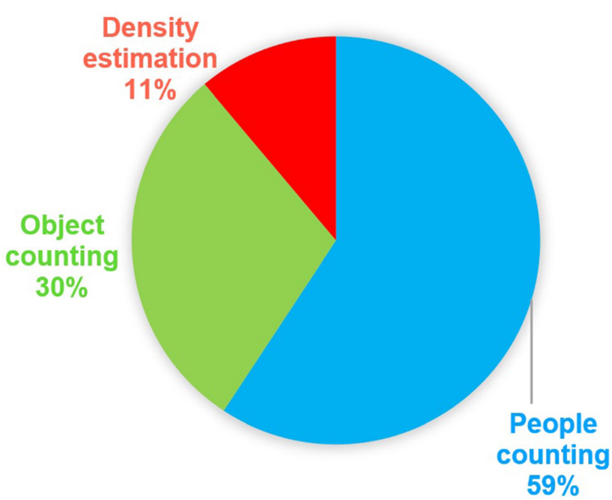


Fig. 3 Existing Variety of crowd counting and monitoring with AI-based optimization algorithms

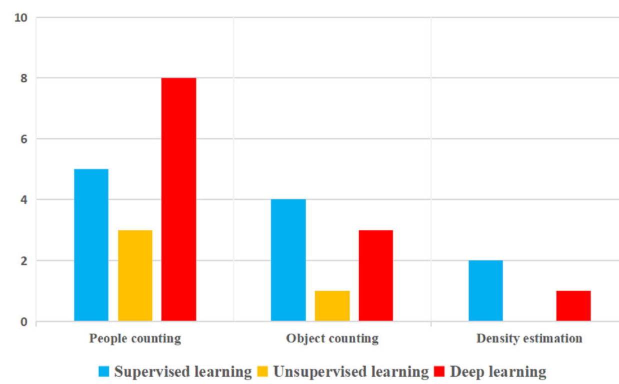


Fig. 4 Existing AI-based optimization algorithms to evaluate crowd counting approaches

human behavior detection in indoor environments. On the other side, object counting using AI-based optimization algorithms provides smart devices and IoT applications to detect and monitor targeted objects in outdoor environments such as smart farming, forests, mountains and public centers of city. For example, UAV or drones can monitor a categorized location for estimating density of crowded objects and send a video stream or set of sequential images to cloud data centers. Then, machine learning algorithms or deep learning methods are applied to the real data for prediction procedure and pattern detection.

- Which AI-based optimization algorithms were applied to evaluation of crowd counting in IoT?

According to existing crowd counting and monitoring approaches, Fig. 4 shows applied different machine learning and deep learning algorithms based on each sub-category of crowd counting approach. Deep learning methods have the highest usage for enhancing prediction and detection procedure on crowd counting.

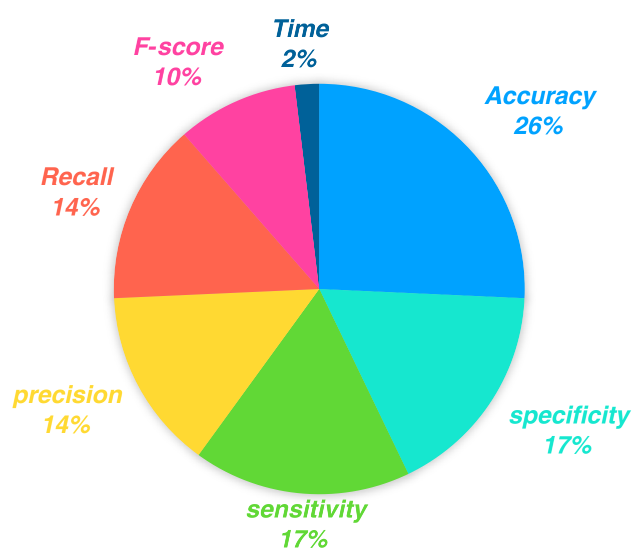


Fig. 5 Evaluation factors for prediction of crowd counting

- Which prediction factors and performance evaluation metrics are applied in this issue?

According to the existing case studies, Fig. 5 illustrates a variety of evaluation factors that have been examined and evaluated for crowd counting, monitoring and detection of people, and objects. According to this figure, accuracy, specificity, sensitivity and precision are important factors that have been evaluated using applied machine learning algorithms in different case studies. On the other hand, some other important factors such as security, execution time, energy consumption of devices and sensors, privacy and throughput can be considered as new challenges of new case studies to analyze and evaluate based on crowd counting.

- What are the most common pairs of words in the crowd counting methods using AI-based optimization algorithms?

According to main variety of applied main topics and keywords in crowd counting and monitoring with machine learning algorithms, Fig. 6 shows a cloud-word illustration based on technical priority of evaluation and accessibility for each category.

6 New innovative challenges and open issues

According to main weaknesses and some gaps between AI-based crowd counting case studies and IoT environment, this section presents some new innovative challenges and open issues for upcoming research studies.

- Energy management for existing smart sensors and cameras to crowd courting object activities is a critical issue based on limited power saving and battery life of existing devices in IoT environments [6].
- Enabling Blockchain technology for supporting security and privacy for video data streams in crowd counting procedure is one of important open issues that should be paid more attention to it. Blockchain technology can influence on storage of data transmitted blocks for each rendering round in counting existing objects.
- Federated learning as one of new and powerful AI-based methods is applied to support privacy factor of critical records in prediction phase. Federated learning can enhance the accuracy and execution time factors for crowd counting methods in parallel [38].
- Indoor/outdoor crowd counting is one of important issues to support density detection of people using the IoT devices [33]. Improving precision counting is a main challenge according to laser scanning and thermal sensors in the real-time camera recording [47].
- Real-time people density counting and detection is very critical for finding terrorist attacks in cyber security and defense activities. In crowded areas, crowd sensing cameras can detect the movements of suspicious people among the crowded location. Optimizing data segmentation on images and video streams is one of major challenges in crowd counting approaches [31].
- Smart traffic management is a critical problem in recent years. Density of vehicles can be detected using crowd counting approaches with respect to the IoT sensors, intelligent cameras, UAV-based monitoring systems. By using crowd counting in outdoor density detection, meta-heuristic algorithms and machine learning methods can be useful for optimizing routing case studies [28].

According to the above-mentioned open issues and new challenges, Fig. 7 illustrates a taxonomy for existing open issues and new research challenges for upcoming research works in the crowd counting approaches in the IoT.

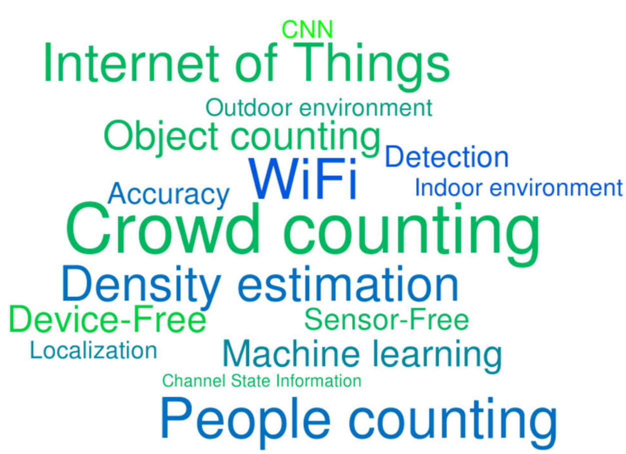
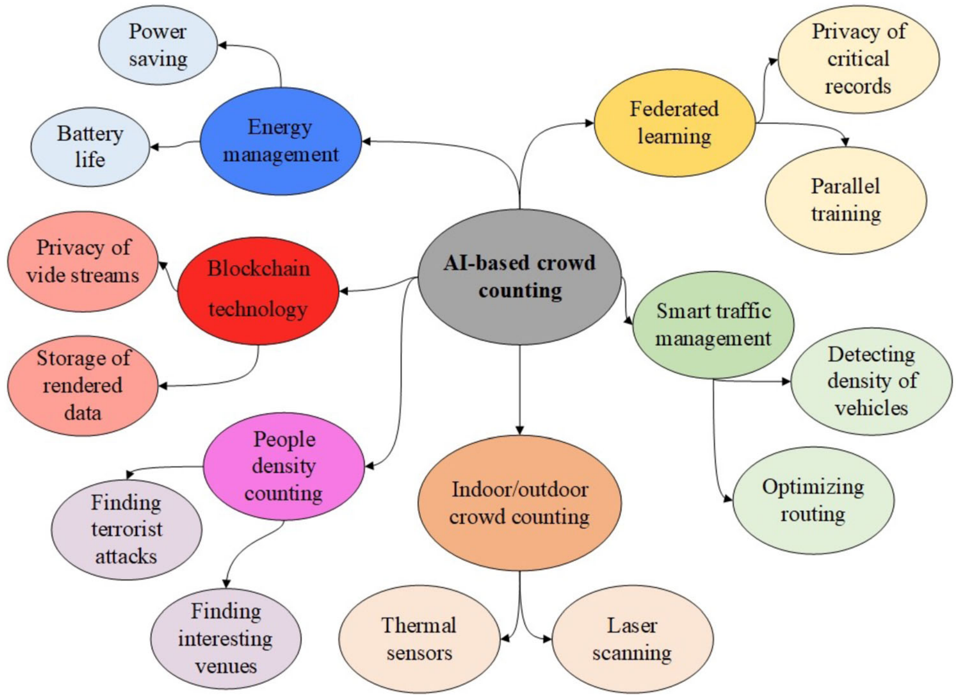


Fig. 6 Cloud-word illustration for crowd counting and monitoring using machine learning algorithms

7 Conclusion and future work

In this paper, a comprehensive discussion was presented for existing crowd counting approaches with respect to technical objectives, optimization techniques based on machine learning methods, deep learning models and existing open issues and new challenges in IoT environments. Also, different crowd counting and monitoring based on existing human activities and targeted objects have been described using WiFi sensing methods. We have categorized existing factors of the crowd counting to three main classes which provide the optimization of crowd monitoring, object detection and people counting according to the prediction factors, environmental activities, smart devices and weakness issues. Then, a detailed discussion on the optimization techniques based on machine learning algorithms and existing evaluation factors have been presented. According to the above-mentioned challenges, the

Fig. 7 Open issues and new challenges of crowd counting



results show that all the lakes of crowd monitoring should be analyzed and research on them is a critical issue that it is necessary to collect more attention in the IoT environments.

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Declarations

Competing interests The authors have not disclosed any competing interests.

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