IoT-Based Crowdsensing for Smart Environments

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1 Introduction

Sensing and monitoring of different aspects of a city (pollution, traffic, and heath) for improving the quality of citizens' life is an essential component of building smart city environments. In recent years, Internet of things (IoT)-based crowdsensing has grown as a captivating approach for sensing and acquiring data for smart environments. Sensors and communication technologies incorporated in regularly utilized smart handheld devices (e.g., smartphones and tablet) and wearables are employed in crowdsensing systems. These devices typically include a large number of sensors, allowing them to acquire a variety of data such as image, audio, video, geo-location, and environmental information. In this context, these smart IoT devices could be utilized for effective monitoring of different dynamics, namely traffic and road condition, environmental pollution, smart home and health. More specifically, IoT-based crowdsensing is helpful to monitor and manage a city's infrastructures as well as its resources efficiently based on the acquired sensor data.

IoT-based crowdsensing has several benefits over standard sensor networks that require the installation of a huge number of stationary wireless sensor units, especially in urban settings [1]. The widespread availability of smartphones and wearables, as well as a large number of built-in sensors, are unquestionably significant facilitators for the effectiveness of the crowdsensing paradigm. The sensors such as accelerometers, microphones, gyroscopes, and cameras are some of the examples

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that have aided the creation of a variety of applications in a variety of settings, including traffic and road conditions, environmental pollution, smart home, and health monitoring. A lot of crowdsensing-based applications were already designed and implemented in the past and are in use today. In order to provide representative examples, Nericel [2], Wolverine [3], and ScanTraffic [4] are some systems for traffic and road condition monitoring. For this purpose, these applications utilize smartphone-equipped sensors like accelerometers and GPS (global positioning system). On the other hand, applications like AirSense [5], HazeWatch [6], Common Sense [7], and GasMobile [8] develop light weight and low-cost devices for air quality assessment. These applications depend on citizens' direct involvement in air quality monitoring, which necessitates the use of IoT-based modules to acquire data. Similarly, several applications are also available for health monitoring and smart home. HealthAware [9] and SPA [10] are examples of smartphone-assisted systems for health care and well-being. Dutta and Roy [11], Lee et al. [12], and Froiz-Míguez et al. [13] are some existing works on various smart home solutions.

In this chapter, the details of IoT-based crowdsensing applications for various city dynamics, available techniques, issues, and solutions are presented. A general four-layered architecture is presented in order to better illustrate different existing crowdsensing-based systems of different dynamics and their working methodology. More specifically, an IoT–cloud-based architecture is provided for this purpose consisting of four layers: sensing layer, communication layer, data processing, and application layer. Several existing crowdsensing-based systems are compared and analyzed in this chapter depending on various aspects such as techniques used, nature of the system, real-time behavior and types of sensors used. Moreover, some open research issues (namely incentives, reliability, privacy, security, and quality) and constraints are also presented to direct future researchers.

The rest of the chapter is organized in the following sections: Section 2 presents four applications of the smart environment of the city. Section 3 provides the system overview explaining the layered architecture and the components used in each layer. Section 4 elaborates the methodology and paradigms used for these applications. Section 5 highlights the current research issues for IoT-based crowdsensing and Sect. 6 concludes the chapter.

2 Smart City Application

2.1 Smart Home

In present days, improvements of low-cost sensors, remarkable progress in crowdsensing along with edge and cloud computing, and a new era of smart homes have been created. Previously in most of the cases, all smart home appliances used expensive controllers as the controlling mechanism. But with the use of IoT–cloud-based system, a wide range and less expensive solutions for smart home are possible. Moreover, in controller-driven systems, control operation is only possible in short-range communication. But for cloud-based systems, as we are using the Internet through our smartphones, it is possible to control the IoT device from anywhere in the world.

In [11], a prototype for smart building/home is generated using IoT, cloud, and fog computing. Different sensors like optical, ultrasound, and gas are used for automation and security of the building. Arduino-UNO is used as a cross-platform software for the connection of firmware attached to the sensors. In [12], an integrated solution for a cloud-based home management system is described. Home management system connected with surroundings generates a solution for community infrastructure, and a community broker is deployed to manage the architecture as a whole. A low-cost fog-based solution for smart home is presented in [13]. Due to fog computing, instead of cloud, the latency of the solution is greatly reduced. Other existing works for smart homes are presented in [14–16]. A review work on fog-based framework is presented in [17]. A detailed review of IoT-based application of smart homes and the related publication statistics are elaborated in [18].

2.2 Health Monitoring

Smart healthcare has gradually developed with the advent of paradigms evolved in computation and information technology. A real-time solution of the detection of medical emergencies can be possible through a smart healthcare system. Similarly, in the remote or ad hoc infrastructure, smart healthcare can be a solution in emergency medical situation.

There are several applications of smart healthcare systems like (i) *Personalized smart device:* in different standard smartwatches, like the Apple Watch and Galaxy Watch Active2, it can monitor heart rate and keep a step count and irregular heart rhythm notification; blood oxygen application is also available in these kinds of devices. It may be used for the recording of 30-second ECG (electrocardiogram). (ii) *Safe home:* smart homes for senior citizens and disabled persons with embedded medical facilities like medical sensors, and monitoring IoT devices. Deviations from the normal conditions are notified through the notification systems in cloud and appropriate authorities take the measures against the data. (iii) *Patient monitoring system:* patients can monitor their health conditions using different applications embedded in sensors and data are stored in cloud via IoT devices. The recommendation system of cloud analyzes the data and sends a warning in case of any anomaly from the normal distribution is recorded.

Several approaches of smart healthcare systems are proposed in different literature. In [19], the authors propose a health monitoring system based on certain basic parameters like heart rate, oxygen saturation, eye movement, and temperature. In [20], a patient and room conditions of the patients are monitored using an IoT environment. In [21], a survey on different aspects of smart healthcare is presented. This paper also discussed the threats related to security and data privacy of crowdsourcing-based health monitoring systems. In [22], using two smartphones a heart monitoring system is proposed. Several other applications of smart health monitoring systems are proposed in several research papers [23–26].

Another approach of smart healthcare systems is personalized health monitoring system known as digital twin. Combining machine learning and artificial intelligence in health centers led to the use of human health digital twin, also referred to as patient's digital twin. In [27, 28], a framework for health twinning is designed for the citizen health and fitness. In [29], a smartphone-based digital framework is designed for smart city. Review works on health twinning have been presented in different recent literatures [30–32].

2.3 *Traffic and Road Condition Monitoring*

One of the key problems that the city authorities face is managing and tracking city traffic and road conditions. Specifically, effective monitoring of several dynamics like traffic flow, traffic density, aggressive driving, traffic jams and road conditions is proved to be a very important and challenging task these days. For instance, due to inadequate managing and tracking of city traffic, road traffic accidents (RTA) have become one of the world's major causes of injury and death, that not only responsible for the loss of human lives but also result in considerable economic losses. According to the World Health Organization, RTAs claim the lives of about 1.35 million people per year. Additionally, non-fatal accidents affect approximately 20–50 million more individuals, with most of them resulting in disability due to injury. In the above-mentioned context, constant assessment of traffic and road conditions at a large scale is necessary for citizens and policy makers for better decision-making.

Several existing works [2–4, 33, 34] focus on building effective road traffic and road condition monitoring systems based on IoT devices. In [2], Mohan et al. developed a system called Nericel in order to monitor road and traffic conditions of a city using the inbuild sensors (e.g., accelerometer, and GPS) of a smartphone. They showed that Nericell could be used for monitoring chaotic traffic conditions (like honking and braking). Another interesting system named Wolverine [3] is presented by Bhoraskar et al. for estimating traffic and road conditions. Specifically, they utilized a variety of smartphone-equipped sensors (accelerometer, magnetometer, and GPS) for identifying congested traffic as well as road conditions (e.g., speed bumps).

Hull et al. introduced a mobile computing framework called CarTel [33] that acquires various sensor data from On-Board Diagnostic (OBD-II) interface on vehicles to monitor their movements. The task to collect, process, distribute, and view data in this environment has been simplified considerably by CarTel. In order to build an Intelligent Transport System (ITS), Alessandrelli et al. designed and implemented a system called ScanTraffic [4] using a network of smart cameras. For parking monitoring, the system collects vehicle flow data and parking area occupancy status. In [35], Thiagarajan et al. present a framework named VTrack for estimating road travel times based on smartphone sensors. Specifically, they focus on providing an energy-aware solution for traffic delay prediction. Moreover, there are several research works on estimating traffic flow [36] and driving patterns [34, 37]. The details of the applications are provided in Table 1 in terms of their contributions, end-to-end system, real-time monitoring, reference, and year.

2.4 Pollution Monitoring

The adverse effects of rapid urbanization and population growth have negative environmental consequences. The existing works highlight that urban air and noise pollution have become a growing source of concern for both the citizens and policymakers around the world [38–42]. In this context, several research activities and community-based initiatives are focused on pollution monitoring in smart cities. More specifically, various IoT-based applications are developed for continuous as well as high granular monitoring and mapping of air and noise pollution levels in smart cities. This subsection provides the details of existing IoT-based pollution monitoring applications.

Several approaches for air quality monitoring in smart cities are described in [5, 43–47]. To illustrate representative examples, the applications like AirSense [5], HazeWatch [6], Common Sense [7], and GasMobile [8] develop light weight and low-cost devices for urban air pollution monitoring. It is worth noting that those systems rely on the active participation of citizens for such monitoring where they need to carry IoT devices for collecting air pollution data. Also, there exist some systems like CUPUS [48] that makes use of wearable sensors to sense ambient air quality levels. Mobile air quality sensors, which are mounted on the tops of public transportation vehicles, are another important research direction that is currently being investigated [49]. Here, air pollution data are recorded as the vehicles travel around the city. Most of the above-mentioned applications employed cloud services from various cloud computing platforms (e.g., AWS—amazon web services [50], GCP—google cloud platform [51]) to store and analyze high granular data for exploring pollution dynamics of the city. Existing literature [52] also assesses urban air quality by combining traditional monitoring stations along with IoT-based air pollution monitoring. Similar to the air quality monitoring, several urban noise pollution monitoring applications [53–56] are available that acquire ambient sound levels to study noise pollution dynamics of the city. These applications mainly utilize citizens' smartphones as IoT devices, which citizens are encouraged to carry for urban noise pollution data collection. For instance, an application called NoiseTube [53] uses GPS-equipped smartphones to collect geotagged ambient noise measurements as well as contextual inputs from the citizens. They provide PoI (point of interest) based pollution maps for visual assessment of urban noise pollution.

Table 1 Details of the smart city applications for pollution monitoring, traffic and road condition monitoring, health monitoring, and smart home

Application type	Application name	Author	Year	Contribution	End-to-end system	Real-time monitoring
Pollution monitoring	Air sense	Dutta et al. [5]	2017	Low-power, low-cost, light weight IoT device called AQMD, developed to monitor air pollution levels	✓	✓
	Noise sense	Dutta et al. [59]	2017	Noise pollution monitoring system, based on context-aware smartphone sensing	✓	✓
	Haze watch	Sivaraman et al. [6]	2013	Low-cost participatory sensing framework for monitoring urban air quality levels	✓	✓
	Gas Mobile	Hasenfratz et al. [8]	2012	Low-cost and light weight off-the-shelf hardware for assessing ozone levels	✓	×
	Noise tube	Maisonneuve et al. [53]	2009	Use GPS-enabled smartphones to determine noise exposure of individuals	✓	✓
	Noise SPY	Eiman Kanjo [56]	2010	Develop a platform for real-time monitoring and mapping of urban noise	×	✓
	Ear-phone	Rana et al. [54]	2010	Urban sensing approach to monitor roadside ambient noise	✓	✓
	Common sense	Dutta et al. [7]	2009	Air quality monitoring using handheld air pollution monitoring devices	×	✓
	–	Gupta et al. [60]	2019	Introduced an IoT–cloud-based framework for real-time assessment of urban air pollution	✓	✓
	JU sense	Middya et al. [58]	2020	Unified framework to combine applications like NoiseSense [59], and AirSense [5] to gain benefits from their interactions	✓	✓

Traffic and road condition monitoring	Neri cell	Mohan et al. [2]	2008	Monitor traffic and road condition of a city using the inbuild sensors of smartphone	×	×
	Wolverine	Bhoraskar et al. [3]	2012	Identify congestion with road conditions based on smartphone sensors (accelerometer, magnetometer, GPS)	×	×
	CarTel	Hull et al. [33]	2006	Acquires, analyzes, delivers, and visualizes data from sensors of cars	×	×
	Scan traffic	Alessandrelli et al. [4]	2012	Collects vehicle flow data and the occupancy status of parking areas for parking monitoring	✓	✓
	D&R sense	Bose et al. [34]	2018	Identify unusual driving patterns and road conditions	✓	✓
	–	Khan et al. [61]	2021	Data fusion-based traffic congestion monitoring and control	×	×
	–	Dhingra et al. [62]	2020	Fog and cloud-based framework for traffic congestion monitoring using IoT	✓	✓
Health monitoring	Smartphone-based ECG monitoring	Joseph et al. [22]	2010	Two smartphone-based ECG acquisition and real-time analysis of statistical anomaly	✓	✓
	–	Islam et al. [20]	2020	Sensor-based monitoring of room and patient	✓	✓
	Health monitoring	Tamilselvi et al. [19]	2020	IoT-based monitoring on preliminary health conditions like saturation of oxygen, and heartbeat	×	✓
	Cloud DTH	Liu et al. [27]	2019	Digital twin healthcare system using cloud infrastructure	✓	✓
	Human digital twin	Barricelli et al. [28]	2020	Smartphone-based twin network for fitness management of athletes	✓	×
	Digital twin	Laamarti et al. [29]	2020	Smartphone-based twin framework for citizens of smart city	✓	×
Smart home	Prototype of smart home	Dutta et al. [11]	2017	IoT-, fog-, and cloud-based prototype for smart and green building	✓	✓
		Lee et al. [12]	2016	Cloud-based home management system	✓	✓
	Home automation	Mignez et al. [13]	2018	Fog-based home automation system	✓	✓
	Home automation	Izquierdo et al. [15]	2010	Indoor ambiance automation	×	✓

Similarly, in [54], the authors developed an end-to-end framework called Ear-Phone for participatory-based urban noise mapping. Becker et al. created a smartphone application named the WideNoise [55], which allows citizens to participate in noise measurement activities. It was created to collect both the objective (i.e., ambient noise) and the subjective (feelings, opinions, and so on) data. Also, there are real-time noise monitoring systems like NoiseSPY [56] in which the developers performed experiments and displayed noise pollution maps. Finally, there are unified frameworks [57, 58] that can combine both air and noise pollution monitoring applications for smart city. For instance, in [58], an urban sensing system named JUSense combines applications like NoiseSense (for noise monitoring), and AirSense (for air pollution monitoring), to gain benefits from their interactions.

3 System Overview

This section presents the details of crowdsensing systems [11, 63, 64] that are used to study various dynamics of a city (e.g., pollution and traffic condition). As shown in Fig. 1, the crowdsensing system can be introduced as a layered architecture. The

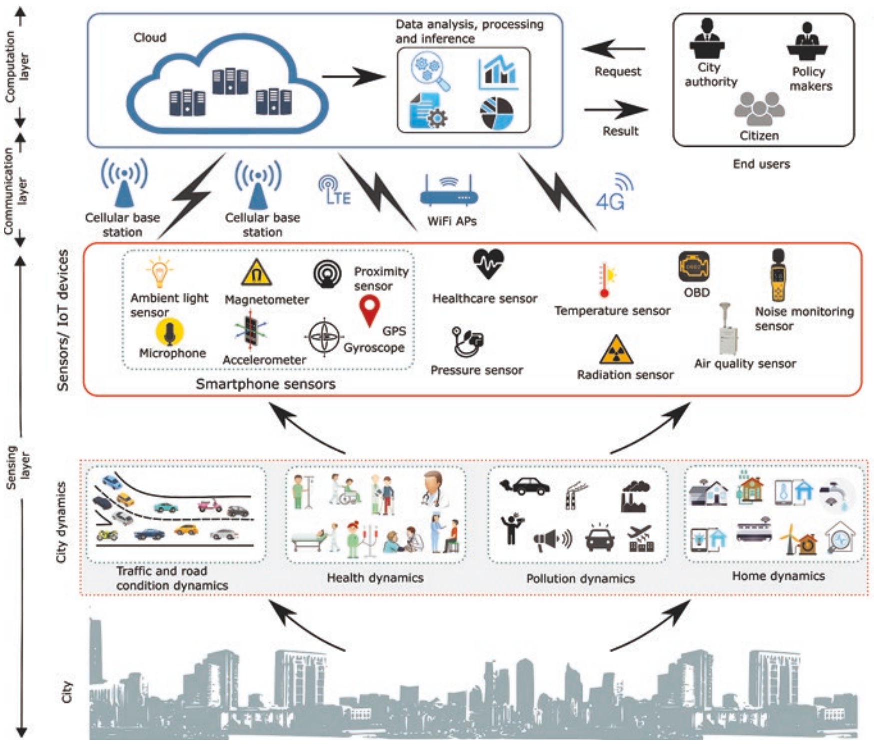

Fig. 1 Framework of crowdsensing system

major parts (i.e., layers) of the architecture are arranged as follows. The bottom layer is the *sensing layer* that mainly includes the city, its dynamics, and the sensors used to sense those dynamics. The *communication layer* is the second layer of the architecture, which consists of communication technologies for delivering data from sensors. *Data processing layer* is the third layer, which has responsibility for the storage, analysis, and processing of the data that has been collected. The last layer is the *application layer* that includes top-level features like participant allocation, assignment of sensing tasks, and services. The following subsections present the major components of different layers in detail.

3.1 Sensor

The sensors used for data collection are the heart of any crowdsensing-based smart city application. The sensing layer involves data acquisition from different dynamics (e.g., traffic dynamics, health dynamics, pollution dynamics, home dynamics, etc.) through IoT devices including smartphones. Specifically, smartphone-equipped sensors along with the specialized sensor modules are employed for the sensing tasks for various applications. Examples of smartphone-equipped sensors include microphones, magnetometers, GPS, gyroscopes, proximity sensors, accelerometers and light sensors. On the other hand, IoT-based external sensor modules often expand the sensing capacity of a smartphone by adding sensing capabilities that the smartphone alone does not provide. Table 2 presents the details of smartphone sensors as well as external sensors used in various applications of different city dynamics.

3.1.1 Smartphone-Based Sensing

In this subsection, we will discuss how smartphone-equipped sensors are utilized to monitor different dynamics of a city.

As given in Table 2, the accelerometer and gyroscope sensors' data were extensively studied as a potential means of developing methods for detecting traffic and road surface irregularities [3, 65]. Most existing traffic and road condition monitoring approaches require that the smartphone be kept in the proper orientation, with its axes aligned with the vehicle's axis. The 3-axes accelerometer's data indicate the acceleration of the vehicle in all three directions. Along with the accelerometer sensor, the GPS sensor is used in many applications for sensing the current location estimates (latitude and longitude) of the vehicle [66, 67]. Moreover, images captured from smartphone cameras are used in various applications to monitor road surface anomalies [65]. Similarly, in the case of city pollution monitoring, smartphone-based sensing is utilized to sense the ambient environment. For instance, environmental sound levels are collected using the microphone sensor of a smartphone along with the GPS location for ambient noise pollution monitoring and mapping. Smartphone sensing can also be used along with the IoT-based external sensor modules for

Table 2 The details of smartphone sensors as well as external sensors used in various applications of different city dynamics

City dynamics	Application name/Author	Smartphone sensors	External sensors
Traffic and road condition monitoring	CarTel [33]	–	Camera, OBD device, WiFi
	Nericell [2]	GPS, microphone, accelerometer	–
	Wolverine [3]	GPS, accelerometer, magnetometer	–
	RCM-TAGPS [69]	–	GPS, accelerometer
	PotSpot [65]	GPS, camera	–
Pollution monitoring	NoiseTube [59]	GPS, microphone	–
	HazeWatch [6]	–	Gas sensor, Bluetooth sensor
	AirSense [5]	GPS	MQ-135, HC-05
	NoiseSPY [56]	GPS, microphone	–
	GasMobile [8]	GPS	MiCS-OZ-47
	Idrees et al. [70]	–	MQ-135, MQ-7, MQ-9, GP2Y1014AU0F, DSM501
Health monitoring	Liu et al. [27]		ECG, DBO, blood pressure meter
	Smartwatch [71]		Blood pressure, heartbeat
	Tamilselvi et al. [19]		Heartbeat, SpO_2, temperature, and eye blink sensors
	Acharya et al. [26]		Blood pressure, eco cardiogram sensor
	Islam et al. [20]		Heartbeat, ambient and body temperature sensor
	PGFIT [68]	Google fit app, smartphone sensors	
Smart home	Dutta et al. [11]		LED, laser, gas, flame, ultrasonic sound, movement detection
	Lee et al. [12]		Touch panel, environmental sensor

monitoring citizens' air pollution exposure (details are provided in Sect. 3.1.2). For example, in [5], ambient air pollution data (PM2.5 and PM10) are collected using DSM501 sensor along with the smartphone data (GPS, user context, and timestamp) for spatial and temporal air pollution monitoring. In smart home systems, different cross-platform software packages like Arduino IDE are used for code editing and compilation of different firmware attached with the sensors. It can be used as the web service and can be attached with smartphones with different applications. In health monitoring systems, smartphones can act as sensors or a sensor can be attached into smartphones. As the mobile device has an advantage of being easily carried out by patient all time, it is easy to collect data on 24X7 basis without restricting the movement. For example, in [22], two mobile phones are used to collect the ECG data, and data is delivered to the system, which enables an online detection (in the present scenario, holter monitoring is used to record continuous ECG data, which is very inconvenient to carry and the data can be retrieved only when all data are recorded and analyzed by a medical person; therefore, a real-time detection or measure of any anomaly is not possible). In [28], a smartphone-based twin network for fitness management of athletes is generated. An app is created in the framework, where athletes have to submit various inputs like their food, rest, practice schedule, and also some qualitative quantity like mood, for the analysis. Similar smart healthcare systems for the citizen based on smartphones are generated in [29], where five sensors collect the data and send the data in smartphones. In [68], the Google fit app is used for data collection, and smartphone sensors are used to capture the input data. Some smartphone-based data collection software packages used for health monitoring are described here: (i) *Teamscope*: it can be used in Android, iOS, and web applications. It is a secure and user-friendly app for the collection of sensitive clinical data. It is cross-platform software and has a high-security feature; (ii) *Open data kit*: it is open-source software used in Android applications. It is open-source and free software. A large community support is available for this software; (iii) *Kobo ToolBox*: it is free and open-source software used in Android and web. It is widely used in nonprofitable organizations for the collection of patient data; (iv) *REDcap*: this software can be used in Android, iOS, and web application. It is used for secure electronic data capture; (v) *Magpi*: it is a mobile data recording app used in Android and iOS. It can be used to generate excel data from different unstructured input; (vi) *Jotform*: it is used in Android, iOS, and web to collect different data types and organize the data. It can generate an alert system or notification to the end user; (vii) *Survey CTO*: it is a reliable, secure, and scalable mobile data collection app that can be used in Android and web for researchers and professionals; (viii) *CommCare*: it is a data collection platform in Android and web. It is widely used for medical data collection. The platform supports both cross-sectional and longitudinal data and data collection through web and is very user friendly.

3.1.2 Sensing Using IoT-Based External Sensor Module

IoT-based dedicated sensor modules are also popularly used for sensing various city dynamics. In the case of monitoring road and traffic conditions, a set of sensors/devices like on-board diagnostic (OBD) scanners, GPS, accelerometers and cameras, are installed in cars for monitoring the movements and behavior of vehicles. Note that OBD is a tool that can continuously monitor the status of the vehicle. Similarly, for different air pollution monitoring applications, several IoT-based external sensor modules are proposed in the literature. In [5], an IoT device called AQMD (air quality monitoring device) is developed that consists of a gas sensor (MQ-135) and a Bluetooth module (HC-05). Note that the MQ-135 is an air quality sensor that can detect the presence of various gaseous pollutants such as NH_3, CO_2 and NO_x. There exist several other IoT-based systems such as HazeWatch [6] and JUSense [58] that also use MQ-135 for acquiring air quality data. Sensor modules like GP2Y1014AU0F and DSM501 are mainly used as dust sensors for measuring particulate matters (PM2.5, PM10). IoT-based external sensor modules containing MiCS-OZ-47 are used for the purpose of sensing the pollutant O_3. Laser (used for security), DHT 11 (temperature and humidity), MQ2/MQ6/MQ7/MQ9 (gas sensor), and flame sensor (used for fire security) are some examples of commonly used sensors for smart homes.

In smart patient monitoring systems, sensors collect data from the patients and send it to some Wi-Fi systems, from where data are collected and processed in cloud. Smartphones are generally used for data collection and security. Some sensors like smartwatch are directly connected with mobile phones, and the information like heartbeats is continuously monitored through smartphones. Another application of mobile smartphones is that to collect data when patients are in a mobile state. Pressure sensors (used to measure blood pressures, almost similar to clinical meter but with a digital display), blood sugar monitoring sensors (used to collect data from blood about the sugar level), and pulse oximetry sensors (measure oxygen saturation and pulse rate) are commonly used sensors used to measure health condition in home. Force sensors (used on dialysis machine to monitor pressure and dialysate weight), thermistors (temperature control), and airflow sensors (detection of ultra-low levels of oxygen) are some of the sensors used in medical facilities. These sensors are Wi-Fi connected, and the data are warehoused in cloud/server for analysis.

3.2 Communication Technologies

The communication layer, depicted in the framework of Fig. 1, contains technologies and methodologies for delivering sensing data to the cloud from smartphones and other IoT devices. Smartphones and IoT-based external devices generally have many radio interfaces (like Bluetooth and Wi-Fi), and there are numerous optimizations that may be made to make the communication interfaces more effective such as avoiding repeated sensor measurements or encoding unnecessary data. The communication technologies could be broadly divided into two classes, namely (i) infrastructured and (ii) infrastructure-less. Cellular and WLAN (wireless local area network) are examples of infrastructured technologies, in which the network depends on the base stations or access points to create a communication connection. On the other hand, technologies like Bluetooth, Wi-Fi-Direct and LTE-Direct, come under infrastructure-less category to enforce proximity-based communication.

3.3 Computation Layer

The computation layer in a crowdsensing framework is mainly responsible for *data management* in cloud and *data processing*. The storage, format, and dimension of collected sensor readings are different aspects of data management. Both databases and data storage are usually employed to store the data collected via smartphones and external IoT devices. The data storage could be centralized or distributed depending on the applications. The format of the data on the other hand indicates whether the data is structured or unstructured. Another aspect of data management involves the data dimension that is associated with the types of data acquired. For instance, multidimensional data involves different types of data from different sensors; e.g., accelerometer data of vehicle and road segment images from dash camera creates a multidimensional dataset for monitoring road condition dynamics. A particular type of sensor, on the other hand, generates single-dimensional data, such as data produced by air quality sensors for air pollution dynamics.

In crowdsensing-based applications, data processing is a critical step. Preprocessing, analysis, and postprocessing are the three major components of data processing. Before analysis, preprocessing tasks are conducted on the acquired data. Frequently used preprocessing tasks in crowdsensing systems involve missing value imputation, context-aware data cleaning, calibration, and map-matching. Through a variety of methodologies, data analysis tries to extract and disclose valuable information. These methodologies generally include various statistical, machine learning and deep learning techniques. Also, several postprocessing tasks are performed for predictive analysis. For instance, in the case of air pollution dynamics, forecasting air pollution levels can be considered as a postprocessing task.

4 Methodologies

In this section, the details of the methods used in data preprocessing, analysis, and postprocessing is provided.

The raw sensor data from various city dynamics suffer from missing sensor readings due to the factors like power disruptions, device failure and irregular maintenance. The methods of imputation are roughly classified into two categories: univariate methods (use single predictor variable to estimate the missing values) and multivariate methods (use multiple predictor variables to estimate the missing values). Unconditional mean (UM), median (MD), last observation carried forward (LOCF), next observation carried backward (NOCB), auto regressive (AR), and auto regressive integrated moving average (ARIMA) are some examples of univariate methods of missing value imputation. On the other hand, several machine learning-based multivariate methods of imputation exist such as random forest (RF), artificial neural networks (ANN) and k-nearest neighbors (KNN). Now, context-aware data cleaning is a preprocessing task to eliminate inaccurate sensor readings not collected in the proper sensing context. Existing literature highlights that machine learning algorithms could be used to first identify the sensing contexts. If an identified sensing context is not appropriate, then the corresponding sensor readings are eliminated to enhance the quality of data. For example, in [72], Rana et al. developed a context discovery module using k-nearest neighbor (kNN) algorithm for noise pollution monitoring in urban areas. Now, calibration is also needed as a preprocessing task to estimate actual sensor readings from the responses of low-cost IoT devices. It is because low-cost IoT devices may not always provide precise, high-quality readings. The existing literature usually develops calibration models by estimating a relationship between the sensor readings and actual ground truth measurements [58]. In applications like pollution monitoring or traffic and road condition monitoring, map-matching is used as a preprocessing procedure that involves mapping raw sampling coordinates (i.e., places where sensor data samples were taken) onto existing road networks. Interactive-voting-based technique [73], probabilistic approach [74], force-directed technique [75], and feature-based technique are some examples of map matching approaches.

In the previous works, after data preprocessing step, several predictive methods are usually employed to perform analysis on the preprocessed data. The statistical, machine learning and deep learning techniques are popularly used as predictive methods. These methods are used to infer knowledge, spot patterns, and discover trends. Environmental pollution monitoring, traffic and road condition monitoring, smart health and smart home, are some of the city dynamics where the crowdsensing-based applications use these techniques. For instance, the application Wolverine [3] uses machine learning techniques in traffic and road condition monitoring. Specifically, they use models like K-means clustering and Support Vector Machine (SVM) to detect road bump, vehicle braking, etc. Statistical techniques like spatial and temporal interpolation are used in many applications of city pollution monitoring for air and noise pollution mapping [1, 58]. In [1], IDW (inverse distance weighting)- and OK (ordinary kriging)-based interpolation techniques are proposed for spatially continuous urban noise pollution mapping. In the case of smart health and smart home dynamics, machine learning- and deep learning-based techniques are frequently utilized for various event detection. For example, in [76], fall detection is performed using machine learning (SVM and NB) and deep learning models. Finally, postprocessing techniques are sometimes employed for predictive analysis, such as forecasting future values. In various application domains of city dynamics, statistical models (ARIMA, Seasonal ARIMA, etc.) as well as deep learning models (recurrent neural network (RNN), long short-term memory (LSTM), bidirectional-LSTM, etc.) are popularly used for forecasting future values [39–41].

5 Research Issues

In IoT-based smart sensing, there are several unresolved issues that required attention from the researchers. For crowdsensing, data are collected from user level, which is an uneven distribution set. It is important that users should participate in data collection, but it is obvious that everyone will not be enthusiastic in a similar manner. Therefore, it is required to device incentive strategies in such a way that quality information can be collected. Now uneven distribution of smart devices for data collection may reduce the reliability of the system. For example, smartphone sensors may vary in a wide range depending on the pricing. Security of the data of the crowd sense system is another research issue to be addressed. As data are stored in public or private cloud, it is difficult to maintain the security of the information both in plain or cryptic text. Sensitive data like medical records should be secured in IoT-based systems. Therefore, lots of research work addressed cloud security. Another research issue in this area is to maintain the quality of service (QoS) of the system. In each layer of the architecture, some quality control measures have to maintain, and it is a challenge for the researchers to improve the standard.

5.1 Incentive

As previously stated, crowdsensing (also known as participatory sensing) is a new paradigm of sensing in which participants acquire high granular data using IoT devices such as smart handheld devices. These data can then be used to investigate different aspects of a city's dynamics (e.g., traffic condition, urban air and noise pollution and road condition). In the case of crowdsensing-based systems for collecting sufficient data for such investigations, active participation of a large number of participants is necessary. However, in crowdsensing-based monitoring of city dynamics, users incur costs because of the energy requirement, bandwidth requirements for sensing, processing, and uploading of data. Therefore, the users might not be able to contribute their resources as the cost issues demotivate them from actively participating in the sensing. In this context, a satisfactory reward or incentive would compensate users and encourage them to participate in the sensing process. An effective reward mechanism would therefore have an important role in sensing and overall performance of the crowdsensing systems for monitoring various city dynamics.

Several incentive strategies [77–80] for crowd/participatory sensing-based frameworks have been developed in the literature to motivate participants in the sensing task. It is observed that most of the existing incentive mechanisms come up with a game theoretic solution. For instance, in [80], Yang et al. introduced an incentive mechanism called IMCC based on a Stackelberg game. Some auction-based game theoretic models such as reverse auction and double auction-based models are also frequently used. Lee et al. [77] developed a dynamic price incentive mechanism with virtual participation credit using a reverse auction. In [81], Wang et al. developed a quality-aware, truthful, individual rational, and budget-balanced incentive mechanism called MeLoDy based on the reverse auction. They consider long-term characteristics of workers' quality that can dynamically change over time. Table 3 provides a detailed list of existing literature that focuses on the issue of incentives in crowd/participatory sensing-based systems. Some attempts are also made to develop incentive mechanisms for air pollution monitoring [82], health monitoring [83] and traffic monitoring [84].

Table 3 A detailed list of works that focus on the issue of incentives, reliability, quality, privacy, and security in crowd/participatory sensing-based systems

Research issue	Mechanism/framework name	Author	Year	Contribution
Incentive	RADP-VPC	Lee et al. [77]	2010	A dynamic pricing incentive model, using reverse auction
	IMCC	Yang et al. [80]	2015	A Stackelberg game-based incentive model
	ABT	Wang et al. [105]	2017	An incentive mechanism, developed for crowdsourcing system ability-balanced team
	Geo-QTI	Dai et al. [106]	2018	A quality-aware incentive model for cyber-physical participatory sensing
	MeLoDy	Wang et al. [81]	2018	A quality-aware, truthful, individual rational, budget-balanced incentive mechanism called MeLoDy is developed based on the reverse auction
	BiCrowd	Zhang et al. [107]	2020	Formulate the incentive model with two optimization goals (namely maximizing the reliability and maximizing the spatial diversity of selected workers) based on the reverse auction
Reliability and quality		Liu et al. [27]	2019	Standardize sensor and communication link
		Restuccia et al. [85]	2017	Develop privacy-preserving, budget-feasible, truthful crowdsourcing-based dataset purchasing framework, quality of information in mobile crowdsensing.
		Truong et al. [86]	2019	Developed a system for evaluating trust in mobile-based crowdsourcing
		Dasari et al. [87]	2020	Game theoretic approach to generate reliable data
	SecPMS	Maitra et al. [115]	2017	Security for patient monitoring system
		Ray et al. [104]	2020	Proactive fault-tolerant system for reliability enhancement in cloud
Privacy and security	CKD	Chi et al. [89]	2017	This paper focuses on combining k-anonymous and differential privacy-preserving mechanisms to preserve location privacy
	Crowd buy	Zhang et al. [90]	2018	Develop a privacy-preserving, budget-feasible, truthful crowdsourcing-based dataset purchasing framework
	PEPSI	Cristofaro et al. [91]	2011	A framework called PEPSI is proposed for protecting the privacy of both data consumers and producers in participatory sensing
	PMP	Agarwal et al. [92]	2013	A system is developed for detecting the access to private data and provide privacy recommendations using crowdsourcing
	PPDCA	Tsou et al. [93]	2018	A C-RR (complementary randomized response) method is developed to ensure the data privacy of individuals
	SecBCS	Lin et al. [94]	2020	Designed a block chain-based security system for crowdsourcing hierarchy

5.2 Reliability

In crowdsourcing-based monitoring, reliability is an important criterion. In crowdsensing, one of the components is human entity. Therefore, the sensing can be biased, judgmental, or even mischievous [85]. For real-time crowd sense systems, another parameter that is connected with the reliability of the architecture is the response time and variation in delay. As the system includes different layers in the architecture, it faces congestion and other communication delays in the system. Delay can be reduced using larger bandwidth, load balancing, and other mechanisms, but variation in delay may cause a reduction of the reliability of the system. Different methodologies for assurance of reliability in crowdsensing-based systems are proposed and tested. Though the reliability of the system is very application specific and no common framework is emerged to date, a lot of research work has been done in that direction. In [86], a trust evaluation mechanism is proposed. In [87], a comprehensive survey on reliability based on the game is done. Another factor that may cause a lack of reliability is the sensor device used for input data collection. Unidrive is a consumer cloud storage application enhances the reliability of the cloud service [88].

5.3 Privacy and Security

The crowdsourcing-based mechanisms usually suffer from potential privacy and security problems because sensitive data of the users are disclosed. For instance, the sensed data might include location information that could implicitly reveal the mobility of a participant. Security refers to preventing illegal access, use, alteration, or damage of the acquired data. In addition to security, a crowdsourcing-based system should protect the privacy of both the users and the crowdsourcer. In most cases, privacy refers to an entity's ability to choose whether, when, and to whom its information is shared or revealed. Hence, an effective crowdsourcing system should be able to handle security and privacy threats, keep the acquired data and processing results out of the hands of unauthorized users, and also keep the system running normally. Issues of security and privacy are becoming increasingly important and challenging in crowdsourcing systems because of human involvement, dynamic network topology and heterogeneity in various communication networks.

The scientific community has spent considerable time and effort in the last few years looking into privacy and security concerns [89–94]. Ding et al. [95] present an application for s-Health (i.e., smart health) and the associated privacy issues. The privacy-aware solution enables them to easily deal with people who have respiratory disorders by suggesting low-pollution paths for individuals in order to alleviate their respiratory-related issues. In [96], Xie et al. proposed a system called PAMS for privacy-aware traffic monitoring. They demonstrated that the collected information can preserve the location privacy of drivers while ensuring effective traffic monitoring. In [97], Zavalyshyn et al. developed a privacy-aware framework called HomePad for home environments. The framework intends to offer the users with control over how applications access and process confidential data acquired by smart devices (such as web cams), as well as to stop applications from running unless they adhere to the privacy constraints set by the users. Also, several other existing works [98–100] focus on the security aspect and privacy of IoT-based health and home environment. Some IoT-based pollution monitoring applications are also focused on privacy issues of the end users [56, 101]. In [27], the authors propose a security system in eight levels, which consider security in the system level, network security, users' personal privacy, information, and application security. Another security system for patient body monitoring system is proposed as SecPMS [102], where a cryptosystem is generated both on user data and sensor data.

5.4 Quality

Quality of service is used to measure the overall service we are delivering through the smart system we are using. It depends on each component used in the system hierarchy. In crowdsourcing, input data are collected from sensors and transferred through a wireless communication system. Data of the crowd sending systems are generally stored in the cloud system, where the quality of service is dependent on the cloud service provider. Moreover, a huge data is processed for analytics in crowdsensing, which can lose the reliability of personalized information. Therefore, to maintain the overall quality, it is required to standardize each level.

5.4.1 Standardization of Sensor

Sensors used for collecting data input from the users are not very standardized in the present scenario. They are different proprietary devices and generate different standardization. ISO/IEEE11077(X73) is a standard protocol for the standardization of the sensors. But only a few devices are using this standardization. Therefore, the other devices have to be standardized. A proper calibration is required for this purpose. A standardization mechanism for sensors and communication link compliant with X73 is discussed in [27]. Quality control of sensors is a prospective research domain for future crowdsensing.

5.4.2 Standardization of Communication System

As discussed in the previous section, the hierarchy uses different kinds of communication link/systems. It can be structured wireless or mobile systems, or unstructured systems. For the unstructured communication, links are not always standardized and may cause interference. For example, Wi-Fi communication may create resonance to other devices used in medical infrastructure. This can be solved using other wireless technologies like Zigbee.

5.4.3 Expert System

Expert recommendation systems for the crowdsourcing data systems should be reliable and secured. The service we are delivering in crowdsensing is very much dependent on the expert systems we are generating. Statistical approaches or machine learning systems are dependent on the input feed used to train or learn the system. It cannot have 100% accuracy. Therefore, for surveillance systems, it can be used in a proper manner but where a critical decision has to be taken, a manual intervention along with the recommendation of an expert system is required. For statistical-based approaches, better interpolation and in machine learning, proper learning and training can deliver a precise recommendation system. Proper feedback from the user level also assures quality service from an expert system.

5.4.4 Cloud Infrastructure

Cloud services used for infrastructure services are not always maintained by all service providers. Moreover, security and privacy of user information are two important issues for quality services. There are different approaches like game theoretic approaches and load distribution algorithms to ensure the quality of services of cloud infrastructure [103]. Cloud federation is a concept where cloud providers share unused resources to generate a fault-tolerant system. It is important for the crowdsourcing system to access a reliable and fault-tolerant cloud hierarchy for storage and computation. In [104], the authors propose a proactive fault-tolerant system for enhancing cloud federation to ensure the reliability of the crowdsourcing system for a smart environment.

6 Conclusion

Crowdsensing and its application can be emerged as key components of the smart environment of a city. This chapter presents the details of crowdsensing systems that are used to explore city dynamics in forms of four applications: smart homes, smart health monitoring systems, air and noise pollution monitoring systems, and road and traffic condition monitoring systems. In this chapter, we introduce the crowdsensing system in a layered architecture. The lowermost layer is the sensing layer, which mainly includes the city, its dynamics, and the sensors used to sense those dynamics. It can be defined as the data collection layer. Both smartphone sensors as well as connected sensors are elaborated. The communication layer is the second layer of the architecture, which consists of communication technologies for delivering data from sensors. The third layer is the data processing layer, where all data preprocessing, analysis, and expert systems are generated. The topmost layer is the application layer that generates the services through the crowdsourcing systems.

In this chapter, we have classified sensors into two divisions: smartphone sensors, where built-in sensors of smartphones are used, and wearable sensors that are connected through IoT devices. A detailed discussion on the sensors generally used in four applications is presented. In the communication layer, both infrastructured and infrastructure-less wireless communication are used. In the computation layer, data is preprocessed and analyzed, and results are generated with feedback. All these components are discussed in the methodology section. Research issues related to crowdsensing are also presented in the chapter.

In crowdsourcing-based applications, paradigms like the IoT, mobile-based or Wi-Fi-enabled sensors, cloud, edge and fog computing, and big data analytics generate a big leap over existing technologies. Crowdsourcing is a concept where inputs are generated by the citizens of smart city collectively. Shared data generates a recommendation system. Sensors are utilized to acquire the data from the individuals. These sensors are cheap, easy to use, generally movable in nature, and connected or communicate with the smartphone device. These collected data are stored in cloud servers, and analytics are derived in the server. For thin client services, analytics can be performed in IoT devices also (fog or edge computing), which is very useful in real-time operation. Privacy, security, and quality of services are of great concern in the real-life implementation of crowdsensing-based infrastructure. Cloud service providers, public or private, are prone to security attack and a lack of data secrecy. Sensitive data can be hacked from the system. Another issue is the power consumption of IoT devices and consequent harm to the environment. Therefore, green computing is another aspect, where the focus should be concentrated.

An in-depth analysis of the chapter focuses and elaborates the scope, architecture, and recommendation system relevant to crowdsensing-based applications in smart city. The review in each topic of concern can serve as a reference for future research work in this area. Moreover, in the future, the research issues and challenges identified in this chapter may be useful to the research community in developing more robust IoT–cloud-based crowdsensing systems.

References

1. A.I. Middya, S. Roy, Spatial interpolation techniques on participatory sensing data. ACM Trans. Spatial Algorith. Syst. **7**(3), 1–32 (2021)
2. P. Mohan, V.N. Padmanabhan, R. Ramjee, Nericell: Rich monitoring of road and traffic conditions using mobile smartphones, in *Proceedings of the 6th ACM conference on Embedded network sensor systems*, (2008, November), pp. 323–336
3. R. Bhoraskar, N. Vankadhara, B. Raman, P. Kulkarni, Wolverine: Traffic and road condition estimation using smartphone sensors, in *2012 Fourth International Conference on Communication Systems and Networks (COMSNETS 2012)*, (IEEE, 2012, January), pp. 1–6

4. D. Alessandrelli, A. Azzarà, M. Petracca, C. Nastasi, P. Pagano, ScanTraffic: Smart camera network for traffic information collection, in *European Conference on Wireless Sensor Networks*, (Springer, Berlin/Heidelberg, 2012, February), pp. 196–211
5. J. Dutta, C. Chowdhury, S. Roy, A.I. Middya, F. Gazi, Towards smart city: Sensing air quality in city based on opportunistic crowd-sensing, in *Proceedings of the 18th international conference on distributed computing and networking*, (2017, January), pp. 1–6
6. V. Sivaraman, J. Carrapetta, K. Hu, B.G. Luxan, HazeWatch: A participatory sensor system for monitoring air pollution in Sydney, in *38th Annual IEEE Conference on Local Computer Networks-Workshops*, (IEEE, 2013, October), pp. 56–64
7. P. Dutta, P.M. Aoki, N. Kumar, A. Mainwaring, C. Myers, W. Willett, A. Woodruff, Common sense: Participatory urban sensing using a network of handheld air quality monitors, in *Proceedings of the 7th ACM conference on embedded networked sensor systems*, (2009, November), pp. 349–350
8. D. Hasenfratz, O. Saukh, S. Sturzenegger, L. Thiele, Participatory air pollution monitoring using smartphones. Mob. Sens. **1**, 1–5 (2012)
9. C. Gao, F. Kong, J. Tan, Healthaware: Tackling obesity with health aware smart phone systems, in *2009 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, (IEEE, 2009, December), pp. 1549–1554
10. K. Sha, G. Zhan, W. Shi, M. Lumley, C. Wiholm, B. Arnetz, Spa: A smart phone assisted chronic illness self-management system with participatory sensing, in *Proceedings of the 2nd International Workshop on Systems and Networking Support for Health Care and Assisted Living Environments*, (2008, June), pp. 1–3
11. J. Dutta, S. Roy, IoT-fog-cloud based architecture for smart city: Prototype of a smart building, in *2017 7th International Conference on Cloud Computing, Data Science & Engineering-Confluence*, (IEEE, 2017, January), pp. 237–242
12. Y. T. Lee, W. H. Hsiao, C. M. Huang and S. C. T. Chou, "An integrated cloud-based smart home management system with community hierarchy," in IEEE Trans. Consum. Electron., vol. 62, no. 1, pp. 1–9, February 2016
13. I. Froiz-Míguez, T.M. Fernández-Caramés, P. Fraga-Lamas, L. Castedo, Design, implementation and practical evaluation of an IoT home automation system for fog computing applications based on MQTT and ZigBee-WiFi sensor nodes. Sensors **18**, 2660 (2018)
14. A. Nedelcu, F. Sandu, M. Machedon-Pisu, M. Aalexandru, P. Ogrutan, Wireless-based remote monitoring and control of intelligent buildings, in *Proceedings of the IEEE International Workshop on Robotic and Sensors Environments, Lecco, Italy, 6–7 November 2009*, (2009), pp. 47–52
15. M.A. Zamora-Izquierdo, J. Santa, A. Gómez-Skarmeta, An integral and networked home automation solution for indoor ambient intelligence. Pervas. Comput. **9**, 67–75 (2010)
16. K. Baraka, M. Ghobril, S. Malek, R. Kanj, Low cost Arduino/Android-based energy-efficient home automation system with smart task scheduling, in *Proceedings of the Fifth International Conference on Computational Intelligence, Communication Systems and Networks (CICSyN), Madrid, Spain, 5–7 June 2013*, pp. 296–301
17. M. Rahimi, M. Songhorabadi, Mostafa Haghi Kashani,Fog-based smart homes: A systematic review. J. Netw. Comput. Appl. **153** (2020)
18. M. Alaa, A.A. Zaidan, B.B. Zaidan, M. Talal, M.L.M. Kiah, A review of smart home applications based on internet of things. J. Netw. Comput. Appl. **97**, 48–65 (2017)
19. Tamilselvi V, Sribalaji S, Vigneshwaran P, Vinu P, GeethaRamani J. IoT based health monitoring system. In: 2020 6th international conference on advanced computing and communication systems (ICACCS). IEEE; 2020. p. 386–389
20. M. Islam, A. Rahaman, M. Sadi, M. Rashedul, *Development of Smart Healthcare Monitoring Systems in IoT Environment, SN computer science* (Springer, 2020)
21. S.M. Riazul Islam, K. Daehan, M. Humaun Kabir, M. Hossain, K. Kyung-Sup, The internet of things for health care: A comprehensive survey. IEEE Access (3), 678–708 (2015). https://doi.org/10.1109/ACCESS.2015.2437951

22. J.J. Oresko, J. Zhanpeng, C. Jun, H. Shimeng, S. Yuwen, H. Duschl, A.C. Cheng, A wearable smartphone-based platform for real-time cardiovascular disease detection via electrocardiogram processing. IEEE Trans. Inf. Technol. Biomed. **14**, 734–740 (2010)
23. S.P. Kumar, V.R.R. Samson, U.B. Sai, P.L.S.D.M. Rao, K.K. Eswar, Smart health monitoring system of patient through IoT, in *2017 International conference on I-SMAC (IoT in social, mobile, analytics and cloud) (I-SMAC)*, (IEEE, 2017), pp. 551–556
24. A.N. Cheeran, Android based health parameter monitoring, in *2017 International conference on intelligent computing and control systems (ICICCS)*, (IEEE, 2017), pp. 1145–1149
25. M.R. Desai, S. Toravi, A smart sensor interface for smart homes and heart beat monitoring using WSN in IoT environment, in *2017 International conference on current trends in computer, electrical, electronics and communication (CTCEEC)*, (IEEE, 2017), pp. 74–77
26. A.D. Acharya, S.N. Patil, IoT based health care monitoring kit, in *2020 Fourth international conference on computing methodologies and communication (ICCMC)*, (IEEE, 2020), pp. 363–368
27. Ying Liu, Lin Zhang, Yuan Yang, et al.: A novel cloud-based framework for the elderly healthcare services using digital twin IEEE Access, Vol. 7, Apr 2019
28. B.R. Barricelli, E. Casiraghi, J. Gliozzo, A. Petrini, S. Valtolina, Human digital twin for fitness management. IEEE Access **8** (2020)
29. H.F. Badawi, F. Laamarti, Y. Ding, F. Arafsha, B. Hafidh, A. El Saddik, An ISO/IEEE 11073 standardized digital twin framework for health and well-being in smart cities. IEEE Access **8** (2020)
30. Y. Chen, O. Yang, C. Sampat, et al., Digital twins in pharmaceutical and biopharmaceutical manufacturing: A literature review. Processes **8**(9) (2020)
31. Steven M. Schwartz, Kevin Wildenhaus, Amy Bucher, Brigid Byrd: Digital twins and the emerging science of self: Implications for digital health experience design and “small” data; Front. Comput. Sci., 2020
32. M. Lytras, P. Papadopoulou, A. Sarirete, Smart healthcare: Emerging technologies, best practices, and sustainable policies, in *Innovation in Health Informatics*, (Elsevier, 2020), pp. 3–38
33. B. Hull, V. Bychkovsky, Y. Zhang, K. Chen, M. Goraczko, A. Miu, E. Shih, H. Balakrishnan, S. Madden, Cartel: A distributed mobile sensor computing system, in *Proceedings of the 4th international conference on Embedded networked sensor systems*, (2006, October), pp. 125–138
34. Bose, B., Dutta, J., Ghosh, S., Pramanick, P. and Roy, S., 2018, February, D&RSense: Detection of driving patterns and road anomalies. In 2018 3rd International Conference On Internet of Things: Smart Innovation and Usages (IoT-SIU) (pp. 1–7). IEEE
35. A. Thiagarajan, L. Ravindranath, K. LaCurts, S. Madden, H. Balakrishnan, S. Toledo, J. Eriksson, Vtrack: Accurate, energy-aware road traffic delay estimation using mobile phones, in *Proceedings of the 7th ACM conference on embedded networked sensor systems*, (2009, November), pp. 85–98
36. A. Katrenko, I. Krislata, O. Veres, O. Oborska, T. Basyuk, A. Vasyliuk, I. Rishnyak, N. Demyanovskyi, O. Meh, Development of traffic flows and smart parking system for Smart City, in *COLINS*, (2020), pp. 730–745
37. B. Bose, J. Dutta, S. Ghosh, P. Pramanick, S. Roy, Smartphone based system for real-time aggressive driving detection and marking rash driving-prone areas, in *Proceedings of the Workshop Program of the 19th International Conference on Distributed Computing and Networking*, (2018, January), pp. 1–6
38. J. Dutta, S. Roy, IndoorSense: Context based indoor pollutant prediction using SARIMAX model. Multimed. Tools Appl., 1–30 (2021)
39. P. Nath, P. Saha, A.I. Middya, S. Roy, Long-term time-series pollution forecast using statistical and deep learning methods. Neural Comput. & Applic., 1–20 (2021)
40. R. Das, A.I. Middya, S. Roy, High granular and short term time series forecasting of $$\hbox {PM} _ {2.5} $$ PM 2.5 air pollutant-a comparative review. Artif. Intell. Rev., 1–35 (2021)

41. A.I. Middya, S. Roy, Geographically varying relationships of COVID-19 mortality with different factors in India. Sci. Rep. **11**(1), 1–12 (2021)
42. B. Chandra, A.I. Middya, S. Roy, Spatio-temporal prediction of noise pollution using participatory sensing, in *Emerging Technologies in Data Mining and Information Security*, (Springer, Singapore, 2021), pp. 597–607
43. G. Spandana, R. Shanmughasundram, Design and development of air pollution monitoring system for smart cities, in *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, (IEEE, 2018, June), pp. 1640–1643
44. M. Khan, H.B. Hossain, R.U. Rahman, M. Arafat, M.A. Jony, *Air Pollution Monitoring System for Smart City* ((Doctoral dissertation, BRAC Univeristy), 2018)
45. ul Samee, I., Jilani, M.T. and Wahab, H.G.A., 2019, December. An Application of IoT and machine learning to air pollution monitoring in smart cities. In 2019 4th International Conference on Emerging Trends in Engineering, Sciences and Technology (ICEEST) (pp. 1–6). IEEE
46. S. Sendra, J.L. Garcia-Navas, P. Romero-Diaz, J. Lloret, Collaborative lora-based sensor network for pollution monitoring in smart cities, in *2019 Fourth International Conference on Fog and Mobile Edge Computing (FMEC)*, (IEEE, 2019, June), pp. 318–323
47. S.R. Garzon, S. Walther, S. Pang, B. Deva, A. Küpper, Urban air pollution alert service for smart cities, in *Proceedings of the 8th International Conference on the Internet of Things*, (2018, October), pp. 1–8
48. A. Antonić, M. Marjanović, K. Pripužić, I.P. Žarko, A mobile crowd sensing ecosystem enabled by CUPUS: Cloud-based publish/subscribe middleware for the Internet of Things. Futur. Gener. Comput. Syst. **56**, 607–622 (2016)
49. A. Marjovi, A. Arfire, A. Martinoli, High resolution air pollution maps in urban environments using mobile sensor networks, in *2015 international conference on distributed computing in sensor systems*, (IEEE, 2015, June), pp. 11–20
50. M. Wittig, A. Wittig, *Amazon Web Services in Action* (Simon and Schuster, 2018)
51. S.P.T. Krishnan, J.L.U. Gonzalez, *Building your Next Big Thing with Google Cloud Platform: A Guide for Developers and Enterprise Architects* (Apress, 2015)
52. A.S. Mihăiţă, L. Dupont, O. Chery, M. Camargo, C. Cai, Evaluating air quality by combining stationary, smart mobile pollution monitoring and data-driven modelling. J. Clean. Prod. **221**, 398–418 (2019)
53. N. Maisonneuve, M. Stevens, M.E. Niessen, L. Steels, NoiseTube: Measuring and mapping noise pollution with mobile phones, in *Information Technologies in Environmental Engineering*, (Springer, Berlin, Heidelberg, 2009), pp. 215–228
54. R.K. Rana, C.T. Chou, S.S. Kanhere, N. Bulusu, W. Hu, Ear-phone: An end-to-end participatory urban noise mapping system, in *Proceedings of the 9th ACM/IEEE international conference on information processing in sensor networks*, (2010, April), pp. 105–116
55. Martin, B., Saverio, C., Donato, F., Louise, F., Pietro, G., Mordechai, H., Andreas, H., Vittorio, L., Juergen, M., Ferdinando, R. and Servedio, V.D., 2013. Awareness and Learning in Participatory Noise Sensing
56. E. Kanjo, Noisespy: A real-time mobile phone platform for urban noise monitoring and mapping. Mob. Netw. Appl. **15**(4), 562–574 (2010)
57. J. Dutta, S. Roy, C. Chowdhury, Unified framework for IoT and smartphone based different smart city related applications. Microsyst. Technol. **25**(1), 83–96 (2019)
58. A.I. Middya, S. Roy, J. Dutta, R. Das, JUSense: A unified framework for participatory-based urban sensing system. Mob. Netw. Appl. **25**, 1249–1274 (2020)
59. J. Dutta, P. Pramanick, S. Roy, NoiseSense: Crowdsourced context aware sensing for real time noise pollution monitoring of the city, in *2017 IEEE international conference on advanced networks and telecommunications systems (ANTS)*, (IEEE, 2017, December), pp. 1–6
60. H. Gupta, D. Bhardwaj, H. Agrawal, V.A. Tikkiwal, A. Kumar, An IoT Based Air Pollution Monitoring System for Smart Cities, in *2019 IEEE International Conference on Sustainable Energy Technologies and Systems (ICSETS)*, (IEEE, 2019), pp. 173–177

61. S. Khan, S. Nazir, I. García-Magarino, A. Hussain, Deep learning-based urban big data fusion in smart cities: Towards traffic monitoring and flow-preserving fusion. Comput. Electric. Eng. **89**, 106906 (2021)
62. S. Dhingra, R.B. Madda, R. Patan, P. Jiao, K. Barri, A.H. Alavi, Internet of Things-based fog and cloud computing technology for smart traffic monitoring. Internet of Things, 100175 (2020)
63. A. Ray, S. Mallick, S. Mondal, S. Paul, C. Chowdhury, S. Roy, A framework for mobile crowd sensing and computing based systems, in *2018 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS)*, (IEEE, 2018, December), pp. 1–6
64. C. Chowdhury, S. Roy, H. Song, R. Srinivasan, T. Sookoor, S. Jeschke, Mobile crowdsensing for smart cities. Smart cities: Foundations, principles, and applications, 125–154 (2017)
65. S. Patra, A.I. Middya, S. Roy, PotSpot: Participatory sensing based monitoring system for pothole detection using deep learning. Multimed. Tools Appl., 1–25 (2021)
66. S. Ghosh, J. Dutta, S. Roy, SenseDcity: A participatory sensing based approach, in *Proceedings of the workshop program of the 19th international conference on distributed computing and networking*, (2018, January), pp. 1–6
67. D. Kar, A.I. Middya, S. Roy, An approach to detect travel patterns using smartphone sensing, in *2019 IEEE international conference on advanced networks and telecommunications systems (ANTS)*, (IEEE, 2019, December), pp. 1–6
68. M. Nobakht, Y. Sui, A. Seneviratne, W. Hu, PGFit: Static permission analysis of health and fitness apps in IoT programming frameworks. J. Netw. Comput. Appl. **152**, 102509 (2020)
69. K. Chen, M. Lu, X. Fan, M. Wei, J. Wu, Road condition monitoring using on-board three-axis accelerometer and GPS sensor, in *2011 6th International ICST conference on communications and networking in China (CHINACOM)*, (IEEE, 2011, August), pp. 1032–1037
70. Z. Idrees, Z. Zou, L. Zheng, Edge computing based IoT architecture for low cost air pollution monitoring systems: A comprehensive system analysis, design considerations & development. Sensors **18**(9), 3021 (2018)
71. T.C. Lu, C.M. Fu, M.H. Ma, C.C. Fang, A.M. Turner, Healthcare applications of smart watches. A systematic review. Appl. Clin. Inform. **7**(3), 850–869 (2016). https://doi.org/10.4338/ACI-2016-03-R-0042
72. R. Rana, C.T. Chou, N. Bulusu, S. Kanhere, W. Hu, Ear-phone: A context-aware noise mapping using smart phones. Pervas. Mob. Comput. **17**, 1–22 (2015)
73. J. Yuan, Y. Zheng, C. Zhang, X. Xie, G.Z. Sun, An interactive-voting based map matching algorithm, in *2010 Eleventh international conference on mobile data management*, (IEEE, 2010, May), pp. 43–52
74. M. Bierlaire, J. Chen, J. Newman, A probabilistic map matching method for smartphone GPS data. Transport. Res. C Emerg. Technol. **26**, 78–98 (2013)
75. E. Rappos, S. Robert, P. Cudré-Mauroux, A force-directed approach for offline GPS trajectory map matching, in *Proceedings of the 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, (2018, November), pp. 319–328
76. T.R. Mauldin, M.E. Canby, V. Metsis, A.H. Ngu, C.C. Rivera, SmartFall: A smartwatch-based fall detection system using deep learning. Sensors **18**(10), 3363 (2018)
77. J.S. Lee, B. Hoh, Dynamic pricing incentive for participatory sensing. Pervas. Mob. Comput. **6**(6), 693–708 (2010)
78. Y. Ueyama, M. Tamai, Y. Arakawa, K. Yasumoto, Gamification-based incentive mechanism for participatory sensing, in *2014 IEEE International Conference on Pervasive Computing and Communication Workshops (PERCOM WORKSHOPS)*, (IEEE, 2014, March), pp. 98–103
79. Y. Chen, X. Wang, B. Li, Q. Zhang, An incentive mechanism for crowdsourcing systems with network effects. ACM Trans. Internet Technol. (TOIT) **19**(4), 1–21 (2019)
80. D. Yang, G. Xue, X. Fang, J. Tang, Incentive mechanisms for crowdsensing: Crowdsourcing with smartphones. IEEE/ACM Trans. Networking **24**(3), 1732–1744 (2015)
81. H. Wang, S. Guo, J. Cao, M. Guo, MeLoDy: A long-term dynamic quality-aware incentive mechanism for crowdsourcing. IEEE Trans. Parallel Distrib. Syst. **29**(4), 901–914 (2017)

82. T. Liu, Y. Zhu, Y. Yang, F. Ye, Incentive design for air pollution monitoring based on compressive crowdsensing, in *2016 IEEE Global Communications Conference (GLOBECOM)*, (IEEE, 2016, December), pp. 1–6
83. C. Gan, A. Saini, Q. Zhu, Y. Xiang, Z. Zhang, Blockchain-based access control scheme with incentive mechanism for eHealth systems: Patient as supervisor. Multimed. Tools Appl., 1–17 (2020)
84. S. Chang, W. Ren, K. Nahrstedt, Dynamic incentive mechanism for traffic surveillance, in *2015 IEEE Globecom Workshops (GC Wkshps)*, (IEEE, 2015, December), pp. 1–6
85. F. Restuccia, N. Ghosh, S. Bhattacharjee, S.K. Das, T. Melodia, Quality of information in Mobile Crowdsensing: Survey and research challenges. ACM Trans. Sen. Netw **13**(4), Article 34, 43 pages (2017). https://doi.org/10.1145/3139256
86. N.B. Truong, G.M. Lee, T.-W. Um, M. Mackay, Trust Evaluation Mechanism for User Recruitment in Mobile Crowd-Sensing in the Internet of Things. IEEE Trans. Inform. Forens. Secur. (2019)
87. V.S. Dasari, B. Kantarci, M. Pouryazdan, L. Foschini, M. Girolami, Game theory in Mobile CrowdSensing: A comprehensive survey. Sensors **20**(7), 2055 (2020). https://doi.org/10.3390/s2007205
88. H. Tang, F. Liu, G. Shen, Y. Jin, C. Guo, UniDrive: Synergize multiple consumer cloud storage services, in *Proceedings of the 16th Annual Middleware Conference*, (2015, November), pp. 137–148
89. Z. Chi, Y. Wang, Y. Huang, X. Tong, The novel location privacy-preserving CKD for mobile crowdsourcing systems. IEEE Access **6**, 5678–5687 (2017)
90. L. Zhang, Y. Li, X. Xiao, X.Y. Li, J. Wang, A. Zhou, Q. Li, Crowdbuy: Privacy-friendly image dataset purchasing via crowdsourcing, in *IEEE INFOCOM 2018-IEEE Conference on Computer Communications*, (IEEE, 2018, April), pp. 2735–2743
91. E. De Cristofaro, C. Soriente, Short paper: PEPSI---privacy-enhanced participatory sensing infrastructure, in *Proceedings of the fourth ACM conference on Wireless network security*, (2011, June), pp. 23–28
92. Y. Agarwal, M. Hall, ProtectMyPrivacy: Detecting and mitigating privacy leaks on iOS devices using crowdsourcing, in *Proceeding of the 11th annual international conference on Mobile systems, applications, and services*, (2013, June), pp. 97–110
93. Y.T. Tsou, B.C. Lin, PPDCA: Privacy-preserving crowdsourcing data collection and analysis with randomized response. IEEE Access **6**, 76970–76983 (2018)
94. C. Lin, D. He, S. Zeadally, N. Kumar, K.K.R. Choo, SecBCS: A secure and privacy-preserving blockchain-based crowdsourcing system. SCIENCE CHINA Inf. Sci. **63**(3), 1–14 (2020)
95. D. Ding, M. Conti, A. Solanas, A smart health application and its related privacy issues, in *2016 Smart City Security and Privacy Workshop (SCSP-W)*, (IEEE, 2016, April), pp. 1–5
96. H. Xie, L. Kulik, E. Tanin, Privacy-aware traffic monitoring. IEEE Trans. Intell. Transp. Syst. **11**(1), 61–70 (2009)
97. I. Zavalyshyn, N.O. Duarte, N. Santos, HomePad: A privacy-aware smart hub for home environments, in *2018 IEEE/ACM Symposium on Edge Computing (SEC)*, (IEEE, 2018, October), pp. 58–73
98. J.M. de Fuentes, L. Gonzalez-Manzano, A. Solanas, F. Veseli, Attribute-based credentials for privacy-aware smart health services in IoT-based smart cities. Computer **51**(7), 44–53 (2018)
99. R. Attarian, S. Hashemi, An anonymity communication protocol for security and privacy of clients in IoT-based mobile health transactions. Comput. Netw. **190**, 107976 (2021)
100. D. Mocrii, Y. Chen, P. Musilek, IoT-based smart homes: A review of system architecture, software, communications, privacy and security. Internet of Things **1**, 81–98 (2018)
101. J. Picaut, A. Can, N. Fortin, J. Ardouin, M. Lagrange, Low-cost sensors for urban noise monitoring networks—A literature review. Sensors **20**(8), 2256 (2020)
102. T. Maitra, S. Roy, Secpms: An efficient and secure communication protocol for continuous patient monitoring system using body sensors, in *2017 9th International Conference on Communication Systems and Networks (COMSNETS)*, (IEEE, 2017, January), pp. 322–329

103. M. Habibi, M. Fazli, A. Movaghar, Efficient distribution of requests in federated cloud computing environments utilizing statistical multiplexing. Futur. Gener. Comput. Syst. **90**, 451–460 (2019)
104. B. Ray, A. Saha, S. Khatua, S. Roy, Proactive fault-tolerance technique to enhance reliability of cloud service in cloud federation environment. IEEE Transac. Cloud Comput. (2020)
105. Y. Wang, J. Huang, Q. Jin, J. Ma, ABT: An effective ability-balanced team based incentive mechanism in crowdsourcing system, in *2017 Fifth International Conference on Advanced Cloud and Big Data (CBD)*, (IEEE, 2017, August), pp. 220–225
106. W. Dai, Y. Wang, Q. Jin, J. Ma, Geo-QTI: A quality aware truthful incentive mechanism for cyber–physical enabled geographic crowdsensing. Futur. Gener. Comput. Syst. **79**, 447–459 (2018)
107. Y. Zhang, X. Zhang, F. Li, BiCrowd: Online Biobjective incentive mechanism for Mobile Crowdsensing. IEEE Internet Things J. **7**(11), 11078–11091 (2020)