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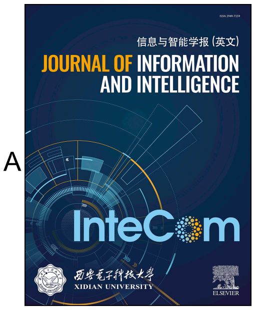

Connecting the Indispensable Roles of IoT and Artificial Intelligence in Smart Cities: A Survey

Hoang Nguyen, Dina Nawara, Rasha Kashef

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Abstract

The pace of society development is faster than ever before, and the smart city paradigm has also emerged, which aims to enable citizens to live in more sustainable cities that guarantee well-being and a comfortable living environment. This has been done by a network of new technologies hosted in real time to track the activities and provide smart solutions for the incoming requests or problems of the citizens. One of the most often used methodologies for creating a smart city is the Internet of Things (IoT). Therefore, the IoT-enabled smart city research topic, which consists of many different domains such as transportation, healthcare, and agriculture, has recently attracted increasing attention in the research community. Further, advances in artificial intelligence (AI) significantly contribute to the growth of IoT. In this paper, we first present the smart city concept, the background of smart city development and the components of the IoT-based smart city. This is followed up by a literature review of the research literature on the most recent IoT-enabled smart cities developments and breakthroughs empowered by AI techniques to highlight the current stage, major trends and unsolved challenges of adopting AI-driven IoT technologies for the establishment of desirable smart cities. Finally, we summarize the paper with a discussion of future research to provide recommendations for research direction in the smart city domain.

Keywords: Smart city, Internet of Things, artificial intelligence, machine learning, deep learning

1. Introduction

Urbanization is growing fast. The city living is rising significantly from 751 million in 1950 to 4.2 billion in 2018 (Nasiri et al., 2019) and, estimated by UN, will cover 68% of the population in 1950. 70% of natural resources are consumed by urban zone, as reported by Bibri, and Krogstie (Bibri and Krogstie, 2017), which has destroyed the human living environment in many ways, such as impurity, ecological imbalance, and energy deficit. Cities are built to help people be employed and decline costs while respecting the environment. Therefore, there is a need to invent and adopt a smart method so the smart city can solve such problems.

According to Techopedia, a smart city utilizes information and communication technologies (ICT) to enhance city functions and the quality of life of its citizens and offer solutions to specific problems, from recycling garbage to form compost to treating sewage water for construction or cleaning purposes.

The innovations of artificial intelligence (AI) and the evolution of the Internet of Things (IoT) technologies are two main aspects that have played an indispensable role in the feasibility of smart city initiatives. Smart city is a concept that can optimize the use of public resources, and enhance the quality of services provided to citizens. The benefits obtained from the deployment of smart cities include, and not limited to, transportation, surveillance, maintenance, and healthcare facilities.

AI has the potential to process and obtains valuable and precise insights from extensive data collected from various sources. Most data generated by smart cities are also unstructured (Pramanik et al., 2021). Data clouds or clusters that exploit the use of scalable and fault-tolerant architecture in distributed databases (i.e., NoSQL) are ideal places to store enormous amounts of unstructured data. Therefore, programming models that can process large datasets, parallelly can handle those big data efficiently.

IoT provides an interconnection network of various physical objects, including computing devices, sensors, and other devices that can connect and exchange data. The statistics in the report presented by Statista Research in 2019 show that there will be approximately 75 billion smart devices (Fizza et al., 2021), adding a huge amount of USD 11 trillion per year to the economy by 2025 (Bauer et al., 2021). All statistics and estimations lead to the conclusion that IoT will be one of the most valuable technologies, with endless opportunities, challenges, and issues ahead in the smart service and applications industry. This survey's primary goal is to explore the role of IoT in transforming cities into smart, sustainable, and efficient ones. (Fig. 1) illustrates the structure of this survey paper.

The main contributions of this work are outlined as follows.

- A brief review of the main concept and background of smart cities (e.g.,

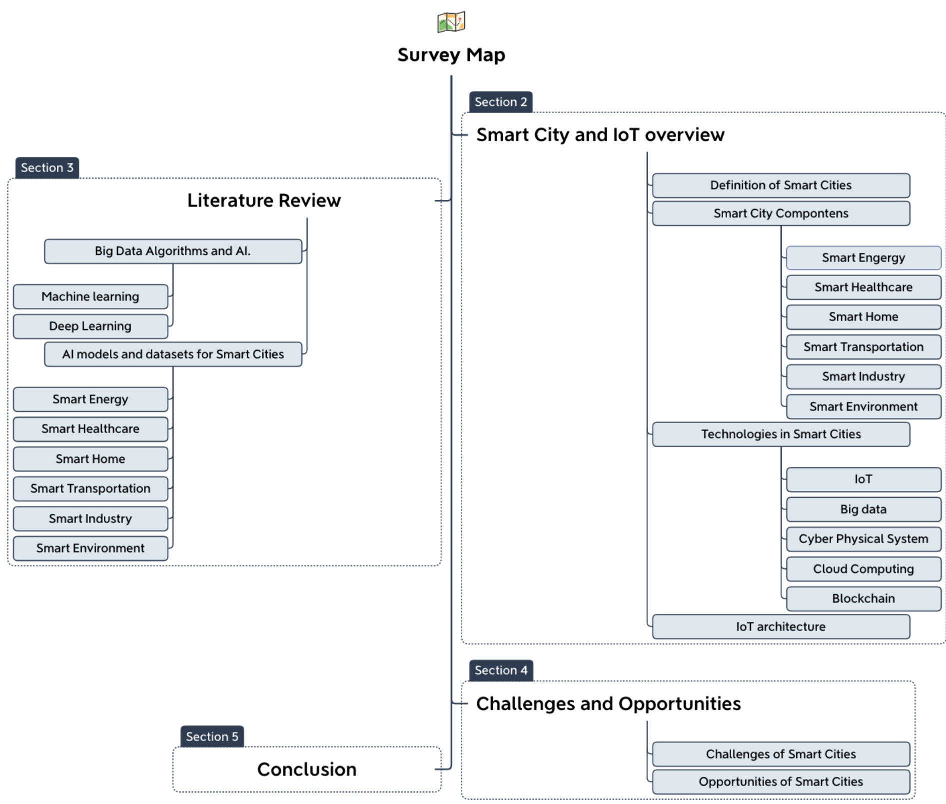

Figure 1: Survey Structure

definition, roadmap, components, and architectures) and applications of IoT in smart cities.

- A detailed analysis of AI-driven methods and data collections widely used in research of IoT-enabled smart cities.
- A discussion of obstacles and opportunities of IoT in smart cities.
- A discussion of future research directions regarding problem formulations and solution techniques.

The remainder of this article is organized as follows. In Section 2, we introduce the fundamentals behind the concept of smart cities and IoT technologies, reviewing the definition of smart cities, presenting different components and architectures, along the applications of smart cities. Section 3 presents available research on AI incorporation, along with state-of-the-art technologies in IoT-enabled smart cities. Finally, the prominent issues and opportunities in the path of smart city, implementation is presented in Section 4, alongside some highlights on potential future research directions in various domains of the development of IoT-enabled smart cities.

2. A brief overview of Smart City and IoT architecture

In this section, we briefly describe the definition of smart cities, the components of smart cities, technologies and platforms to support smart cities, and finally IoT architecture of smart cities.

2.1. Definition of smart cities

Table 1: Definitions of smart city from the research community.

Authors	**Definitions**
Kulkarni et al. (Kulkarni and Farnham, 2016)	The smart city means a local entity, for example, a distinct region, city or small locality which follows a holistic strategy that applies advanced technologies combined with real-time analysis to maintain and develop sustainable economic developments.
Nelson et al. (Nelson et al., 2019)	The smart city is a territory with a high capacity for learning innovations built by its residents' creativity and their digital infrastructure that creates, exchanges, or uses data or information in a digital form for communication and knowledge management.
Wilson et al. (Wilson, 2019)	With many higher educated citizens, high-tech jobs, planning systems that are output-oriented, creative activities and initiatives that target sustainability, a smart city has high productivity.

There are many definitions for "smart city" in the research community. Different research groups give their various definitions, and some of them even replace "smart" with other words, namely "digital", or "intelligence". Table 1 shows different definitions and concepts of a smart city from researchers. There is no single way or solution to build a smart city (O'grady and O'hare, 2012). However, from a technical point of view, we can consider that smart cities are cities where information and communication technology are broadly

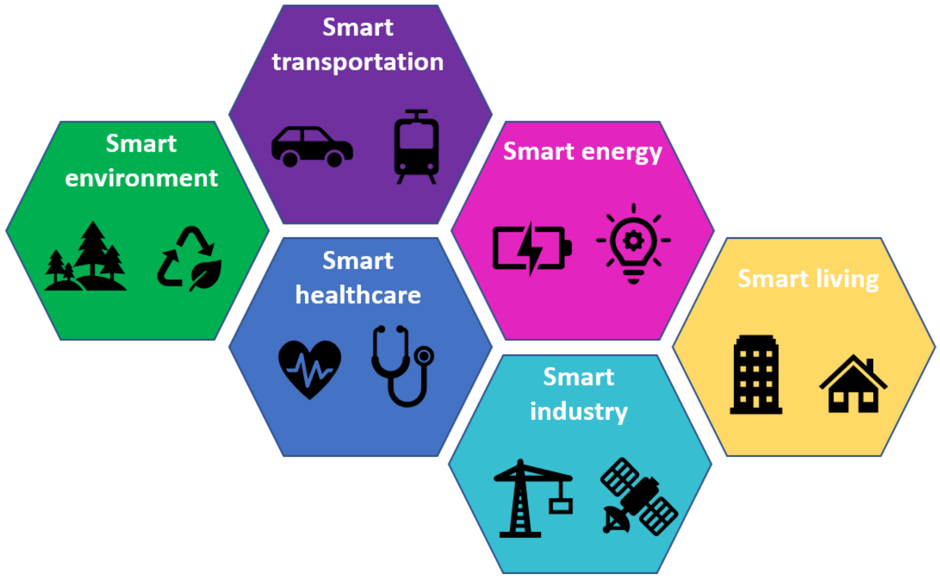

Figure 2: Smart city's components (Syed et al., 2021a).

adopted to build, maintain, and develop fundamental and crucial services and infrastructure (Washburn et al., 2009; Singh et al., 2020).

Information and communication technology is used widely in many smart applications, ranging from artificial intelligence, smart vehicles, smart homes and the decision-making process in many machines (Privat et al., 2014). The smart city uses many sensors, actuators, cameras and devices in vehicles, buildings, or houses to monitor their physical structure and integrate with other related applications (Bakıcı et al., 2013; Hancke et al., 2012; Liu and Peng, 2013; Barrionuevo et al., 2012). For example, a traffic management system monitors and responds to cars with cameras and sensors attached in real-time.

2.2. Components of smart cities

A smart city is built upon many critical components that apply information and communication technology to monitor the physical world by collecting data via thousands of sensors and hardware devices i.e. cameras, actuators, wearables, etc. through the Internet. We can divide those components into six main categories: smart energy, smart vehicle or transportation, smart healthcare, smart home or living, smart environment, and smart industry (Fig. 2). We describe some typical components below.

2.2.1. *Smart energy*

Smart energy is an essential component in a smart city, as it powers many other components. Energy researchers have recently brought out many advanced applications of sustainable, green, and smart energy. Simply put, smart energy manages the non-sustainable power source so that its adverse effects on nature are limited and helps to meet sustainable power requirements (Liao et al., 2019).

2.2.2. *Smart healthcare*

By taking advantage of networks and digital infrastructures of smart cities, many intelligent healthcare systems can provide correct diagnosis and health monitoring, such as keeping track of the body's temperature or blood pressure levels, which boosts the productivity of doctors and hospitals as well as reduces health risks of patients (Ding et al., 2016; Ni et al., 2016; Catarinucci et al., 2015). More specifically, the whole health information about any patient can be stored in a database, which is accessed and analyzed easily, enabling doctors to detect infectious or chronic illnesses in much earlier stages compared to traditional and manual diagnosis methods (Zhang et al., 2017).

2.2.3. *Smart living*

Smart home or smart living provides households with a management system which combines many intelligent appliances or devices around the living area to make human life more efficient and convenient, such as enhancing energy consumption (Li et al., 2011). Furthermore, many appliances can be remotely monitored for energy saving, education or entertainment. Finally, smart living applications can help to manage the waste recycling process more effectively, which provides residents with greater life experience and a sustainable environment (Zhang et al., 2017).

2.2.4. *Smart transportation*

By employing data collected from in-vehicle sensors, smart transportation applications not only boost the efficiency of the transport systems but also improve safety, speed, and reliability for citizens (Mohanty et al., 2016). For example, it can introduce smarter uses of the electric vehicle charging stations (Aouini and Azzouz, 2015; Petinrin and Shaaban, 2012). Another example is that people can use their smartphones to search or navigate the most economical routes for their destinations or just to find the closest buses and trains for their trips. Finally, smart transportation applications make plate license recognition systems easier (Vlahogianni et al., 2016).

2.2.5. Smart industry

The industry in the smart city aims to integrate all its intermediary functionaries, which can work well with each other (Syed et al., 2021a). The vision of the smart industry is made possible thanks to the applications of the Internet of things (Haverkort and Zimmermann, 2017). By applying the Internet of things in the industry, manufacturing schemes such as industrial resources and processes are well optimized, leading to better quality products or safer working environments. However, there are still vital issues for the Internet of things usage. Current smart industry solutions do not deal well with coordinating many different types of hardware devices and machines, flexible configuration, and quick implementation (Tao et al., 2018).

2.2.6. Smart environment

Smart environment applications aim to build sustainable societies of smart cities. By employing information and communication technology, those applications can track and reduce pollution and waste in societies (Zanella et al., 2014). More remarkably, smart environments can provide data on greenhouse gases, monitor forest conditions, or track city noise, which can help to forecast and anticipate environmental disasters much earlier and make the development more sustainable (Tang et al., 2015).

2.3. Technologies and platforms to support smart cities

This section provides information about the latest technologies and platforms that enable smart cities. Four popular technologies support smart cities: the Internet of Things, Big Data, Cyber-Physical Systems, Cloud Computing, and Blockchain.

2.3.1. Internet of Things

The Internet of things (IoT) describes how physical objects, namely hardware devices and machines with sensors, processing units, software, and other technologies, enable them to access, give and receive data with other devices and systems via the Internet or other network protocols (Tcholtchev et al., 2018). Apart from sensors and hardware that collect data directly on the field, middleware should be used to manipulate, visualize, and present data to administrators. All the data collected from a huge number of devices is

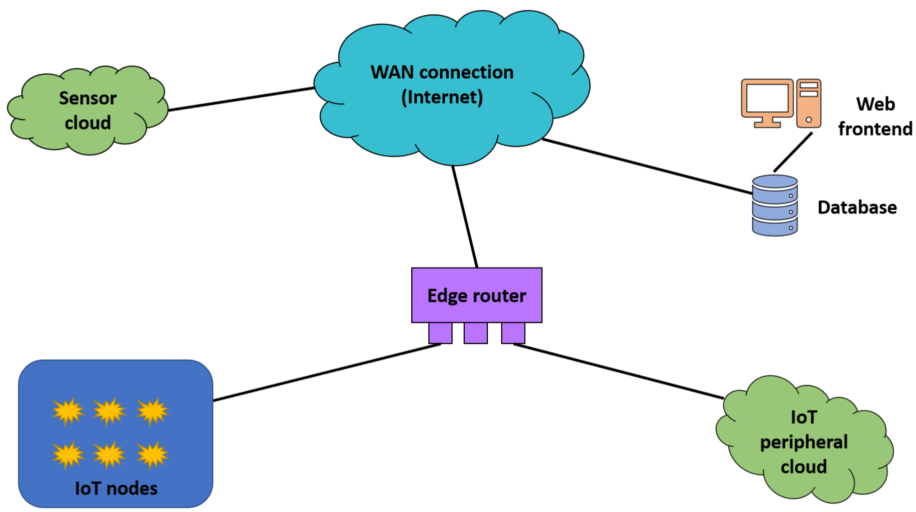

Figure 3: An example of an urban IoT network using the web approach (adopted from (Zanella et al., 2014)), where IoT nodes and IoT peripheral cloud that connect to WAN connection via Edge router, and the sensor cloud connects directly to WAN connection. All of the data collected is saved into the database. Web frontend applications pull out the data from the database to serve end users.

sent over the network and stored in the database to be processed. By keeping track of the data frequently, smart city's administrators can get to know the city's progress and then plan, control, and coordinate those gadgets (Zanella et al., 2014). Fig. 3 illustrates a typical example of an urban Internet of things network using the web approach.

2.3.2. Big data

As we know from previous sections, smart city applications need to collect and process a huge amount of data, and sometimes they need to do it in real-time. This is where they need the Big data approach. There are five characteristics of Big data, which are shown in Fig. 4. 'Volume' indicates the huge amount of information that flows into the systems to be processed and analyzed. 'Variety' indicates the diversity of data types, including text, numbers, images, raw data, unstructured data, and semi-structured data. 'Velocity' means the speed at which smart city applications receive, save, and process data, for example, images and videos captured by cameras around the city and streamed to the database and end-user applications. Those processes should be fast enough to help city administrators respond quickly to

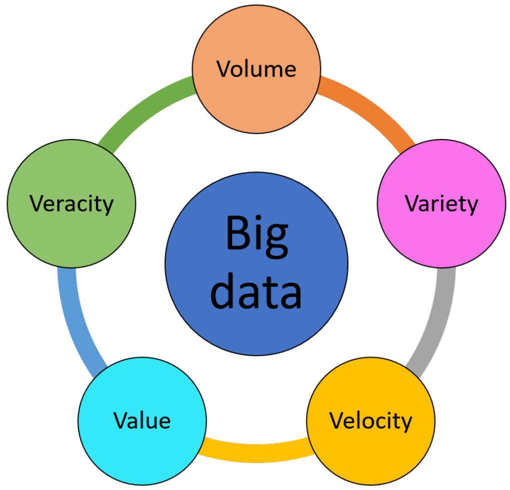

Figure 4: Characteristics of Big data (Talebkhah et al., 2021).

citizens' issues. 'Veracity' indicates the accuracy or the correctness of the data and information. For instance, low-quality data sources may lead to incorrect sensor readings and disappointments. 'Value' is the most important characteristic of Big data. It usually comes from the output of pattern recognition or insight discovery processes. 'Value' of Big Data enables smart city administrators to operate and manage more effectively and efficiently, which brings benefits for the whole city (Hashem et al., 2016).

2.3.3. Cyber Physical System

A cyber-physical system (CPS), or an intelligent system, is a system with sensors, processors, actuators and applications that identify, capture, and process data and interact with human end users (Juma and Shaalan, 2020). CPS enables smart city administrators to organize activities or events within the city efficiently through communication networks between components and machines. It also integrates information from different firms, organizations and stages within a smart city (Fromhold-Eisebith, 2017).

2.3.4. Cloud computing

Cloud computing refers to the computer resources that can be used and shared by many applications in different places without any manual management. Maintaining in-house databases or physical servers is not easy, especially for smart city administrators, who need to handle a huge amount of data, thousands of hardware devices and software applications. That is

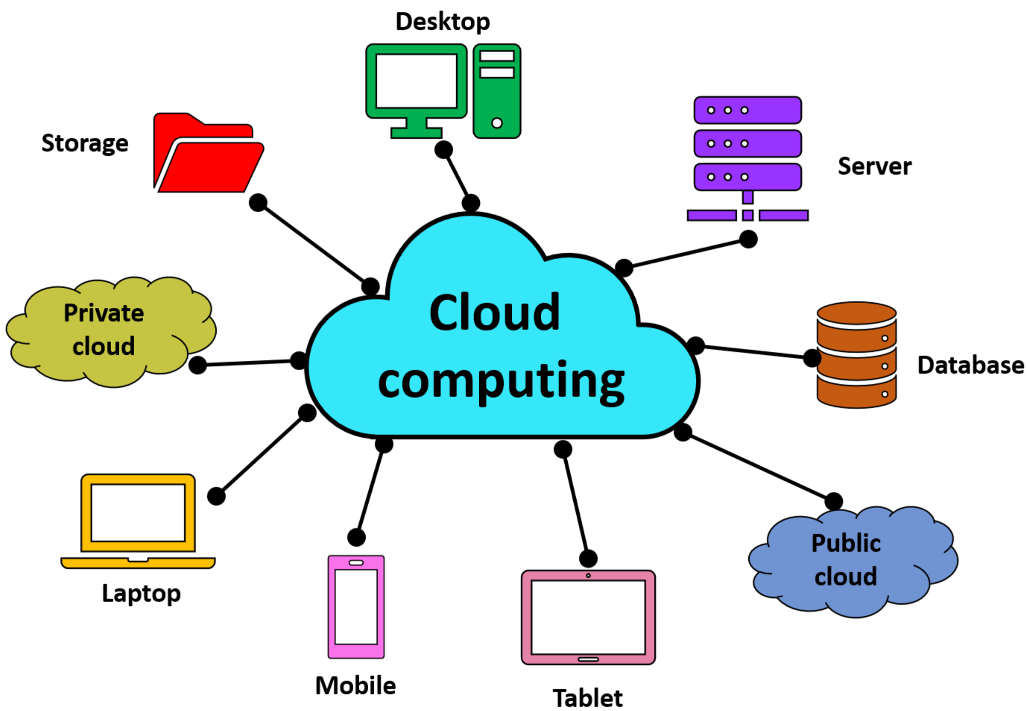

Figure 5: Example architecture of cloud computing.

why many current applications in smart cities are implemented based on cloud computing. A cloud provider, such as, Amazon, Microsoft, or Google, provides cloud services and resources which can be shared and accessed from many devices at the same time (Alam, 2021), as shown in Fig. 5. Moreover, these services can gather, analyze, store, and process data 24 hours a day, 7 days a week, with minimum supervision. There are many cloud-based Internet of Things applications from big corporations that have useful roles in a smart city, such as Bosch IoT Suite (Bosch), ABB Robotics (ABB), or Caterpillar (Marr, 2017).

2.3.5. Blockchain

Big data or cloud computing takes advantage of distributed systems. However, the distributed system is still centralized (one central unit receives, stores, analyzes, and processes data). There is a need for decentralized sys-

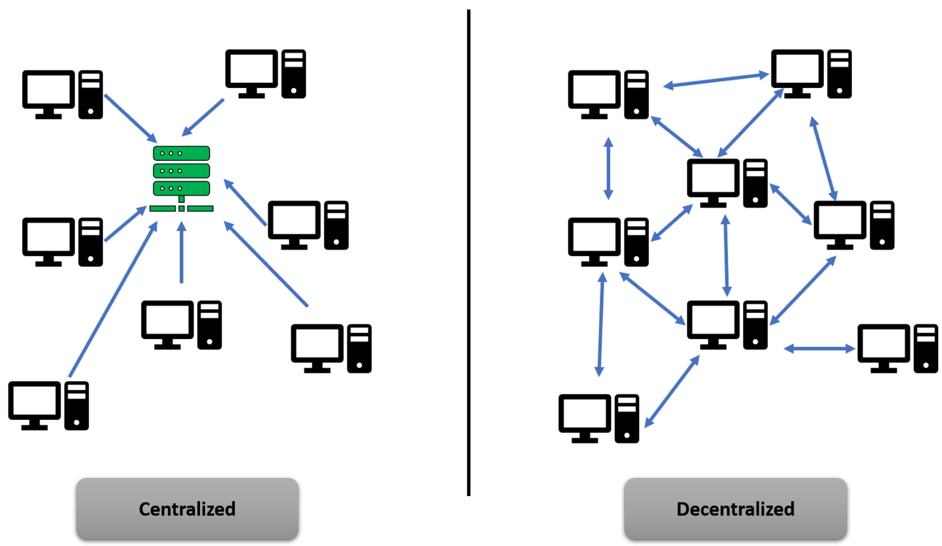

Figure 6: Comparison between centralized and decentralized networks.

tems, where information is exchanged in a peer-to-peer manner, as shown in Fig. 6. And blockchain is a distributed, immutable and decentralized ledger in which transactions cannot be mutated and controlled by one centralized entity. Every node in the blockchain network shares the same version of the ledger. That simple reason makes blockchain a secured database and hard to be hacked. The difference between a standard database and a blockchain is how the data is stored. A blockchain gets information in blocks. Blocks are linked to each other, which forms a chain of data. Fig. 7 illustrates a typical diagram of a blockchain, where a transaction is created, added to a block, and the block is sent to all the nodes in the network. Those nodes validate the transaction and then receive rewards. The block holds the transaction's information and is added to the existing blockchain, marking the transaction completed (Monrat et al., 2019).

IoT applications use blockchain to store and process secured data records via nodes. Those records in blockchains can be explored and traced back to anyone with appropriate authentication to the IoT's blockchain. By doing this, the blockchain in IoT applications can improve the security of network communication (Alam, 2019).

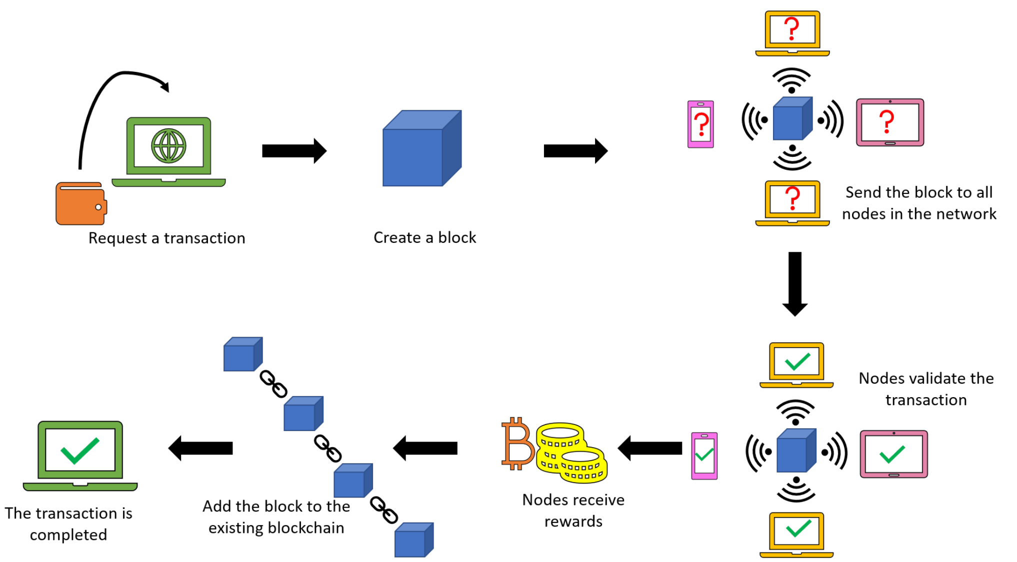

Figure 7: A typical diagram of blockchain.

2.4. IoT architecture of smart cities

IoT is an interconnected network of different devices or "things", where these devices can be RFID, NFC, sensors, actuators, etc. This interconnected network enables the exchange of data and device's related information using a unique identifier (UID) for each device. IoT is a multi-layered architecture that is proposed to meet industrial requirements and needs. There are two main architectures that exist for IoT systems in smart cities, technology-based and data-processing-based.

Based on the technology, the architecture is composed of four layers where the operation of the current layer links to the previous one. Fig. 8 depicts this architecture and the entities inside each layer.

- Physical layer (Sensing layer): This is the layer of hardware devices that collect or gather data on the field and surrounding environment. These devices have radio frequency identifiers (RFID). In the context of smart cities; these sensors capture the physical parameters, such as light, motion, pressure, etc. A smart city needs many different data types, including temperature, light, humidity, etc.

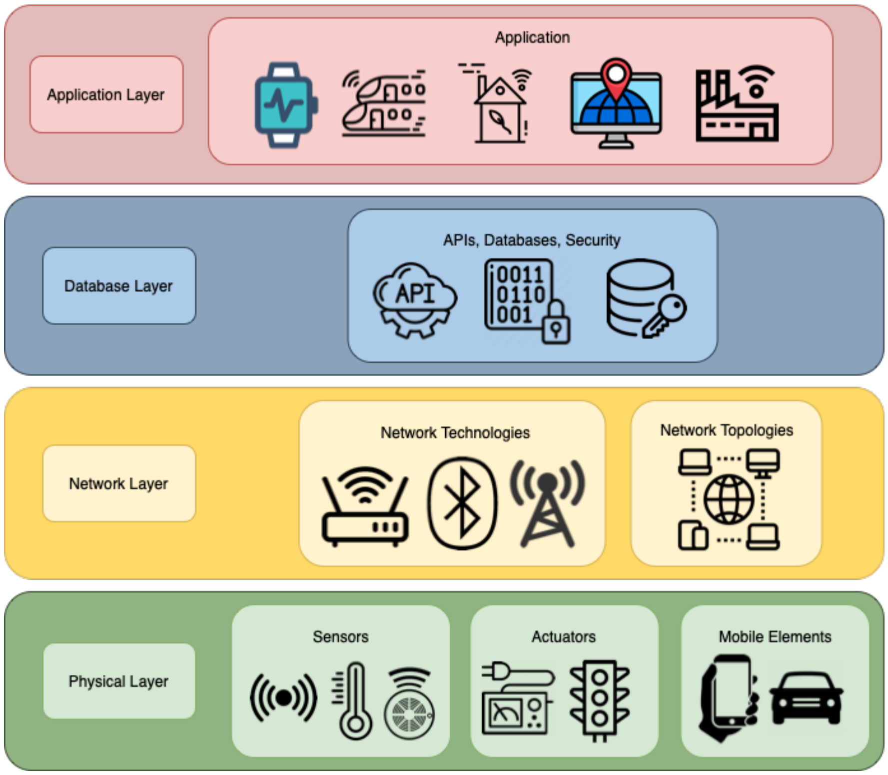

Figure 8: Technology-based IoT Architecture (Syed et al., 2021a).

- Network layer: When we connect data sources to a management dashboard for smart city administrators, the network layer or transmission layer comes into play. It serves as a communication infrastructure that enables the exchange of data between devices. This layer includes short-range wireless communication technologies, such as Bluetooth, ZigBee, RFID, or Near Field Communication (NFC). Some applications, such as smart buildings or smart water networks, can use these short-range wireless technologies from the personal area network, which benefits from their lower bandwidth and low energy consumption (Jawhar et al., 2018). Also, some applications require long-range wireless communication technologies (WiFi, LTE), such as smart transportation and industry (Jawhar et al., 2018).

- Database layer: This is a layer that comes in the middle between the physical and application layers, which is sometimes called the Middleware layer. The layer usually consists of databases and servers, which offer various generic API interfaces for the sensing layer to save, update, and store data, and for the application layer to retrieve, update, and analyze information. In addition to that, the database layer incorporates real-time processing capabilities. Also, it provides users database management services to ensure all connections to the data are secured (Syed et al., 2021a).

- Application layer: This is the layer that interacts with end users, namely smart city administrators or citizens. It translates the raw data collected from devices and sensors into meaningful insights, user experiences, or actions. It includes many applications, ranging from mobile-based to web-based apps. Those applications connect to the database layer to retrieve information, visualize, monitor, and analyze it using many analytic platforms (Syed et al., 2021a). Automation is a prime aspect of the application layer, where it enables the implementation of automated responses based on triggers or thresholds.

The architectures can be categorized into three main groups based on data processing responsibilities.

- Cloud Computing Model: This model proposes that the data processing operations of many different components in the Internet of things systems should run and process information in the cloud. Cloud computing enables remote machines to access shared resources over the same network, such as computing power, data storage, or API services. More specifically, cloud computing can allocate resources efficiently and effectively without manual supervision or schedule services that are connected via various platforms (Mell et al., 2011). However, it has some challenges needed to be dealt with. It is the farthest away from edge devices, increasing the decision-making processes' latency. It is also less robust and secure due to its centralized characteristics (Syed et al., 2021a).

- Fog Computing Model: This model was proposed in (Bar-Magen, 2013), aiming to solve some issues of the cloud computing model, which argues that most of the data is produced in the sensing and network layer. It distributes some data processing responsibilities from the centralized cloud servers to edge devices on the local network. Network devices within the network layer can handle those responsibilities. With the advancement of technology, many network devices are capable of processing simple data operations such as collection, aggregation, or simple decision-making. Network devices have advantages as they can access the local state of specific regions, which helps to localize decision-making processes (Aazam et al., 2018). By doing so, the data flow could be more lightweight and secure (Syed et al., 2021a). Furthermore, the latency and management costs of the network can be improved.

- Edge Computing Model: This model pushes data processing responsibilities further to the sensing layer. Edge computing refers to the data processing steps carried out at edge devices, such as sensors, actuators, or other hardware devices that usually collect data (El-Sayed et al., 2017). Those devices can make decisions or process data on a smaller scale compared with the Fog computing model's devices. The fog and edge computing models aim to decentralize the whole system to reduce cost and improve robustness, scalability, and latency (Syed et al., 2021a).

3. Literature review

In this section, we first describe the commonly used algorithms, regarding two main groups of artificial intelligence (e.g., *Machine Learning* and *Deep Learning*), in smart cities. Afterwards, we discuss the development path for each component throughout the years.

3.1. Big Data Algorithms and Artificial Intelligence

3.1.1. Machine Learning

In the field of smart city applications, machine learning algorithms have proven effective in addressing different learning problems, such as classification, regression, clustering, etc. These ML techniques are incorporated by the research community due to their robust performance. Nevertheless, constructing a machine learning model requires human intervention and domain knowledge, as the selection of meaningful features plays a crucial role in achieving maximum model performance.

The most widely employed machine learning algorithms are categorized into main groups:

- *Supervised Learning Approaches:* These approaches involve labeled data. Some of these supervised algorithms are Logistic Regression (LR) (Cox, 1958), Support Vector Machine (SVM) (Cortes and Vapnik, 1995), Random Forests (RF) (Ho, 1995), and Decision Tree (DT) (Wu et al., 2008). For example, the authors in (Khan et al., 2020b) addressed the challenges of electricity theft in the face of increasing incidents using an Extreme Gradient Boosting algorithm. In another work done in (Buzau et al., 2019); the non-technical losses that lead to significant revenue depletion in power utilities are addressed. These losses were detected by incorporating extreme gradient-boosted trees.

- *Unsupervised Learning Approaches:* Used mainly to discover patterns in the absence of labeled data. Some of these algorithms are K-Means (Lloyd, 1982) and K-Nearest Neighbor (KNN) (Peterson, 2009). For instance, the authors in (Gupta et al., 2023) addressed the security concerns in Intelligent Transport Systems (ITS) by proposing a solution that combines lightweight cryptography and graph-based machine learning algorithms. The focus of their work was on resolving authentication and security issues in the Vehicular Ad-HOC Networks (VANETs) environment.

- *Semi-Supervised Learning Approaches:* These approaches consume both labeled and unlabeled data. Some of these models are utilized in reinforcement learning algorithms used for smart buildings' signal localization (Mohammadi et al., 2018).

3.1.2. Deep Learning

The evolution of smart cities presents opportunities for advancements in public safety, citizen experience, and connectivity. Intelligent systems such as computer vision and deep learning models are employed to identify many challenges, such as traffic rates, smart driving, etc. Deep Learning (DL) can address the limitations of machine learning approaches.These methods can automatically extract hidden features from raw signals, easing the efforts of feature engineering procedures. They can also extract the temporal correlation in time series data and the spatial patterns in images. However, they are a black box that requires more effort in tuning and maintaining. Well-known DL algorithms are: Deep Boltzmann Machines (DBMs) (Salakhutdinov and Hinton, 2009), Autoencoder (AE) (Ng et al., 2011), Generative Adversarial Network (GAN),(Goodfellow et al., 2020). Deep Neural Network (DNN), Convolutional Neural Network (CNN) (Fukushima and Miyake, 1982), Recurrent Neural Network (RNN) (Medsker and Jain, 2001) and Graph Neural Network (GCN) (Sperduti and Starita, 1997). For instance, related work was done in (Dabiri et al., 2020) where Dabiri et al. focused on identifying travelers' transportation modes based on their GPS trajectories. A deep self-supervised Convolutional Autoencoder and a convolutional network. In the next subsection; we will project the applications of artificial intelligence in the realm of smart cities.

3.2. AI models and datasets for Smart Cities

In this subsection, we highlight the AI-driven implementing solutions for some of the most noticeable components of IoT-based smart cities.

3.2.1. Smart Energy

The main objective of smart energy is to monitor and optimize the use of energy (i.e., electrical and hydro-power) consumption for any purpose, which guarantees sufficient usage without polluting the environment (Belli et al., 2020). Smart energy is built upon a Smart grid is an IoT technology-based system. Hence, it mainly focuses on three smart grid tasks: smart grid energy load forecasting, energy stability assessment and power grid security.

Smart grid energy load forecasting is used to estimate load/energy consumption; hence balance between the demands and availability (Shirazi and Jadid, 2018). In 2017, Al-Wakeel et al. (Al-Wakeel et al., 2017) proposed an unsupervised ML approach to estimate energy usage. K-Means first clusters the load profiles of historical data, and then the missing or future consumption is measured by employing distance functions. The dataset used in this study is obtained from Irish Smart Metering Customer Behaviour Trials (CBT), which contains the profiles whose time window is up to 24 h (for Energy Regulation , CER). A KNN approach is presented by Valgaev et al. (Valgaev et al., 2017). Multiple KNN forecasters are built based on historical data. The results are then combined using a predefined combination function such as permutation merge to predict the load for the next 24 h. In their work, they use the dataset about electricity consumption in three buildings (e.g., a housing, a student dorm, and a school campus) for Aspern Smart City Research (ASCR, 2017). (Vrablecová et al., 2018) formalizes the problem of forecasting electricity load for Irish CER (for Energy Regulation , CER) as a regression problem and solves it by employing a supervised learning approach based on Support Vector Machine (Cortes and Vapnik, 1995). Later, Kong et al. (Kong et al., 2017b,a) demonstrated a solution for extracting the temporal correlation among the different energy consumption behaviors. In this work, the proposed predictive model is built upon a long short-term memory (LSTM) architecture, a variant of RNN methods. In contrast, the work proposed by Amarasinghe et al. (Amarasinghe et al., 2017) investigates the effects of using CNN on energy load forecasting. The authors of (Dong et al., 2017; Hosein and Hosein, 2017; Ke et al., 2019; Han et al., 2020a) suggest not to restrict to uni-model and uni-data, so they recommend employing multiple models and data sources to improve the energy load accuracy. The work in (Dong et al., 2017) proposes to use CNN with the K-means algorithm to achieve a good performance. Meanwhile, in (Hosein and Hosein, 2017), many deep learning models such as stacked autoencoders (AE), CNN, and RNN are utilized to construct the load forecasting. They conduct extensive experiments to show that employing multiple algorithms can improve the overall results and reduce the error rate compared to a single model. The works of (Ke et al., 2019; Han et al., 2020a) not only employ multiple predictive models (e.g., DNN, stacked AE, and RNN) but also incorporate the additional information (i.e., weather information and holiday information) used for their framework. The authors in (Huang et al., 2018; Liu et al., 2019; Taïk and Cherkaoui, 2020; Fekri et al., 2022) present several frameworks assisted by edge computing technologies for monitoring resources in the smart grid scenario. In (Fekri et al., 2022), the authors develop a federated learning process to train their proposed forecasting model. Their experimental results demonstrate that federated learning is beneficial in distributed computational resources.

Stability assessment aims to proactively assess the grid's real-time stability, enabling timely intervention for protecting the grid system. Several AI-driven solutions have been proposed in this domain. In the ML track, Xiao et al. (Xiao et al., 2020) deployed a multivariate RF regressor approach for the oscillatory stability assessment (OSA). Even though the setting is simple, the model still shows its robustness and efficiency in the task. Voltage stability assessment is addressed in (Wang et al., 2021a; da Cunha et al., 2022). Wang et al. (Wang et al., 2021a) present a technique by utilizing SVM, while Cunha et al. (da Cunha et al., 2022) a DT approach is employed for interactive VSA. Regarding the DL track, the authors in (Shi et al., 2020) present a framework based on CNN for the OSA system. Along with the development of various DL techniques, Tian et al. (Tian et al., 2022) propose a solution based on the concept of a hybrid model built upon CNN and LSTM.

Recently, Liu et al. (Liu et al., 2022a) suggest using a transformer to monitor the stability of the grid system.

Power grid security aims to guarantee the security of the network from cyberattacks. The works of (Nguyen et al., 2015; Liu et al., 2022b) use decision trees to classify the data transmission events. In (Shuan et al., 2019), the authors propose to utilize ML (e.g., RF) and DL (e.g., CNN) methods together for detecting energy theft. Zhou et al. (Zhou et al., 2018) develop a stacked denoising autoencoder to detect and label four types of cybercrimes in the smart grid. In summary, smart energy offers major functions such as:

- Self-healing function that enables the smart grid to analyze and correct major faults.
- Smart grids have an interactive platform that facilitates the information exchange between consumers and providers.
- Smart grids offer better power quality by maintaining constant voltage through the monitoring and control systems.

The use of AI-driven models in IoT-based Smart Energy components is summarized in Table 2.

3.2.2. Smart healthcare

IoT technologies and AI advances have been widely used for various purposes of a smart healthcare system, such as remote monitoring, patient administration, telemedicine, adverse drug interactions, and community healthcare (Ramanujam et al., 2021). Among these purposes, human activity recognition (HAR) and disease diagnosis are the two most major applications of IoT in smart healthcare (Syed et al., 2021b).

The objective of HAR is to monitor the physical activities of patients/users via raw time-series signals tracked by many sensors such as accelerometer, gyroscope, magnetometer, camera and biosensor. These sensors can be wearable, built into smart devices (i.e., phone or watch) or non-wearable, which requires installation in a specific location (i.e., room). Tran et al. (Tran and Phan, 2016) employ SVM to predict six common human actions based on the signal received by acceleration, gyro and accelerometer sensors built into a smartphone. The works of (Yacchirema et al., 2019; Batool et al., 2017; Castro et al., 2017) also take advantage of wearable devices with built-in accelerometers. They propose to use machine learning methods (e.g., RF/DT)

Table 2: Models and datasets used for Smart Energy projects.

Application	Analytical Model	Data Type	Dataset
Energy/Load consumption forecasting	K-Means (Al-Wakeel et al., 2017)	Homogeneous	(for Energy Regulation , CER)
	KNN (Valgaev et al., 2017)	Homogeneous	(ASCR, 2017)
	SVM (Vrablecová et al., 2018)	Homogeneous	(for Energy Regulation , CER)
	CNN (Amarasinghe et al., 2017)	Homogeneous	(Georges and Alice, 2017)
	RNN (Kong et al., 2017b,a; Taïk and Cherkaoui, 2020; Fekri et al., 2022)	Both	(UMass Trace Repository, 2013; Dataport, 2019; Fekri et al., 2022)
	CNN and K-Means (Dong et al., 2017)	Homogeneous	(Dong et al., 2017)
	RNN (Han et al., 2020a)	Heterogeneous	(Georges and Alice, 2017; PJM Interconnection LLC, 2018)
	DNN and DRL (Liu et al., 2019)	Homogeneous	(Liu et al., 2019)
	AE and RNN (Hosein and Hosein, 2017; Ke et al., 2019)	Heterogeneous	(Hosein and Hosein, 2017; Ke et al., 2019)
Power stability	RF (Xiao et al., 2020)	Homogeneous	(Xiao et al., 2020)
	SVM (Wang et al., 2021b)	Homogeneous	(Wang et al., 2021b)
	DT (da Cunha et al., 2022)	Homogeneous	(da Cunha et al., 2022)
	CNN (Shi et al., 2020)	Homogeneous	(Pai, 1989)
	RNN and CNN (Tian et al., 2022)	Homogeneous	(Tian et al., 2022)
	Transformer (Liu et al., 2022a)	Homogeneous	(Mohamad et al., 2011)
Power grid security	DT (Nguyen et al., 2015; Liu et al., 2022b)	Both	(Nguyen et al., 2015)
	RF and CNN (Shuan et al., 2019)	Heterogeneous	(for Energy Regulation , CER)
	AE (Zhou et al., 2018)	Heterogeneous	(Zhou et al., 2018)

Table 3: Models and datasets used for Smart Healthcare projects.

Application	Analytical Model	Data Type	Dataset
Human activity recognition (HAR)	SVM (Anguita et al., 2012; Tran and Phan, 2016)	Heterogeneous	(Anguita et al., 2012)
	RF (Yacchirema et al., 2019; Batool et al., 2017)	Heterogeneous	(Anguita et al., 2012; Casale et al., 2011; Sucerquia et al., 2017)
	DT (Castro et al., 2017)	Heterogeneous	(Castro et al., 2017)
	RBM (Fang and Hu, 2014; Zhang and Wu, 2012; Uddin et al., 2017)	Heterogeneous	(Crandall and Cook, 2010; Hirsch and Pearce, 2000; Uddin and Sarkar, 2014; Uddin, 2016)
	CNN (Santos et al., 2019; Khraief et al., 2020)	Both	(Mauldin et al., 2018; Soomro et al., 2012)
	RNN (Queralta et al., 2019)	Heterogeneous	(Vavoulas et al., 2016)
	CNN and RNN (Mekruksavanich and Jitpattanakul, 2021; Khan et al., 2022; Li and Wang, 2022)	Both	(Shoaib et al., 2016; Khan et al., 2022; Kwapisz et al., 2011; Reiss and Stricker, 2012)
	AE and CNN (Zou et al., 2018)	Heterogeneous	(Zou et al., 2018)
Disease diagnosis	DT (Nahar et al., 2021)	Heterogeneous	(Naranjo et al., 2016)
	SVM (Zhang et al., 2021)	Heterogeneous	(Zhang et al., 2021)
	SVM and LR (Jiang et al., 2021)	Heterogeneous	(Jiang et al., 2021)
	RL (Dhanusha and Kumar, 2021)	Heterogeneous	(Mannucci et al., 2017)
	CNN (Naz et al., 2022; Pezzano et al., 2021)	Homogeneous	(Sandeep et al., 2017)
	RNN (Cheng et al., 2021)	Heterogeneous	(Cheng et al., 2021)
	Transformer (Hussein et al., 2022)	Homogeneous	(Kuhlmann et al., 2018; Shoeb, 2009; Brinkmann et al., 2016)
	CNN and Transformer (Xie et al., 2021)	Homogeneous	(BioNetworks, 2013)
Pharmaceutical industry	GNN (Zitnik et al., 2018b; Xiong et al., 2021)	Heterogeneous	(Zitnik et al., 2018a; Ramakrishnan et al., 2014)
	GAN (De Cao and Kipf, 2018)	Heterogeneous	(Ramakrishnan et al., 2014)

to continuously monitor the movement data of wearers. Even though these methods achieve good performance with the recognition accuracy of above 90% for varying datasets (Wang et al., 2019), these methods are not used to deal with image data signals. DL seems to be superior to ML. RBMs are among the first models successfully employed to solve the problems in HAR domains. Fang et al. (Fang and Hu, 2014) propose using a four-layer RBM to identify 10 daily activities in a smart home. Similarly, Zhang et al. (Zhang and Wu, 2012) and Uddin et al. (Uddin et al., 2017) also apply RBM for pattern recognition, but for different types of signals which are human voice and face, respectively. However, due to its complexity in training, RBM-based models are not commonly used in recent research topics. The works of (Santos et al., 2019; Khraief et al., 2020) propose a smart healthcare system in fog and edge environments for fall detection. Their proposed system uses CNN. Meanwhile, the authors in (Mekruksavanich and Jitpattanakul, 2021; Khan et al., 2022; Li and Wang, 2022) argue that hybrid models could enhance the model performance since they inherited all the characteristics of the base models. In their works, they use CNN and RNN for their proposed model. Zou et al. (Zou et al., 2018) take further steps in combining generative and discriminative models to helps improve the classification accuracy in HAR.

IoT with AI in smart health has been utilized for real-time monitoring of patients' activities and assisting patients and doctors in earlier diagnosis and treatment. Various DL-based platforms have been created for detecting various types of illnesses such as Parkinson's seizure (Nahar et al., 2021; Zhang et al., 2021), Alzheimer's disease (Dhanusha and Kumar, 2021; Naz et al., 2022), cardiovascular disease (Jiang et al., 2021) and epileptic seizure (Cheng et al., 2021; Hussein et al., 2022). Mostly in these papers, the authors formulate the illness diagnosis as a classification problem in which the label can indicate the existence of disease (Ramana et al., 2022) or the severity of illness (Helaly et al., 2022). In contrast, some works focus on identifying or highlighting the anomalies in patients' data, such as lung nodule segmentation (Pezzano et al., 2021) or kidney segmentation (Xie et al., 2021).

Drug-related topics such as drug invention or adverse drug interaction can be another subject that merits more investigation. Most recent works on this topic employ GNN to model the complex interactions between molecules to extract the latent space. For example, Zitnik et al. (Zitnik et al., 2018b) propose three GNNs to model three separate relations between drug-drug, protein-protein and drug-protein. The unknown drug-drug relations are later inferred from the learned model. Meanwhile, in (Xiong et al., 2021; De Cao and Kipf, 2018), the authors focus on using GNN to predict the synergistic drug combinations, which can significantly contribute to the drug formulation process. IoT with AI also helps to accelerate many other factors in the pharmaceutical industry, such as medical equipment regulation (Zhang, 2018).

Table 3 summarizes the use of AI-driven models in IoT-based Smart Healthcare.

3.2.3. Smart home

Smart Home is central to citizens' life, so it is one of the major components of smart cities. Smart homes are households equipped with ubiquitous sensing units, trackers and electronic devices that can be controlled remotely by phone or computer. These sensors might be activity monitors, motion trackers or temperature sensors.

Activity recognition is one of the most important features of a smart home. Elderly people usually encounter different problems in their daily (i.e., difficulty in mobility or medical emergency), causing them not to feel satisfied or comfortable living in the environment. Therefore, we need methods to detect and predict abnormal behaviors to help them improve the quality of their life. In (Zerkouk and Chikhaoui, 2019), Zerkouk et al. use time-series data generated from a network of active and passive motion sensor are collected to monitor elderly people's activities. They use an LSTM-based deep learning model to detect and forecast the anomalies to send prompt medical assistance or other help to patients. Park et al. (Park et al., 2018) and Khan et al. (Khan et al., 2020a) have a similar installation in which data from various sensors sources, including presence, temperature, water float, and motion, have been used to classify activities performed at home. In their experiment, they use RNN for the classification task to extract human behaviours' dynamicity through time. Fall detection has been performed by (Thakur and Han, 2021; Zhu et al., 2021) on two datasets with data collected from the accelerometer, gyroscope and BLE's RSSI. These signals are then passed through KNN to detect falls. Through extensive experiments, the result achieved by their method outperforms all similar works in this field with an accuracy is around 99.7%, which means that their proposed framework can distinguish fall and fall-like motions. The authors in (Vimal et al., 2021; Pan et al., 2020a) propose to train a CNN-based detection model locally at the edge devices without waiting for the data transmission. These works are also practical since they illustrate how AI can be adopted and integrated into the edge computing system.

Indoor localization also plays a vital role in IoT. Localization and security problem can be partly solved, i.e., unauthorized people detection or locating elderly people in homes, etc. Indoor positioning has been performed by Poulose et al. (Poulose and Han, 2020), which is based on Wi-Fi RSSI heat maps. They use RSSI heat maps instead of raw RSSI, which fluctuates and can be interfered with by the other indoor channel signals. They propose a concept of hybrid deep learning based on CNN and RNN, which can enhance the overall performance and reduce positioning errors. Adeogun et al. detect human presence and estimate the number of occupants in (Adeogun et al., 2019). They gather data from IoT sensors and manual recording, then pass them to a deep neural network to detect the status of occupancy and presence with high accuracy. In (Leeraksakiat and Pora, 2020), Leeraksakiat et al. present a method to forecast people's entry/exit habits to optimize the usage of electrical devices to reduce energy consumption. Transfer learning on LSTM is used in this paper in order to improve detection accuracy if there is a change in a person's behavior, or a new person enters the room.

Another application of the smart home domain is home automation. With the help of AI, home automation provides a comfortable, safe and energy-efficient environment. Gaddipati et al. (Gaddipati et al., 2021) introduce a home security surveillance system by detecting human intrusion and responding in a timely manner. Video captured from a camera connecting to Wi-Fi is segmented, preprocessed and passed to SVM to identify intruders. A cloud-based home automation system is deployed by Bhide et al. in (Bhide and Wagh, 2015). They propose a method to locate the malfunctioning sensors and decide which technicians to call. This is accomplished using a Naïve Bayes classifier, with the inputs being measurements from various sources of ambient sensors. Murray et al. address the intelligent consumption problem in (Murray et al., 2019), where they present two different neural network architectures using CNN and RNN for state classification and average power consumption estimation. Their result shows excellent generalization ability and outperforms the state-of-the-art. Recently, comprehensive research works focused on improving this task by utilizing LSTM (Kaselimi et al., 2019, 2020a) or GAN (Pan et al., 2020b; Kaselimi et al., 2020b, 2021) due to their superiority in temporal patterns in the load.

Table 4 summarizes the use of AI-driven IoT technologies and datasets for training in Smart Home.

Table 4: Models and datasets used for Smart Home projects.

Application	Network	Data Type	DataSet
Activity recognition	KNN (Thakur and Han, 2021)	Homogeneous	(Tabbakha et al., 2019; Kaluža et al., 2010)
	CNN (Vimal et al., 2021; Pan et al., 2020a)	Homogeneous	(Vimal et al., 2021; Pan et al., 2020a)
	RNN (Zhu et al., 2021; Khan et al., 2020a; Zerkouk and Chikhaoui, 2019; Park et al., 2018)	Heterogeneous	(Cook and Schmitter-Edgecombe, 2021; Alshammari et al., 2018)
Localization	DNN (Adeogun et al., 2019)	Heterogeneous	(Adeogun et al., 2019)
	CNN and RNN (Poulose and Han, 2020)	Homogeneous	(Poulose and Han, 2020)
Energy management	SVM (Gaddipati et al., 2021)	Heterogeneous	(Gaddipati et al., 2021)
	Naïve Bayes (Bhide and Wagh, 2015)	Heterogeneous	(Bhide and Wagh, 2015)
	RNN (Kaselimi et al., 2019, 2020a)	Heterogeneous	(Makonin et al., 2013; Murray et al., 2017; Kolter and Johnson, 2011)
	CNN and RNN (Murray et al., 2019)	Heterogeneous	(Kolter and Johnson, 2011; Kelly and Knottenbelt, 2015; Murray et al., 2017)
	GAN (Pan et al., 2020b; Kaselimi et al., 2020b, 2021)	Heterogeneous	(Kelly and Knottenbelt, 2015; Murray et al., 2017)

3.2.4. Smart transportation

Smart transportation has become a more popular topic as the population increases dramatically, especially in modern city areas. Smart transportation applications can be categorized based on the objective of the problems they are trying to solve, such as routing, parking, accident detection, and infrastructure.

The growing number of vehicles often causes traffic congestion, and in order to address this issue, route optimization (routing) rises as a method to suggest the most efficient route to a given destination, aiming to minimize traffic congestion. By reducing the congestion, both travel time and vehicle emissions are mitigated. For example, in (Yang et al., 2020), the authors use Deep Belief Network (DBN) and K-Means to measure the distance from the centers to the suppliers in order to estimate the ideal number and location of the processing centers to minimize the cost. Long-term and short-term traffic forecasting is first addressed using ML/DL in (Hou et al., 2014). This work formulates the task as a regression problem and compares the performance of three regressors (e.g., RF, DNN, and DT) against the baseline predictor. Liu et al. (Liu and Wu, 2017) solve this via a classification formulation using different environmental factors. Recently, more works have focused on employing DL approaches to predict the traffic flow using multiple sensing modalities such as photoelectric sensors or satellite navigation systems. Wangyang et al. (Wei et al., 2019), Xiao et al. (Xiao and Yin, 2019), and Majumdar et al. (Majumdar et al., 2021) use deep sequential modeling approaches to predict traffic. Along with the temporal patterns, the spatial patterns are extracted by employing CNN-based models in Li et al. (Li et al., 2022), and Zhou et al. (Zhou et al., 2022a) for forecasting. Recent works of (Reza et al., 2022; Chen et al., 2022) propose to replace RNN with a Transformer to decode the temporal information. Meanwhile, the results in (Chen et al., 2021; Li and Zhu, 2021) proposed that GCN can efficiently handle these features.

Regarding parking, this problem has been extensively explored in smart transportation implementation to assist users in finding parking locations with less time and effort. For this problem, the training of AI models is based on representations inferred from different modalities, such as imaging or digital signals from sensors. PKLot dataset, published in (de Almeida et al., 2015), is a collection of images of parking lots. In the paper, the authors apply the SVM classifier to detect parking lot vacancy from the images. Many

Table 5: Models and datasets used for Smart Transportation projects.

Application	Analytical Model	Data Type	Dataset
Routing	K-Means Yang et al. (2020)	Heterogeneous	Yang et al. (2020)
	DT/RF/DNN Hou et al. (2014)	Heterogeneous	Hou et al. (2014)
	RF Liu and Wu (2017)	Heterogeneous	Liu and Wu (2017)
	RNN Majumdar et al. (2021); Xiao and Yin (2019)	Homogeneous	Majumdar et al. (2021); Xiao and Yin (2019)
	CNN and RNN Li et al. (2022); Zhou et al. (2022a)	Homogeneous	WebTRIS; Caltrans (2022); Zhang et al. (2018)
	AE and RNN Wei et al. (2019)	Homogeneous	Caltrans (2022)
	Transformer Reza et al. (2022); Chen et al. (2022)	Homogeneous	Bai et al. (2020); Guo et al. (2019); Song et al. (2020); Li and Zhu (2021); Chen et al. (2021)
	GCN Chen et al. (2021); Li and Zhu (2021)	Homogeneous	Chen et al. (2021); Li and Zhu (2021)
Parking	SVM de Almeida et al. (2015)	Homogeneous	de Almeida et al. (2015)
	KNN Stolfi et al. (2017)	Homogeneous	Stolfi
	RF/XGBoost/Ensemble Garg et al. (2020); Raj et al. (2019); de Almeida et al. (2015); Koumetio Tekouabou et al. (2022); Nazarenko et al. (2019)	Homogeneous	de Almeida et al. (2015)
	CNN Nyambal and Klein (2017); Thomas and Bhatt (2018); Amato et al. (2017)	Homogeneous	de Almeida et al. (2015); Amato et al. (2016)
	RNN Gupta et al. (2022); Kasera and Acharjee (2022); Ali et al. (2020)	Homogeneous	de Almeida et al. (2015); Stolfi
	CNN and RNN Yang et al. (2019); Hung and Chakrabarti (2022)	Homogeneous	de Almeida et al. (2015); Amato et al. (2016); Yang et al. (2019); Chen et al. (2014)
Road management	SVM/RF Dogru and Subasi (2018)	Heterogeneous	Dogru and Subasi (2018)
	Adaboost Ghosh et al. (2017)	Homogeneous	Ghosh et al. (2017)
	DNN Ozbayoglu et al. (2016)	Heterogeneous	ISBAK (2010)
	CNN Bibi et al. (2021); K et al. (2021)	Homogeneous	Sachin Patel (2019)
	CNN and RNN Jiang et al. (2022)	Heterogeneous	Jiang et al. (2022)
	AE and CNN Kumaran Santhosh et al. (2022)	Homogeneous	Loy et al. (2008)
	Transformer Kang et al. (2022)	Homogeneous	Chan et al. (2017)
	GCN Wu et al. (2022)	Heterogeneous	Zhong et al. (2019); Yu et al. (2021); Hu et al. (2020); Zhou et al. (2020, 2022b); Zhang et al. (2020); Wang et al. (2020); Heglund et al. (2020); Tišljarić et al. (2020)

following works have been conducted in this dataset by exploiting various ML techniques such as RF (Garg et al., 2020; Raj et al., 2019; Nazarenko et al., 2019), XGBoost (Garg et al., 2020), and ensemble learning (Koumetio Tekouabou et al., 2022). Further, in the DL track, various approaches are also tested on this dataset, including CNN (Nyambal and Klein, 2017; Thomas and Bhatt, 2018; Amato et al., 2017), RNN (Gupta et al., 2022; Kasera and Acharjee, 2022) and hybrid model (i.e., CNN and RNN) (Yang et al., 2019; Hung and Chakrabarti, 2022). In contrast to the classification solutions, regression solutions are provided in (Stolfi et al., 2017; Ali et al., 2020) to predict a parking lot occupancy rate.

As an important part of smart transportation, accident detection aims to reduce the risk of an accident by identifying accident-prone zones or notifying driving emergencies. Various novel ML/DL approaches (e.g., SVM and RF) are presented in (Dogru and Subasi, 2018; Ozbayoglu et al., 2016). Recently, in the work of Kang et al. (Kang et al., 2022), they argue that potential accident factors such as traffic infrastructure or objects should be recognized in advance and informed to the drivers to reduce accident scenarios. The transformer is used to extract the latent representation to score the level of each scenario. Later, the attention score for the regions in each video is computed to warn drivers of critical obstacles. This problem is also known as road anomaly detection. Recent research in this topic (Kumaran Santhosh et al., 2022; Bibi et al., 2021; K et al., 2021) are primarily based on CNN since they deal with image and video data. GNN is also worth further investigation to deal with different types of anomalies, as suggested in (Wu et al., 2022). Looking at this problem from a different perspective, the authors in (Jiang et al., 2022; Ghosh et al., 2017) study the relations between the drivers' consciousness and the driving behaviors to promote safe driving habits. Jiang et al. (Jiang et al., 2022) propose to deploy a CNN and RNN-based hybrid model to predict unsafe driving conditions learned from inattentiveness features while Ghosh et al. (Ghosh et al., 2017) utilize AdaBoost to process the image of the driver.

The models and datasets discussed for smart transportation are summarized in Table 5.

3.2.5. Smart industry

The smart industry has become a popular trend in manufacturing companies nowadays. Development in smart industry technologies provides digital infrastructures for a more sustainable industrial production, which encourages automation in the industrial process, hence, reducing human intervention, enhancing productivity and minimizing mistakes.

One of the biggest applications of IoT in the domain of the smart industry is process monitoring, which includes fault detection and anomaly detection. In (Scheffel et al., 2021), Scheffel et al. present a method to collect temporally aligned vibration, provided by vibration sensors, of an Additive manufacturing process and store them in a high-security system. Then, they use those data to conduct a CNN model to detect faults and online monitors. The approach of Zheng et al. in (Zeng et al., 2021) proposes an intelligent system to identify the small fault in coal mines. Their method utilizes SVM to achieve higher overall performance in terms of accuracy than the principal component analysis method. Machine vision is applied by Benbarrad et al. (Benbarrad et al., 2021) to find defective products. The authors build a CNN model and conduct experiments on 2 datasets, including casting manufacturing products and flotation plants. A wide range of research works employing deep learning to perform this task includes (Dey et al., 2021; Bazi et al., 2022; Geng et al., 2021; Liu et al., 2021).

Another application of AI-empowered IoT smart industry is production management. Han et al. (Han et al., 2020b) are interested in predicting carbon content and temperature value in molten steel by utilizing spectrometer data in a cloud-based system. System disruption monitoring is introduced in (Brik et al., 2019) by Brik et al. The disruption is detected based on resource localization from employees' activity and location data. Fog computing architecture is also proposed to be used in this work to support local processing with low latency. Wu et al. (Wu et al., 2022) investigate the use of GNN for anomaly detection in the industrial IoT environment.

Predictive maintenance helps the factory schedule maintenance more effectively; it prevents unexpected breakdowns during the production process, which causes unplanned reactive maintenance or financial loss. Data analysis tools and techniques process data collected from various sensors to detect anomalies to help to forecast possible defects so you can fix them before they result in failure. In this work (Scott et al., 2022) by Scot et al., they use fault signature data from measurements and utilize MK-SVM to determine the operational condition of the circulating water system in a nuclear power plant. The authors in (Zonta et al., 2022) present a DNN model that automatically inputs sensor telemetry and operating information to optimize the production maintenance schedule. In (Kwon and Kim, 2020) of Kwon et al., random forest and SVM are used to create a predictive maintenance scheme. Data

Table 6: Models and datasets used for Smart Industry projects.

Application	Analytical Model	Data Type	Dataset
Process monitoring	CNN (Scheffel et al., 2021)	Homogeneous	(Scheffel et al., 2021)
	CNN (Benbarrad et al., 2021)	Homogeneous	(Kantesaria et al., 2020; Oliveira, 2017)
	SVM (Zeng et al., 2021)	Homogeneous	(Zeng et al., 2021)
	CNN and RNN (Dey et al., 2021; Bazi et al., 2022)	Heterogeneous	(Dey et al., 2021; PHM Society, 2010; Agogino and Goebel, 2019)
	Transformer (Geng et al., 2021; Liu et al., 2021)	Heterogeneous	(Geng et al., 2021; Li et al., 2009)
Production management	CNN (Han et al., 2020b)	Homogeneous	(Han et al., 2020b)
	RF (Brik et al., 2019)	Heterogeneous	(Brik et al., 2019)
	GNN (Wu et al., 2022)	Heterogeneous	(Zhong et al., 2019; Yu et al., 2021; Hu et al., 2020; Zhou et al., 2020)
Process maintenance	SVM (Scott et al., 2022)	Heterogeneous	(Scott et al., 2022)
	DNN (Zonta et al., 2022)	Heterogeneous	(Microsoft, 2020)
	RF and SVM (Kwon and Kim, 2020)	Heterogeneous	(McCann and Johnston, 2008)
	AE and RNN (Bampoula et al., 2021)	Heterogeneous	(Bampoula et al., 2021)

for this work is gathered from different sensor sources, including pressure, temperature and vibration.

Table 6 summarizes the AI methods and common datasets used for the IoT-based Smart Industry.

3.2.6. Smart environment

The smart environment includes all aspects related to environmental data monitoring, climatical forecasting, and environment analysis which aims to reduce contamination and maintain sustainable living conditions. The smart environment is quite a broad term consisting of natural resources, weather, natural disaster, waste, etc. Given that the Smart Energy component already discussed natural resources, we will discuss the other factors. Three major domains of IoT with AI in the smart environment are environmental monitoring, waste management and climate management.

Environment monitoring involves the monitoring and tracking process (i.e., quality monitor or pollutant level control) of different environmental elements (i.e., air, wind, soil or radiation). The most popular sensors for environment monitoring are typically based on chemical and ambient sensors, which are used to measure the properties of element compositions. The work of Tagliabuea et al. (Tagliabue et al., 2021) estimates indoor air quality, specifically in school buildings, based on the level of carbon dioxide concentration. Their proposed framework suggests using RNN to deal with time-dependent parameters such as temperature or humidity. Afterwards, they discuss utilizing this framework to regulate the heating, ventilation and air conditioning systems (HVAC systems) in real-time such as sensor installation or data collection. Similarly, many other research works show the high correlation between air quality, carbon dioxide concentration (Pino-Mejías et al., 2017), and other variables (i.e., occupancy) (Zuraimi et al., 2017), which results in a significant improvement in the control algorithms. In (Ameer et al., 2019), Ameer et al. compare the performance of the four most popular ML/DL (e.g., DT, RF, gradient boosting (GB) and DNN) techniques in the task of air pollution prediction in more open areas (e.g., cities). Many spatial-temporal frameworks based on DL have been proposed in this domain. Most of them employ RNN in their architecture (Li et al., 2020; Du et al., 2021; Wang et al., 2021a; Nath et al., 2021). Soil moisture, Humidity, Temperature, water and light in the greenhouse are controlled in order to assist farmers in controlling their field remotely (Shinde and Siddiqui, 2018; Elsherbiny et al., 2022). In (Cordeiro et al., 2022; Dahane et al., 2022), the authors design an intelligent irrigation system by using an IoT-based alternative architectural approach (i.e., edge computing architecture) on DL techniques (e.g., RNN) and conduct experiments in various real-world datasets to show the feasibility of IoT and AI in the context of the smart environment.

Waste management is also a merit for further investigation in a smart environment. One of the critical issues in most cities today is urban waste collection. Therefore, governance continuously searches for a more efficient and innovative waste management system. Waste management focuses on three main tasks: waste characterization, quantification, and waste management practices. The objective of waste characterization is to classify waste streams into several categories. This task is usually achieved based on the trash item images. CNN-based models seem to be the best fit when dealing with these input images (Kambam and Aarthi, 2019; Altikat et al., 2022; Yoo et al., 2021). The aim of waste quantification studies is for the quantitative estimation of the amount of waste generated by different sources. Meza et al. (Solano Meza et al., 2019) explored the performance of varying ML/DL models (e.g., SVM/DT/LSTM) in forecasting the generation of urban solid waste. A similar setup for waste management has been presented in (Fan et al., 2022; Vu et al., 2022; Kontokosta et al., 2018) where temporal-based learning models are used to predict the waste from different sources (i.e., household, factory or city). Meanwhile, waste management practices mainly involve analyzing strategies for waste minimization, environmental restoration, or waste recycling (Ajayi et al., 2017; Cooper, 2000).

Regarding climate management, this domain includes weather analysis and disaster forecasting systems. Ma et al. (Ma et al., 2021) present a comprehensive study of ML-based research which predicts landslides on image data. The authors in (Anuradha et al., 2022) formulate this problem as a classification task. They use LSTM to model the temporal pattern of signals, such as temperature and humidity, by transmitting and processing in real-time via wireless devices. An edge computing system for flood detection is presented in (Samikwa et al., 2020), where a single LSTM model is trained separately at each edge device. Real-time weather prediction with high accuracy is feasible with the help of IoT, and AI (Darmawan et al., 2022).

Table 7 summarizes the use of IoT-based AI in a Smart Environment.

Table 7: Models and datasets used for Smart Environment projects.

Application	Analytical Model	Data Type	Dataset
Environment monitoring	RNN (Tagliabue et al., 2021; Pino-Mejías et al., 2017)	Heterogeneous	(Tagliabue et al., 2021)
	DT/RF/GB/DNN (Ameer et al., 2019)	Heterogeneous	(Liang et al., 2016)
	RNN (Dahane et al., 2022; Cordeiro et al., 2022)	Heterogeneous	(Cordeiro et al., 2022; Enslin et al., 2016; Beniaguev, 2020; City of Melbourne Open Data Team; Amirmohammad, 2019)
	CNN and RNN (Li et al., 2020; Du et al., 2021; Wang et al., 2021a; Elsherbiny et al., 2022)	Both	(Li et al., 2020; Zheng et al., 2015; Chen, 2017; Elsherbiny et al., 2022)
	AE and RNN (Nath et al., 2021)	Heterogeneous	(Central Pollution Control Board, 2020)
	Ensemble learning (Siwek and Osowski, 2012; Lin et al., 2021; Surakhi et al., 2020)	Heterogeneous	(Siwek and Osowski, 2012; Lin et al., 2021)
Waste management	K-Means/DNN (Fan et al., 2022)	Homogeneous	(Fan et al., 2022)
	SVM/DT/RNN (Solano Meza et al., 2019)	Homogeneous	(Special Administrative Unit of Public Services, 2017)
	RNN (Vu et al., 2022)	Heterogeneous	(Kontokosta et al., 2018)
	CNN (Kambam and Aarthi, 2019; Altikat et al., 2022)	Homogeneous	(Yoo et al., 2021; Altikat et al., 2022)
	Ensemble learning (Namoun et al., 2022)	Homogeneous	(Namoun, 2022)
Climate management	RNN (Anuradha et al., 2022; Samikwa et al., 2020)	Heterogeneous	(Anuradha et al., 2022; Melbourne Water Open Data Hub, 2020)
	DNN (Darmawan et al., 2022)	Heterogeneous	(National Centers for Environmental Information)
	AE and RNN (Kao et al., 2021)	Homogeneous	(Kao et al., 2021)

4. Smart Cities' Challenges and Opportunities

This section discusses the current and potential challenges we may encounter when developing a smart city IoT system. Then, we briefly define opportunities with the help of the latest advances in smart city technologies that have been recognized.

4.1. Challenges for smart cities

Fig. 9 shows some major problems in the implementation of IoT-enabled smart cities, namely (1) *Smart Sensors*, (2) *Big Data Analytics*, (3) *Security and Privacy*, (4) *Networking*, and (5) *Cost*.

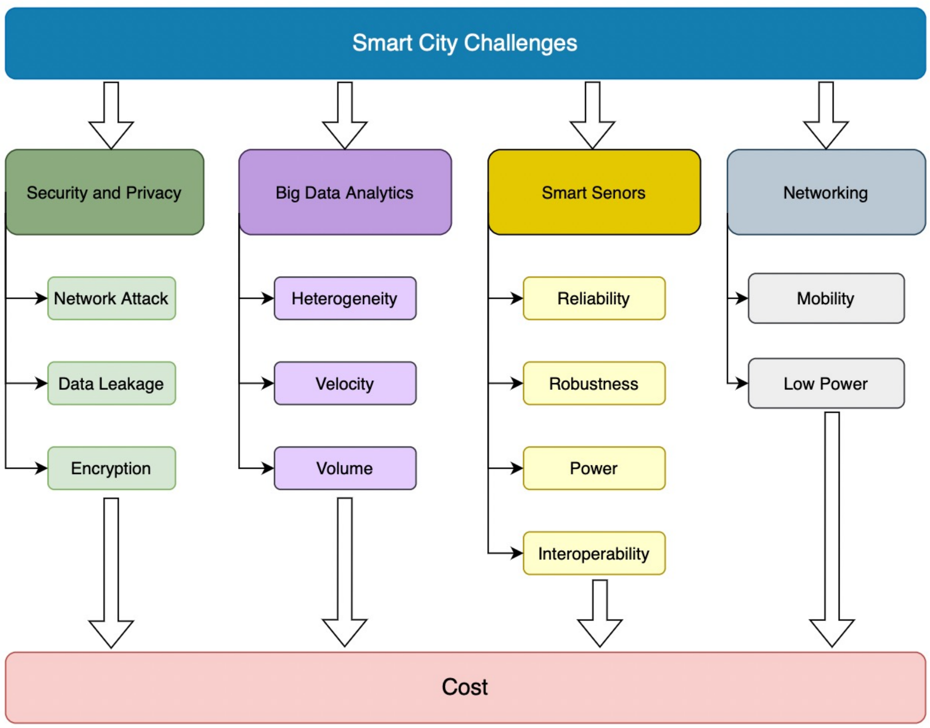

Figure 9: Challenges for IoT in Smart Cities.

4.1.1. Smart Sensors

The integration of sensors is crucial to establish a smart city. Sensors in smart cities serve the purpose of measuring the physical characteristics of devices. There are many types of sensors utilized in smart cities, including biosensors, electronic sensors, chemical sensors, etc. For example, electronic sensors are utilized as parking sensors, speedometer sensors, or sensors that measure any magnetic anomalies. On the other hand, chemical sensors, include oxygen sensors, or carbon dioxide sensors. In addition to that, biosensors are utilized to function in detecting analytes in biomedicine. The integration of sensors into smart cities faces some key challenges (Sharma et al., 2021), such as safety and security management, where delays in reporting emergencies remain despite improved services. Privacy and security concerns are also crucial, with integrated RFID addressing security issues. Scalability and energy limitations in wireless network sensors are also a challenge. Some of these challenges are being addressed in the literature, where, for instance, solutions such as adopting smart metering tools to avoid traffic control and parking issues are developed. Addressing the privacy and security concerns through including the stakeholders and policymakers are also introduced(Wang et al., 2023).

4.1.2. Big data analytics

- **Heterogeneity.** Different IoT devices, sensors, and equipment are placed at many corners of the smart city to enable the widespread ability of the smart city environment. Each device generates a large and unpredictable amount of data with different formats, including unstructured data, semi-structured data, and structured data, thus leading to some serious problems, such as heterogeneity problems. These happen during the data storage, transfer, merge, and analysis stages. Therefore, there is a need for a specialized infrastructure which helps to preprocess, manage, and organize heterogeneous data coming from diverse applications. Some solutions were proposed to solve the heterogeneity problem in the literature, for example, the authors in(Yu et al., 2023) proposed a sensor mapping method based on a similarity algorithm by employing Deep Adversarial Transfer Network.

- **Velocity.** The velocity of the data imposes two main challenges to IoT-enabled smart cities. The first challenge corresponds to the speed at which data is generated and collected. With the increase in the deployment of many smart city applications and their usage frequency, the data is updated more frequently. This data should be transmitted to the destination with minimal latency to enable the analysis step to be triggered as soon as possible (Hashem et al., 2016), which forces more proper architectural solutions to be developed to acquire the high-velocity streaming data efficiently. The other challenge is related to the data analysis and processing once they are acquired in the local storage from the remote (Tong et al., 2021; Firouzi et al., 2022; Heidari et al., 2022). However, there are many problems arising in this step, such as aligning the new incoming data with the historical records. This requires more in-depth time dependency analysis over conventional simple aggregation analysis methods (Sarker, 2022).

- **Volume.** The volume of data is growing exponentially due to the rapid expansion of the population and the development of technologies (Tan et al., 2021). For example, in the context of smart homes, there are more and more houses equipped with various IoT devices and sensors. These devices generate an enormous and unprecedented amount of data daily. This leaves a challenge in handling these big data efficiently since they can aid users in many aspects of their life. For example, to get used to knowledge from processed big data, a vast amount of data should be collected and stored at a suitable core storage system. This process may require data filtering, reading, and writing innovation. In the later stage, big data analysis should be improved to assemble, extract, and interpret the knowledge in order to produce new information and advance decision-making strategies in the smart city environment.

4.1.3. Security and Privacy

The network of smart cities keeps collecting multiple sources of data, including data related to the citizens. This kind of data should be kept confidential and ensured inaccessible or intact from unauthorized applications or entities. Data can be transferred through multiple stages, including data collection, data transfer, data storage, and data translation. The data can be invaded by cyber-crime at any stage of the data flow. For example, once data is stored in the database, the criminals may gain unauthorized access to the system to steal the data, or they can devastate the data stream during the transmission stage (Bhuyan, 2021). It is crucial to preserve the safety of the citizens' private data when they are using the smart city structure. Privacy-preserving solutions can be adopted to face this challenge (Makhdoom et al., 2020). Data privacy and security are the fundamental requirements during the establishment of smart cities leading to additional costs in design and maintenance.

4.1.4. Networking

The capability of sending and receiving information to each other plays a crucial role in IoT. Further, it is a big challenge to provide networking such that smart devices are closely connected. The issue arises when IoT is deployed globally, and the number of connected devices and sensors increases significantly (Talebkhah et al., 2021; Fraga-Lamas et al., 2021). Current networking methods are not good enough to provide a service with the demanding quality for smart city components. Many solutions have been suggested, including defining access points, local networks, etc., to solve this problem.

4.1.5. Cost

Among all challenges, the cost seems to be the central issue in creating smart urban cities (Shamsuzzoha et al., 2021). The cost is mainly associated with two primary purposes (i.e., design/development costs and operating costs). Development expense refers to implementing and integrating smart cities into reality. This can include the cost of planning the strategies that meet the citizens' requirements (Agbali et al., 2019). Further, installing and configuring several devices, sensors, and software is time-consuming and costly. Therefore, the cost is crucial to bring the vision of smart cities into reality. Operational cost is related to regular operation and maintenance procedures. Sufficient resources should be allocated to maintain the efficiency of a smart city through its life cycle. This could ensure the users and the citizens receive benefits from the smart facilities without any interruptions. Some of the solutions that were proposed to address the cost include the use of renewable energy sources(Hoang et al., 2021), including solar, wind, hydropower, etc.

4.2. Opportunities for smart cities

As a newly emerged concept that brings solutions for enhancing the quality of daily life and social wellness; citizens' demands for IoT smart city technologies and applications are continuously evolving globally. Despite this, the widespread testing and implementation for IoT-enabled smart cities remain limited to developing countries. As a result, more research on cost-effective design and implementation, which can boost the popularity of smart cities and make them feasible worldwide, is strongly encouraged. We can imagine a digital era with interconnected objects, people, and devices which assists us in solving our problems in every aspect of our lives.

A massive amount of big data and information are generated daily by the dense network of smart devices. Given this immense data, the conventional data analysis methods and technologies that require access to the entire dataset seem antiquated (Gaur et al., 2021). Therefore, we expect big data analytics integration to manage the data flow in a smart city environment. Many investigations have been conducted to identify and solve this problem. Nevertheless, these research works only propose theoretical frameworks and do not present practical ways to solve them.

Data security is also a prominent investigation topic for future smart cities. A low guarantee for security when using the smart city's ICT platform will make the citizens feel vulnerable and keep them avoid being involved in the smart city's operations. Security measures for personal data processing should be considered a high priority and urgent need requiring deeper investigations to build a sustainable smart city environment.

The introduction of developing an interconnecting network of heterogenous devices operated in different platforms, which provides in-depth and comprehensive assistance, is an interesting research field (Talebkhah et al., 2021). This makes the corresponding area in which how the information aggregation at the 'application layer' is worth further investigation.

5. Conclusion and future directions

In this survey, we comprehensively reviewed advanced AI models and datasets for IoT-enabled smart cities. We defined the concept of a smart city while introducing some important backgrounds, such as the roadmap and the components of smart cities. Later, we represented an in-depth and broad survey of recent literature, including the analytical methods and datasets used on several popular topics in the smart city research area. Afterward, we summarized the main unsolved challenges in establishing a smart city. Nevertheless, this leads to many opportunities that are versatile and have potential in this domain. Based on the discussion on the challenges and opportunities of a smart city in Section 4, in the remaining of this section, we further present the future research direction that can be made for IoT-enabled smart city projects, which aims to provide a deeper understanding to help executors, researchers and developers involved in smart city deployment.

- **Big data analytics.** Huge efforts have been made to develop efficient distributed big data processing models operating on heterogeneous devices. More investigations should be conducted in different stages of data processing. For example, to reduce the cost and latency in the data storage stage, we can process the streaming data at the network's edge using fog computing instead of transmitting all the data to the central node. Further, many parallel computing models such as MapReduce framework, FPGA programming and GPU processors can be employed to process the data gathered from multi-source in a distributed manner. (Talebkhah et al., 2021). However, there are still many flaws in the current research works, which require the extension to be well adopted in real-time estimation. For the analysis models, the fast-paced development of AI brings many potential works. These include the development of AI-driven advanced techniques for better data fusion which can extract meaningful hidden patterns from multi-source data collected from smart cities. Efficient data reduction and feature selection methods to ensure the removal of data redundancy. Regarding the predictive algorithm, explainable ML and DL algorithms are more in favour of rather than conventional ML and DL counterparts. Further, data drift should be considered to ensure that the developed models fit well with the continuous data change. Techniques such as incremental learning or online learning should be extended for this purpose.

- **Security and privacy.** There are various research areas to strengthen IoT data security and privacy in smart cities (i.e., encryption/decryption algorithms, authorization technologies and data anonymization tools). The most noteworthy advance, blockchain technology, is designed to support the execution of security techniques. In the smart city domain, blockchain has been advocated to safeguard and protect the application environment by employing a decentralized architecture for the system design (Chen et al., 2018). Smart contracts on the blockchain are promising solutions for cybersecurity. However, these areas are not sufficiently addressed in current research works; therefore, in the future, given information-centric smart cities consisting of many components, more studies focusing on blockchain could help to allow a more secure environment and enable the interconnection between the different components.

- **Priority components.** some components are expected to be more focused in the future. Smart energy (i.e., smart energy, green energy, and sustainable energy) is critical in building a sustainable environment and a strong foundation for implementing smart cities. Smart healthcare can be another topic which is attached a lot of attention as the demand for a more convenient healthcare service management and accurate disease diagnosis, the use of a smart healthcare system that reduces medical costs and responds to medical conditions is further reinforced by many different advanced technologies such as AI-based (Maxwell and Grupac, 2021).

- **Smart city awareness.** More efforts should be put into encouraging the citizens' engagement in a smart city. As the smart city network has expanded recently, the citizens may not be comprehensively aware of the provided services and applications. As a part of smart cities, the citizens also play an indispensable role in the success of smart cities, especially in the planning and implementation (Talebkhah et al., 2021) processes. If the citizens are educated properly about this concept, they may recognize various potential advantages and benefits of smart city projects. As a result, they may be more responsive in providing useful input and feedback for service outcomes and quality. This feedback would allow the government and developers to be aware of their needs and opinions, directly adjusting the services' development.

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Conflict of Interest

Authors declare no conflict of interest

Authors