Smart Cities Data: Framework, Applications, and Challenges

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Contents

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Abstract

Recent technological developments and the availability of enormous amounts of real-time data have played a vital role in the expansion, evolution, and success of smart city projects. Smart data can be used in a variety of smart city applications, but difficulties in managing such data are pushing smart cities toward the adoption of data management frameworks. Many studies have brought into focus the importance of these frameworks as they combine data collection, processing, analysis, management, and visualization and provide privacy and security features for different smart city applications, i.e., transportation, to promote a better quality of life. This chapter highlights key components of the data management framework, reviews various smart city applications, and discusses privacy and security challenges associated with smart city data. From the perspective of data frameworks, it is seen that the data used in smart city applications is unstructured coming from heterogeneous sources, i.e., sensors and social media, besides others. Therefore, the collection, processing, analysis, management, and visualization of such data are challenging. To perform these tasks, recent technologies, i.e., Internet of Things (IoT), sensor networks, machine learning, etc., have been used. Moreover, the use of smart data for smart government and governance provides several facilities for the public and business. The smart data is revolutionizing the daily communication of users along with their mode of transportation by introducing Social IoT (SIoT) and autonomous vehicles. Lastly, the challenges related to privacy and security of the data in smart cities that needed to be addressed are highlighted. This chapter will guide academics and enterprises to progress in data management framework and its applications in smart cities in the near future.

Introduction

Big data is a massive flow of data produced by the digital world such as the Internet of Things (IoT), multimedia, and social media that can be analyzed for more accurate business decisions and strategic moves. The organizations continuously capture this rapidly increasing volume of detailed data from the Internet of Things, multimedia, and social media. The total amount of big data is beyond imagination as it is increasing at a rapid pace around the globe. People are exchanging information, ideas, and data on web application all the time. Moreover, this big data has enormous potential in the utilization of services in smart cities. In smart cities, a significant role is played by information and communication technology (ICT) as it makes data available, which is collected from the digital city. The information and communication technology (ICT) is also known as the Internet of Things. Smart city associates a city with the digital city, and it links them via the Internet of Things. The smart cities sensors capture data through the IoT devices from various smart city gateways and resourcefully process it to execute it in a specific region.

Data and smart cities have made life more comfortable around the globe by creating better cities. The smart city and IoT have helped the government of China in creating new traffic routes to avoid congestion. The smart city and IoT have cut cost in their road construction. Nanjing information center has installed one million sensors into private cars and 10,000 into taxis and 7000 into busses to collect and analyze traffic data. After processing the data, they send updates via smartphones to the commuters. In Italy, sensors are installed in the trains, and the major rail operators get the real-time messages about the mechanical condition of each train. This data has helped the officials to prepare a course of action for any unfortunate event by providing a process for better maintenance predictions. The systems and services are reliable due to this innovative technology and prevent cities from major interruptions. Los Angeles (LA), USA, is switching to new light-emitting diodes (LEDs) and replacing approximately 4500 miles of streetlights. These LEDs are connected with the smart devices that will update the officials about the status of each bulb in the city. This data will help the team to repair any malfunction in the LED. LA is planning to use these lights as a signal to warn citizens about the precarious conditions in the future. The city is thinking of changing the colors of the LED or maybe making them blink which will solve the problem.

The population of urban areas and smart cities are ever rising. Smart city sensors monitor almost everything. Such innovation will not stop until they can monitor each and everything from sources of energies, to road constructions, to trash cans and streetlights. This data comes with challenges like effective management of data so it can be accessed, analyzed, combined, and used across departments and organizations. A smart city should have the ability to share data in real time so that the private and public sectors can work seamlessly together, which poses a challenge of integration between these sectors. Furthermore, smart cities deploy different types of sensors, and each sensor usually requires a new database, triggering a procurement process. The high cost of storing big data reflects on the cost of the smart city, adding to the financial backing needed upfront (Deren et al. 2015). Moreover, it is difficult to do knowledge mining in big data as big data contains rules and knowledge associated with data. These data rules and knowledge are obtained by conducting in-depth data mining and analysis. However, the fundamental properties of big data automatically make it difficult to process and to analyze the smart city data especially dataset containing spatial information (Li et al. 2001).

This chapter consists of five sections. The section "Smart Data Framework" gives an overview of key components of data management frameworks for smart cities, and the section "Smart Data Applications" describes the application of smart data in smart cities. The section "Privacy Challenges in Smart Cities" discusses the privacy and security challenges regarding smart city data, and lastly, section "Conclusion" concludes this chapter.

Smart Data Framework

In this section, each component of a data management framework for smart cities are discussed. Figure 1 gives a graphical illustration of the data framework for data management in smart cities.

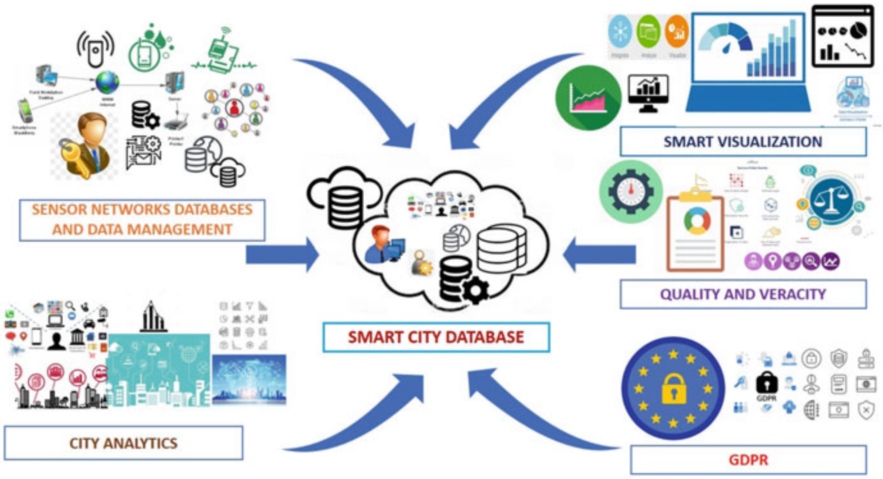

Fig. 1 Smart cities data management framework

Sensor Network Databases and Data Management

Sensor network databases involve a blend of sensor and stored data. Sensor network is a set of sensor devices (nodes) with resources, which are connected to each other wirelessly and installed in an area to collect environmental elements such as humidity, temperature, light, gas density, motion, pressure, and so on (Plageras et al. 2018) and process the data to store them in database (Changbai et al. 2008). Sensor network allows the user to remotely monitor the physical information of the environment (Küçükkeçeci and Yazıcı 2018). Sometimes sensor database is identified as in-network sensor query processing systems (ISQPS), which had been designed to collect, process, and aggregate data from sensor network/wireless sensor network (Luo and Wu 2007). In recent years, with the rapid development of information and communication technologies, the sensor network is collecting a massive amount of environmental data based on query processing construct. The challenge nowadays is how to reduce the volume of data collection and to transfer them from the node to the base location. Due to this issue, (Changbai et al. 2008) developed a new query language construct called SNQL, for dealing with large sensor database. The result indicated that the developed SNGL database increases the efficiency of the network and query flexibility.

A study by (Plageras et al. 2018) has proposed a sensor management system for collecting tremendous data generated from sensors installed in the smart buildings. This proposed system found to be a solution for accumulating and handling sensor's data in a smart city. The sensor network is one of the advanced technologies for smart buildings. It collects several types of data from various sources. It is essential to consider the reduction of energy consumption and operating expenses. Owing to these reasons, (Azri et al. 2019) carried out research and proposed 3D geo-clustering techniques/algorithm that assists in organizing information of sensor network stored in a database. The result shows that the algorithm can stabilize the node energy utilization and extension of the network. Network power consumption needs to be reduced when the database was queried, which aided in decreasing the traffic. The research conducted by (Tsiftes and Dunkels 2011) proposed an Antelope database management system for network sensor devices. This result shows the proposed system enables it to reduce congestion for network power consumption.

In order to improve power consumption, it is vital to understand the physical data and query processing between network layers and applications. The research was carried out by (Sudha and Nagesh 2018) that listed the most important query, which includes queries on multidimensional ranges, queries on historical data, long-time continuous queries, snapshot queries, and event-related queries. Similarly, investigation of the query layer design for sensor network and interaction between the query layer and in-network aggregation was studied by (Yong Yao 2012). Incremental time slot algorithm was proposed to explore how to record the data transmission between nodes. The result showed the successful performance of the proposed algorithm. The SINS database system was developed by (Dekkers et al. 2017) using a network sensor, which was installed in five different rooms to capture daily activities in a home environment for 1 week which included 16 activities. The sensor network comprises of 13 nodes. The purpose of the study was to investigate the activities carried out in the house using the benchmark system. The normalized confusion matrix was used for analysis. The result showed that the best performance was found in the hall and the worst in the bedroom.

City Analytics

The world is rapidly urbanizing, with future global population growth projected to occur mostly in cities and towns, and the environmental impression of cities encompasses beyond what is sustainable (Moglia et al. 2018). These developments provide some innovations such as economy creativities, the transformation of economy innovations into solutions, and a safe haven for the functional development of urban cities. Moreover, information and communications technologies (ICTs) are major tools that facilitate the developments and configuration of urban devices (Valls et al. 2018). Users must know how to use and operate the technologies in an urban environment, which will aid their adaptability to the environment. With the expansions in smart computing and mobile technologies, the collection of datasets in urban cities is improving geometrically that capture the pulse of urban life (Galbrun et al. 2016). These publicly available datasets have created opportunities for both the government and other authorities to make use of them to improve the quality of life for the people living in the city.

With recent trends and development of low-cost sensors, miniaturization of computing and electronics, actuation and control systems, nanotechnology, and wireless communication have contributed to emerging research areas in urban computing with overlapping themes and challenges. These technologies enable urban computing research to be deployed in the wild, in the real context of cities as the living laboratory, situated within public spaces, facilitating open interactions with individuals, groups, and communities. Recently, the nature of pervasive computing technologies has made our lives to revolve around smart objects/things that are always connected to the Internet, which have changed the way we live, communicate, and work in a smart urban environment (Salim and Haque 2015). However, this has created both technological and interactional opportunities for citizens in smart cities through urban-computerized projects.

Studies by (Krieg et al. 2018) have shown that urban data gathered can be used to develop a parking system to reduce traffic congestion in cities. In this regard, the authors developed and implemented SmartPark in San Francisco cities. The system depends on pervasive Wi-Fi and cellular infrastructure, which is capable of providing drivers with real-time parking availability information. In the city of Montreal, (Malandra et al. 2018) used LTE embedded into a web-based application to support a huge amount of machine-to-machine (M2M) traffic communication model. The model provides the precise location of different sets of machines such as traffic lights, smart meters, bus stops, etc. It also enables the study of the traffic produced by realistic M2M components in smart cities environments. Recently, (Honarvar and Sami 2019) used real urban dataset collected and extracted from multiple sources in the city of Aarhus, Denmark, to develop a prediction of particulate matter model in the city. The data collected are related to urban buildings, road traffic, air pollution, weathercasts, and points of interest (POI). The model is based on transfer learning and is validated using RMSE and MAE.

The urban big data supported by the IoT are progressively becoming related entirely through regularly and automatically sensed data, especially in smart sustainable cities. The IoT and ICT tools are used for generating the datasets using routine and automatic sensing, which replaces the conventional approach (Bibri 2018). Besides, ubiquitous sensing is the main feature of smart sustainable cities of the future, which typically rely on the fulfillment of several ICT visions of ubiquitous computing, particularly the IoT. A smart, low-cost, static, acoustic sensing device based around consumer hardware was implemented by (Mydlarz et al. 2017) in New York City (NYC) using microelectromechanical systems (MEMS) microphone in order to generate consistent decibel levels. The NYC is known as an urban sound environment having the following characteristics loud, disturbing, exciting, and dynamic. The urban sound environment has an intense influence on the quality of life of the city's inhabitants.

Deep Learning

Bu, Wang, and Gao (2019), the authors, presented a multi-projection deep computation model (MPDCM) to generalize DPDCM for smart data in the Internet of Things (Bu et al. 2019). MPDCM maps the input data into multiple nonlinear subspaces to learn the interacted features of IoT big data by substituting each hidden layer with a multi-projection layer. The used learning algorithm is based on backpropagation and gradient descent that are designed to train the parameters of the presented model. Finally, the authors conduct an extensive experiment based on the two representative datasets, i.e., Animal-20 and NUS-WIDE-14, to verify the presented model by comparing with DPDCM.

Chenhui, Shuodong, Zhuo, and Peng (2019) presented a deep learning model for potentially diagnosing gallbladder stone with big data from the medical Internet of Things (Yao et al. 2019). Gallstones can be classified into four types, i.e., cholesterol stones, bile pigment stones, mixed stones, and other rare stones, based on the chemical composition of gallstones convolutional neural network to learn the features of the collected data. The authors used a convolutional neural network model to learn the features of the collected imaging data of the gallstones. Moreover, the authors have described an effective learning approach for training the developed convolutional neural network.

Leyi et al. claimed to accurately predict protein subcellular locations (Wei et al. 2018). The authors have proposed a deep learning-based predictor called DeepPSL by using stacked autoencoder (SAE) networks. The authors claimed that the predictor automatically learns high-level and abstract feature representations of proteins by exploring nonlinear relations among diverse subcellular locations. Experimental results evaluated with threefold cross-validation show that the proposed DeepPSL outperforms traditional machine learning-based methods. It is expected that DeepPSL, as the first predictor in the field of PSL prediction, has great potential to be a powerful computational method complementary to existing tools. The authors initially used an unsupervised approach to automatically learn the high-level latent feature representations in the input data and initialize parameters and then use a supervised approach to optimize these parameters with the backpropagation algorithm. Using the computational power of graphical processing units (GPUs) and CUDA, they have trained the deep networks efficiently. The authors also considered two well-known feature representation methods. The first one is based on physico-chemical properties of proteins, while the other is based on adaptive skip dipeptide composition. Both features have been proven effective in multiple bioinformatics problems. Finally, the authors claim that by fusing the above two feature types, they yielded a total of 588 features (= 188 + 400) as the input of deep network (Wei et al. 2018). The proposed DeepPSL achieved satisfactory overall performance, obtaining 37.4% in terms of overall accuracy (OA) for the ten-class subcellular localization prediction.

Sannino and De (2018) have proposed a novel deep learning approach for ECG beat classification (Sannino and De Pietro 2018). The proposed approach has been developed using the TensorFlow framework, the deep learning library from Google, in the Python programming language. A deep learning technique is introduced in this work to meet the challenges faced by classifying the ECG beats. The authors used the dataset for each subject of the MIT–BIH database; they have computed four preprocessing steps. Furthermore, they have removed from the dataset the last 14,828 items. Additionally, the authors claimed it was necessary in order to balance the dataset due to the fact that the classes were imbalanced, namely, we had too many normal beats (N) compared to abnormal ones (V, S, and F). In fact, in these cases, conventional algorithms are often biased toward the majority class because their loss functions attempt to optimize quantities such as error rate, not taking into consideration the data distribution. In the worst case, minority examples are treated as outliers of the majority class and are ignored, the learning algorithm simply generating a classifier that classifies every example as the majority class. To avoid these problems, the authors decided to select only 2288 items representing the normal beats class (N) from the initial 66,750, randomly selected from all the subjects. Therefore, the final dataset was composed of a total of 4576 items, 2288 representing the normal beats class (N) and 2288 representing the abnormal beats class (A).

Smart Visualization

Visualization of data is the process in which the data can be visualized, and more information can be shown with the help of pictures, graph, and charts. This technique helps in deciding on challenging issues in the data visually. When it comes to big data visualization, it becomes more challenging because of its characteristics. Application of big data in smart cities makes it more complex and challenging as the data is coming from several sources, and it also has a significant impact on decision-making. However, with the development of virtual reality (VR), augmented reality (AR), mixed reality (MR), and Google Maps have changed the practical efficiency of smart city application (Hashem et al. 2016).

In smart cities, data is collected with the help of different sensors automatically, and then this data can be used for long-term analysis. In order to make long-term decision depending upon the data, several tools can be used. Usually, in smart cities, a benchmark approach is used aimed to have a better result while comparing the performance and data usage between cities (Osman 2019). Similarly, data now in smart cities is available to the habitant of the city via the Internet using different visualization methods like dashboard, etc.; this smart dashboard may be a compromise of fact and figures in the form of chart and statistics that explain how much affects are there on citizens from such policies (Osman 2019). For example, noise value can explain the effects of noise pollution on citizen and others as well.

Visualization of data via dashboard can have multiple view categories like data streams, format of data, and resources of data that involved key challenges and processes (Ben Sta 2017). In order to display the data in a specific format, first data should be in a standardized format that includes visualization and understanding (Lim et al. 2018; Rathore et al. 2016). Visualization and understanding can also be made easy with the involvement of graphs and plots and different pictures. While in a phase of development of the dashboard, there may have several data resources that have to be considered. In the smart city project, data may come from different (1) experimental setup like temperature, sound, barometer, and others and (2) third-party data like project partner. Firstly, data is fully controlled by the project manager and member of the project and then send it to the database in a particular format. These preprocessing methods are easier as the data is under a controlled environment and continuously under critical monitoring phase so that all the bugs and other mistakes can be fixed at this stage (Lee et al. 2014; Pan et al. 2016). Preprocessing will guarantee that the values sent to the database must be correct and dependable. Secondly, for privacy reasons, there exist some degree of uncertainty in the data as it is hard to know what the team member has implemented on his behalf.

For example, one may use a different file like JSON file with values and time stamp, but on the other hand, the team members may have the complex format of CSV file with time stamp and other parameters.

Special care may be needed for external and legal data. For this reason, first, the data need more care for retrieval from sources to be processed and converted to a standard format so that it can be inserted into the database. The data is now ready for visualization with the help of frontend. Concerning the frontend, one of the major challenges was to settle the color palettes because it helps the user while navigating the database. Chart, graph, and other visual basic can be done with the help of JavaScript add-on called Chart.js, which is an open-source and free to use package. This package helps to build smooth, simple, and very informative charts. Visualization of data is always a challenging task, and it depends upon the data and constraints.

GIS-Based Visualization

Geographic information system (GIS)-based visualization is now widely used for analyzing and decision-making for spatial data. It has earned a high level of popularity in urban planning, traffic data monitoring, environmental decision, and modern mode of transportation. Visualization in a smart city context is challenging as it provides an interactive and easy-to-use environmental tool for users (Hashem et al. 2016; Pan et al. 2016). Such an environment can integrate 3D touch screen integration with smart city application. These integrations can enable policy-maker to translate data into knowledge or information, which is the most critical in quick response or fast decision-making platform (Hashem et al. 2016). The information extracted from different platform and environment will be used to represent information based on the requirement of the user. GIS-based visualization will create efficient and flexible devices for smart city toward realizing the vision of a smart environment.

Quality and Veracity

In modern time, cities are expanding more and more, and almost half of the world's population lives in developed cities according to the environmental statistics with more than six devices connected (Habibzadeh et al. 2019) to the Internet. This concludes that there exist billions of devices connected to the Internet, namely, smart light, traffic road signals, pedestrian management system, smart security cameras, smart monitoring room, and control rooms and smart healthcare. Furthermore, smart homes and the devices connected to them are also part of smart cities (Habibzadeh et al. 2018a, 2019). Moreover, application connected to the smart cities has benefits for both citizens and the underlying environment (Habibzadeh et al. 2018a). Similarly, smart cities include smart economy, smart governance, smart people, smart mobility, smart environment, smart security system, smart surveillance, and smart living standards (Appio et al. 2019). With all the advantages of smart cities, one of the integral components of real-world smart cities includes data management. Data management consists of data acquisition and processing, and it relies on quality and veracity of data. A smart city collects data from heterogeneous IoT devices, such as pollution, noise, weather, and traffic among others. The quality of smart city data depends on three factors, i.e., (1) precision of collection devices or measurement errors, (2) quality of data communication and environmental noise, and (3) level of detail of the measurements and observations in temporal and spatial dimensions (Barnaghi et al. 2015). The quality of information issues become more prominent when different data with varying quality has to be integrated for use in smart city applications that use data with high dynamicity, velocity, and volume.

Smart city applications include futuristic applications such as Ambient Assisted Living (AAL), which helps the elderly to live independently for as long as possible (McNaull et al. 2012); smart parking, which helps drivers to find empty parking spaces; smart environment, which help in conserving energy by adjusting temperature in fully automated workplaces and homes; and smart transportation, which issues bad traffic condition warnings to drivers (Habibzadeh et al. 2018b). These applications are reliant on the veracity of smart city data. The veracity of smart city data depends on the precision of data collection devices, measurement errors, quality of communication, and environmental noise. The veracity of smart city data can be assured by using trustable resources or using a combination of resources to verify the data.

General Data Protection Regulation (GDPR)

In 2016, the European Union (EU) introduced a law to protect the data and privacy of all individual citizens of EU and European Economic Area (EEA). This law is known as the General Data Protection Regulation (GDPR). The primary goal of GDPR is to give its citizens the control to their own data (Team 2017). As discussed in previous sections, smart cities collect and use an overwhelming amount of personal data.

As smart cities collect more and more data of the citizens, the concerns about the security of smart city data protection measures become more noticeable, especially prominent in cases of data breaches in private companies like Yahoo (Trautman and Ormerod 2017). These privacy flaws are highlighted by the EU's GDPR as it helps in securing the huge amount of data collected and stored by smart city technologies. Many smart cities were unprepared for privacy practices introduced with GDPR, for they are not looking for solutions in the private sector. The major sticking point of GDPR for businesses and organizations is the requirement for the appointment of a data protection officer, whose role requires dual skills in data protection laws and IT. Apart from the data protection officer, the compulsory implementation of a local cyber security plan is also a big concern to smart city data protection operators. Local cyber security plan is in place to secure the storage of data, but it will increase the cost of smart cities initiatives. Hence, in the implementation of GDPR, a substantially stricter form of personal data protection in the EU and EEA, the question arises: Will GDPR slow down the development of smart cities? GDPR will certainly affect the development of smart cities, but it shouldn't be seen as a hurdle in its development as it will help in building trust with the citizens as they will reduce the fear of possible abuse and they will have control over their information and privacy in smart city models (Vojkovic 2018).

Smart Data Applications

Smart Government and Governance

In the public sector, the promising transformation has been observed over the past few years. Cities are being turned into smart cities by governments around the globe to address challenges (Allwinkle and Cruickshank 2011). This gave birth to a new phenomenon known as "smart government." Previously, the term smart government was used to refer to a government that is aware of its social roles and performing its tasks effectively by using its capabilities (Kliksberg 2000). Development projects like public administration and e-government were initiated to meet the needs of individuals and companies which also motivates governments to become smart (Schedler et al. 2004; Schedler and Proeller 2010). The smart government can be viewed as an effort of using the latest digital innovations to achieve promises that have not yet been achieved in previous development initiatives, i.e., e-government (Guenduez et al. 2017). In addition to few new features, i.e., data-based decision, creativity, resilience, etc., most of the features, i.e., sustainability, integration, effectiveness, efficiency, public administration, etc., known from the literature of e-government were also listed as the smart government features (Schedler et al. 2004; Gil-Garcia et al. 2016).

The smart government is still a fuzzy concept as in the literature there are only a few definitions of smart government, and none of them are widely accepted (Harsh and Ichalkaranje 2015; Mellouli et al. 2014; Scholl and Scholl 2014; von Lucke 2016). This makes it difficult for the implementation and governance of smart government initiative. The smart government can be referred to as "using advanced technologies to improve the effectiveness of public services, establish a commercial setting for companies and start-ups, and reduce both expenditure and energy utilization." Emerging technologies such as the Internet of Things (IoT), machine learning, cloud computing, and sensor networks have enabled objects to connect, interact, exchange, and process data in smart cities (Schedler 2018; Paola and Rosenthal-Sabroux 2014). Thus, smart cities tend to enhance financial and political effectiveness, enable sociocultural- and industry-driven growth, and solve social, financial, and environmental issues (Hollands 2008; Townsend 2013). IoT also offers unique possibilities for people to engage and impact smart city policies, create, and test them (Viale Pereira et al. 2017). IoT-enabled artificial intelligence-based solutions are being used as key areas of smart government to enhance governance effectiveness and the living standards, i.e., energy management (Chatterjee et al. 2018; Axelsson and Granath 2018).

It can be assumed that a smart government will generate cooperative environments and foster cooperation between government and nongovernment organizations (NGO) besides citizens (Nam and Pardo 2014). Whereas, smart governance is usually described as the ability to use digital technologies and smart information processing and policy-making practices (Scholl and Alawadhi 2016). Rational, political, cultural, and institutional perspectives have been used for understanding smart governance. The rational view perceives governance as the results of the rational study. The political view takes governance as the consequence of a trade-off between various significant values. The key idea of the cultural perspective is that governance is primarily meaningful among stakeholders. Whereas, the outcomes form the combination of past practices, principles, standards, procedures, and conventions form the institutional perspective (Meijer and Thaens 2018). A study also differentiates smart city governance perspectives including smart government, smart decision-making, smart management, and smart communication (Meijer et al. 2016).

The notion of smart government has a vital role in the increasing smart city debate and grows alongside other smart city aspects including smart environment, smart economy, smart mobility, smart living, and smart people (Pereira et al. 2018). Smartness in these fields occurs in the domain-specific assessment and by combining huge volumes of structured and unstructured data. This allows self-learning algorithms to produce more accurate predictions about certain facts, communities, and individuals which enables a far more efficient and user-friendly way of automating or executing certain tasks (Guenduez et al. 2019). Governments and authorities lack thorough knowledge of success factors for smart government, i.e., in Switzerland, numerous municipality governments are adopting a smart city strategy, some are in their inception, whereas others are very developed (Hollands 2008). This study has demonstrated on how smart public projects can be introduced by a recent study (Guenduez et al. 2017). They concentrated on technology, big data, algorithms, and individual participation. However, in smart cities, public authorities are still at the initial stage of the journey to the smart government (Mettler 2019). Currently, the most serious challenge in exploring the potential of emerging technologies in smart cities is probably not realizing what needs to be done for smart governments (Praharaj et al. 2018).

The important success factors for smart government projects were reported as institutional, organizational, and leadership (Guenduez et al. 2018). There are already many successful examples of this transformation toward smart cities. Artificial intelligent bots in France are helping and advising the individual in searching for jobs. Analysis of traffic data in Los Angeles improves road safety. Big data-based surveillance of fishing quotas paves the way for evidence-based decisions in Germany. Automatic data retrieval in Sweden is saving user's time. Moreover, government agencies and real-time data make rapid, focused, and even preventive police operations possible in Estonia (Kankanhalli et al. 2019; Ruhlandt 2018). Initiatives for real-time monitoring of water quality and flood detection using sensor networks can be used address prevailing situations of water crisis (Bilal et al. 2019a). The change toward smart government is not easy as the present institutional, organizational, financial, and technical barriers present significant difficulties for government authorities (Schedler et al. 2017).

Social Networks

A "social network" is a digital space where people share opinions and ideas, connect and communicate with individuals, and create a sense of virtual community (Clemons et al. 2007). Online social networks (OSNs), i.e., Facebook, Twitter, Pinterest, and Instagram, are extremely popular, and more and more people are using the OSNs to connect with their friends and acquaintances. OSNs altered the means by which individuals connect and triggered a lively debate on whether the affordances of such OSNs will also change the means by which individuals communicate (Kumar et al. 2010). Social networking platforms produce an enormous quantity of information on a regular basis, and the social network analysis research is increasing exponentially due to the diversity, volume, and complexity of data (Eirinaki et al. 2018). Social networking sites have provided individuals with access to the huge source of data with little or no restrictions (Pang and Lee 2008). The OSNs have become a major source for the acquisition and distribution of data in various fields such as commerce (Beier and Wagner 2016), entertainment (Shen et al. 2016), technology (Chen 2016), and contingency planning (Stieglitz et al. 2018). Online social media data has the ability to predict user profile attributes (Kosinski et al. 2013). It is essential to provide the consumer with the information they are searching because of the rapidly growing data. In order to profile user interests, social recommendation systems have been implemented (Jamali and Ester 2010; Tang et al. 2012). Researchers have been using social media data to predict the outcome of the elections, political debates and its influence on the individual, and perspectives into reactions to health and disease outbreaks and spread of news via social networks (Bilal et al. 2019b; Nawaz et al. 2017; Hermida et al. 2012).

Social network analysis (SNA) incorporates network and graph theory methods to study and explore social interactions. Within social networking sites, people, users, items, or objects are regarded as nodes, while relationship, interaction, and association are depicted as edges (Otte and Rousseau 2002). Web 2.0 has empowered people to interact efficiently, establishing networks with mutual interests, sharing the information, and posting huge volumes of valuable, user-generated content (Tan et al. 2011). Moreover, the application program interface (API) provided by social media platforms can be used to crawl and retrieve data. "Data analytics" can be used to derive perceptions, relations, patterns or behaviors, and insights from these tremendous amounts of data from OSNs (Bendoly 2016). SNA is considered as the most common and very well-established data analysis sub-domain. It provides a broad range of tools, techniques, methods, and principles for collecting, processing, and analyzing huge amounts of social media data that contain valuable information (Wasserman and Faust 1994; Gandomi and Haider 2015). Machine learning (ML), natural language processing (NLP), and text mining are among the most popular methods for sentiment analysis, SNA, and data mining (Stieglitz and

Dang-Xuan 2013). It is a common perception that the social relationship usually influences communication between smart devices. This indicates that social networking theory can be utilized to boost the quality of service for those social connections. Furthermore, the key concepts of social networks, i.e., centrality and community, were studied in order to efficiently understand the recent architectures of the wireless network. A study provides a detailed overview of social networks and reviews their applications in wireless communication (Jameel et al. 2018).

Presently, the focus of researchers on SNA is rapidly increasing, and several studies have explored various characteristics of social networks. The application of social networks in the wireless network has been widely studied. The social network can aid healthcare services by providing location-based facilities and monitoring individual behavior (Falk 2011). A study used one of the renowned social networking websites Vk.com to search and collect public data related to the user in a systematic manner (Bagretsov et al. 2017). An SNA-based rising star forecasting model was reported to produce the best results when compared with baseline models based on other approaches (Ning et al. 2017). On the basis of social media profile and social relationships, one can accurately predict an individual's personality. A number of studies had explored language variation from the perspective of demographic and psychographic characteristics (Bamman et al. 2014). Various recommendation systems, such as recommendations for movies, recommendations for friends, etc., use enormous social media data to find trending topics and friends recommendation (Jiang et al. 2016). Different features extracted from social media data were used to develop machine learning algorithms to identify the missing link between individuals (Fire et al. 2013). Content-based fitness and health assessment were carried out by using Twitter data (Kendall et al. 2011). A proposed system introduced comprehensive geographical features based on topics discussed on Twitter and maps consumers' geographical preferences (Vosecky et al. 2013).

The social network of influential individuals and their followers can be identified with SNA. SNA is also used to study user behavior to assess its causal relationships on the network as a whole. Social media firms have acknowledged the significance and role of influencers in the purchase or replacement of products. The content of social networks has been used in the information systems to identify and to analyze information dissemination (Zhang et al. 2016). The businesses use data from social media to target audiences, to identify preferences of clients, and to get feedback of product or services. Social networks have many advantages along with some disadvantages (Wendling et al. 2013). It is also necessary to study and to analyze events such as spreading fake news and rumors along with the reputation of the user across social networking sites (Qin et al. 2015). With the increasing user-generated content across social networks, it has become increasingly important to profile consumers by extracting information shared on OSNs. Social profiling is an emerging approach to address the challenges faced in meeting user demands. A study reviewed and classified social profiling research, describing methods, sources of data, limitations, and open challenges (Bilal et al. 2019c).

Social media analytics is generally described as a complex process. Therefore, the entire method and steps involved need to be standardized. Recently, the Internet of

Things (IoT) has been seen as an efficient technique for improving asset management (Lee et al. 2015). The IoT connects computers, devices, sensors, and individuals, and it is anticipated that this technology will connect billions of devices in the near future. However, it is very difficult to use traditional techniques for integrating and maintaining a huge network of these devices. Social networks are capable to connect and maintain communication with billions of people using social interactions. This leads to an emerging field of Social IoT (SIoT) that connects and maintains billions of devices in IoT networks using principles of social networks (Thangavel et al. 2019). The concept of SIoT resulting from the integration of social media in IoT has been introduced in fields such as management of product lifecycle, vehicle tracking, and employee assistance (Cai et al. 2014; Schurgot et al. 2012; Kranz et al. 2010). Twitter has provided users with an API that can be used by users and applications to post messages and manage the user account. The efficient communication between devices can be achieved using such APIs, and this leads to the rapid implementation of IoT solutions. Twitter can assist the devices in the IoT network to interact and communicate with inter-network devices, intra-network devices, and people, thereby increasing the strength of the IoT as a whole (Ortiz et al. 2014). But with such a broad user network and their related information, Twitter also attracts spam or fraudulent users who foster their illegal activities or attempt to deceive users and influence the feelings of specific social communities (Schulz et al. 2017).

Mobility and Transportation

One of the twentieth-century significant socioeconomic transitions was the widespread use of automobiles (Geels 2012). There is an ongoing global discussion on how new technologies, e.g., automated cars, communication applications, and IoT, will improve mobility for individuals and groups. Furthermore, it is stated that "smart mobility" transformation, which combines these emerging technologies to improve the organization and operation of the transportation system, has already started. Like any socio-technical transformation, the questions of how the change will be handled and how the advantages and disadvantages will be managed are important (Docherty et al. 2018). Smart mobility is mostly described as a transition of equal reach with respect to automobility, centered on a variety of positive developments in how individuals travel. The smart mobility was described as a future vision in which transportation will be presented as a service accessible on request, with people having immediate access to a clean, renewable, effective, and convenient transportation system (Wockatz and Schartau 2015). Followed by the extensive adoption of integrated and autonomous vehicles, it was argued that somehow the smart mobility will offer potential benefits in safety and fewer travel expenses by efficient use of transport infrastructure and automobiles. These new frameworks with shared ownership of mobility resources and real-time data integration will also reduce the hold of big companies on transport supplies (Fagnant and Kockelman 2015). The capacity for autonomous cars to decrease journey times for a diverse range of trips will have a much greater impact on individuals and the economy rather than only saving time (Wadud et al. 2016).

There are some key characteristics of smart mobility that are being discussed and common among all feature perspectives (Kuosa 2016). Mobility is taken as a service in which companies replace individual ownership of automobiles, i.e., the capacity of the individual to buy transport facilities package operated by certain operators. This is supported by the embedded aggregator and payment systems capable of processing huge volumes of real-time data to meet user demands (Thakuriah et al. 2016). The user's decisions of mobility and non-mobility are being influenced by real-time crowdsourced user-generated content (Toole et al. 2015). Smart infrastructure, such as connected automobiles, uses individual operational data and gives real-time feedback to monitor the behavior of travellers and enhance system efficiency (Alam et al. 2016). Nowadays, automobiles are being electrified using renewable energy from batteries, hybrid, and other new technologies. The use of smart power grids in electric cars can be emission-free as well as provide a solution for the use of renewable energy (Bakker et al. 2014). The autonomous vehicles enable all passengers in a vehicle to perform their task during travelling where no user is required to drive the vehicle (Fagnant and Kockelman 2015).

The recent trend toward the installation and use of vehicle automation and communication systems (VACS) in automobiles is due to significant advances in ICT and sensor networks. VACS provided users with comfort and safety along with controlling traffic and emissions for connected automobiles (Diakaki et al. 2015). The volume of VACS-equipped connected autonomous cars will rise quickly over the next decade. In addition, human-driven vehicles still retain their place in global markets. However, the roads will soon be shared by both human-driven and autonomous vehicles (Levin and Boyles 2016). It is essential that we know how users adapt to the existing smart transportation system, given the advantages of a connected environment. Vehicular social networks (VSNs) inherited features make it difficult to enable smart mobility and efficiency in data transfer. The Internet of Vehicles (IoVs) has emerged where automobiles operate as sensing terminals to collect data of in-vehicle and smartphone devices and then release it to users. VSN is a new framework that attracts scholarly and industrial attention, but the integration of social networks with IoVs is in its early stages. Incorporating smart controllers and connectivity techniques in smart cities create a whole new domain for IoVs as automobiles have considerably transformed (Rahim et al. 2018).

There are still many obstacles, i.e., the distribution of messages and analysis of big trajectory data, trust, security, and anonymity, to use VSN for enabling smart mobility. The literature related to overcoming these challenges faced by VSNs is very limited until now. Therefore, it is necessary to develop social trust-based techniques for secure and reliable connections in VSNs (Rahim et al. 2018). There are many examples of smart mobility in various smart cities throughout the globe. London ranked second in the world's smartest city ranking, according to the Cities in Motion Index (CIMI). London's transport system integrated number plate identification for managing traffic flow to effectively reduce traffic jams during rush hours. It also involves Wi-Fi accessibility, smart roads, and bike share programs (Berrone et al. 2016). The green city index of the United States and Canada recognized San Francisco as the greenest city. The San Francisco transport authority adopted the approach to substitute single-occupant automobiles with shared electric, connected, and automated vehicles which solved many problems with the time-consuming and costly transport (Silva et al. 2018). One of the potential problems faced by the upcoming transportation systems is developing smart mobility governance techniques that use wireless communication to accomplish worldwide roaming. In addition, it is necessary to integrate and interoperate advanced mobility governance techniques in heterogeneous networks to integrate prospective wireless systems in smart cities (Yaqoob et al. 2017). With the evolution of smart mobility, the key system components will be reconfigured resulting in different outcomes of mobility, i.e., patterns of land use, jobs, housing, etc. (Kim et al. 2015).

Smart Environment

Smart environment means the living standard, living style, and the things around the smart city, not the actual environment of the city. It aims to provide the basic necessity of life and provide a better interaction between the citizen and their surroundings. The smart environment is provided with the help of artificial intelligence and machine learning, thus creating a responsible, adaptable machine into the environment (Jain and Nagarajan 2016; Augusto et al. 2013), for example, data collection from different microphone sensor and cameras located in the city and applying different machine learning algorithms to detect emotions and gesture recognitions, especially in case of smart classrooms, where the instructor and students both adjust their learning with the help of visual aids. In a smart environment, data can be from different nodes with different format because of the diverse nature of devices connected in a particular environment, which further generates the ranges of senses like communication, data, and security of data (Jain and Nagarajan 2016; Sheu et al. 2016).

Smart Streetlights

Smart streetlight is one of the most adaptable applications in smart cities. Smart streetlights can help in energy consumption optimization. This can be done with the help of sensor nodes as well as monitoring with smart cameras. The saved energy can be supplied to that area where the energy is needed. Sensor nodes are efficiently deployed to monitor the streetlights. These nodes also have a camera for the visual insight of the location so that action can be taken as per need. The smart light system can also be found in the literature review, like Veena et al. (Gharaibeh et al. 2017) has proposed the smart streetlight system for smart city, in which the hardware application is capable of taking video as an input with the help of a camera and detect the movement of vehicles and pedestrian to switch on or off streetlight. This feature will optimize energy as well as the consumption of energy in an efficient manner. Sheu et al. (Sheu et al. 2016) have introduced the light-emitting diode (LED) for streetlight with multiple colors, using high-power integrated circuit (IC) and high-quality image processing for accurate decision. In case there is fog or high rain, the system immediately generates the alert to activate the LEDs with the help of power IC so that with the help of multicolor, pedestrian and drivers can recognize the exact path.

Smart Homes and Smart Building

Inside the smart environment, there are two different applications named as smart homes and smart buildings. These applications can ensemble different sensors and actuators that are deployed in homes and buildings to improve the energy efficiency (Bellido-Outeiriño et al. 2016; Collotta and Pau 2015) and consumption of utilities (Crowther et al. 2012; Daher et al. 2017) and ensure security (Zeng et al. 2017), which connect smart homes to homes and overall smart applications like smart grid (Zhang et al. 2015) and smart health management system (Zhang et al. 2015) for citizens.

Smart Surveillance in Smart Cities

It is the most challenging part of the smart city application for the past recent years, mainly due to the improvement and advancement in image processing and its application. In previous, IBM Db2 (van Zoonen 2016; White 2001) and IBM WebSphere (White 2001), IBM smart Surveillance Systems (S3) can generate the system alert and security alert with the extraction of information and detection of a vulnerability in the system.

Privacy Challenges in Smart Cities

Smart cities are developed that reforms the society and quality of life through several features like digital connectivity, digital transport system, smart health management, and increased inefficiency and accessible in cities. Similarly, the interest of smart cities has been increased up to a certain threshold with the deployment of information and communication technology (ICT). Long-term objectives of smart cities are organized in order to enhance the quality of services provided to the citizen, and that will ultimately improve the lifestyle up to mark (Khatoun 2017). One of the basic features of smart cities is the development of infrastructure, construction of road, and introduction of smart health. Without an efficient transport system, the concept of the smart city will not be fulfilled. Intelligent transport system (ITS) has been known as one of the primary building blocks for a smart city. Indeed, road infrastructures have been benefiting from ICT for a decade (Menouar et al. 2017). Although the advanced level of ITS has been deployed to update, the technology is continuously evolving. By the symmetry of continuous inventions, next-generation ITS technologies like smart health card, smart vehicles, either finished or about to complete toward large-scale worldwide deployment. The concept of smart cities will be demolished if the citizens are reluctant to participate and involve in the construction of smart cities. However, by incorporating benefits, on the other hand, it also opens for security and privacy challenges in smart cities, along with the people living in these cities (Menouar et al. 2017; Braun et al. 2018). Maintaining user privacy and ensuring data security are one of the challenge tasks in smart cities, especially for those scenarios where the public is involved directly like the health system, transport system, communication system, and other critical systems. These challenges may include privacy preservation with high-dimensional data, securing a network with the large surface attack, establishing reliable data sharing practices, properly utilizing artificial intelligence, and mitigating failure cascading through the smart network (Braun et al. 2018).

Security and Privacy Challenges

As a core concept, security is not absolute, but, in fact, it is dynamic, a basic and phenomenal method to prevent attacks on smart cities and its inhabitants. These can be directly or indirectly related to the citizen through digital or physical connections. So, security challenges will always be the most abundant opportunities for security risks in a smart city environment. Specifically, while taking privacy into account, Elmaghraby and Lasovio's are the first two principles that help regarding the preservation of privacy and cyber privacy. These principles state as (1) "activities within the home have the greatest level of protection" and (2) "activities that extend outside of the home depend on reasonable expectations of privacy" (Elmaghraby and Losavio 2014).

Privacy Threats

Due to the nature of the interconnectivity of smart cities, data will be manipulated throughout the processes, with multi-access among multiparties. This property makes the data open for the vulnerabilities. An attacker can get access from any point of entry into the system and get the most secret information of the citizen. Furthermore, since every stakeholder of the smart city have different priorities and will have exits gaps between intermediate and other stakeholder's privacy standards.

Privacy threats are prevalent in public sector organizations, such as hospitals and transportation authorities that provide essential services to citizens (Braun et al. 2018; Ijaz et al. 2016). Unlike the private sector, public authorities will have more scope to ensure the privacy protections as it should not be like its funding, and livelihood may be affected while achieving its goals. In smart cities, this gap in the protection of privacy will have a higher stake as compared to other cities. Roughly, the health system may involve public and private partnership while achieving the desired goals in terms of maintaining privacy and security (Khatoun 2017). While in public sector, hospitals may be on administer care and be under central decision-making authority so that the distribution of patient and medicines can be achieved efficiently through public and private partnership (van Zoonen 2016; Elmaghraby and Losavio 2014; Khokhar et al. 2016). In this way, the critical and sensitive information can be taken by the respective authorities for a decision regarding the transferring of patients, treatment schedule, and home address.

Privacy-Enhancing Technologies

Indeed, cities are developing to become "smart cities," where the applications suffer a severe concern regarding security and privacy of user's data. In the paradigm of new information and networking, a smart city should have the following properties to maintain or to be declared as a smart city. These are the properties like information from unauthorized resources, disclosure, modification, inspection, disruption, and annihilation. The most common security properties that the smart city should have in order to provide secure information, communication, and physical world are confidentiality, integrity, non-repudiation, availability, scalability, access control, and privacy (Salas Mccluskey 1988). Besides all the general and basic concern, still smart cities are facing numbers of security challenges. Smart cities, on the one hand, collects sensitive data and information directly from lives of citizens and manipulates the collected data in respective scenarios and influence citizens accordingly. This unique characteristic of data opens many security loops.

Data Privacy in Data Sensing

The data is processed after it is successfully collected and transmitted over the network; therefore, it creates loopholes for an attacker to inject vulnerabilities into the data to manipulate and misuse the data. This privacy concern in the smart city may be compromises of user's identity, location, health reports in the healthcare system, lifestyle inferred from intelligence, smart energy, home, and society even in the community so on and so forth. It would be a very large security damage if such information can be stolen from the smart city system. To overcome and address this issue of privacy and security of data, some off-the-shelf security and privacy techniques can be applied. These techniques may include encryption, anonymity, and access control (Khokhar et al. 2016; Salas Mccluskey 1988). Martinez et al. have proposed a set of privacy and security concept for general privacy requirements for smart cities and their applications. This privacy may include the identity, query, location, and biometric prints like footprints. After that, the owner is identified and provides the basic idea to overcome the general problem. However, still, there exists some portion of private information leakage that can be treated as a strong concern in this era (Jones et al. 2015). Similarly, in smart cities, especially in the smart home, a surveillance camera is used to detect abnormal behavior or theft. This act of taking information from home may acquire secret information of smart home, and it is prejudicial to the privacy of home (Elmaghraby and Losavio 2014; Salas Mccluskey 1988). To overcome such intruders, many application or existing security and privacy protection measures are taken into account. However, the potential attackers like an agent, a security guard, and an employee of the smart home who can have access to the surveillance record or security record may take the private information and leave it to the attacker (Cherdantseva et al. 2016). Moreover, the data in a smart city are on the highly granular scale as it comes from diverse types like the privacy requirements which may differ for different types (de Bruijn and Janssen 2017). It is still a challenge to develop a phenomenal mechanism that can balance between the efficiency and privacy of smart cities.

Privacy and Availability

The smart cities have comprehensive and remarkable benefits of using the cloud server to provide services to the citizen as well as data storage and information. It creates a security threat for smart cities due to the untrustworthy nature of cloud servers. In case, if the data is not protected and it is saved in plaintext into the cloud, then it can quickly reveal to many attackers especially if the cloud admin itself revealed the data (van Zoonen 2016; Braun et al. 2018). To overcome this problem, the other way to save user data is to encrypt the data and save it in the form of ciphertext so that server admin can see user data (Baig et al. 2017; Amin et al. 2014; Aldairi and Tawalbeh 2017). In this, the cloud server admin can see the encrypted data and cannot perform any kind of operation over encrypted data of applications of smart cities. Furthermore, the use of a fully homomorphic encryption scheme to protect the data in the cloud can improve the security of data in the cloud. However, on the other hand, this method also allows operation on encrypted data like summation and comparison. So, this also has opened a new way for researchers to dig it out more, and still it is a challenging work for researchers, especially in smart cities where there is already massive data. Similarly, data sharing and access control are also a challenging issues in smart cities, where the data is being shared to another point for a particular operation such as in healthcare, the patient data is shared with a doctor for analysis or in traffic data where the data is collected from a smartphone, a surveillance camera or GPS in a crowdsourcing way. For all over the globe, yet it is a challenging and security risk to define the common policy for data sharing and access control (van Zoonen 2016; Martinez-Balleste et al. 2013; Lacinák and Ristvej 2017). Data sharing and access control policy for homomorphic encryption are still open for research.

Conclusion

With the increasing research, advancement in technology, and attempts toward the transition of cities into smart cities, the concept of smart cities is becoming more complex and ambiguous. To overcome this challenge and grasp the various characteristics of smart cities, this research organized the current literature from the perspectives of smart data framework, applications, and challenges. The increasing volumes of data being generated by the sensors network have been collected, processed, and organized in a variety of ways using deep learning techniques and smart network databases. The datasets generated form IoT, and ICT tools are used for routine and automatic sensing, which replaces the traditional approaches. However, the communication of user-rich and private data over public networks also leads to several challenges, i.e., privacy and security. The proper and secure use and analysis of this rich data collected by using advanced technologies, i.e., IoT, WSNs, VSNs, etc., lead to a wide range of services. The most prominent applications of using smart data include smart government and governance of smart cities, smart mobility, and smart communication. However, the change toward smart government is not easy as the present institutional, organizational, financial, and technical barriers make it difficult. From the perspective of social networks, SIoT is an emerging field as it connects and maintains billions of devices in IoT networks using principles of social networks. Similarly, several solutions have been proposed for smart mobility and transportation, which introduce mobility as a service in which a user can request a transport service provided by different companies. The introduction of autonomous vehicles is also revolutionizing the domain of smart mobility to a great extent. The open challenges faced by the current research on the provision of services in smart cities and data management are also highlighted. This study will help practitioners and researchers to grasp concepts, characteristics, and current state of literature for smart cities data and how emerging technologies are being used to manage such huge volumes of data in real time.

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