Machine Learning for Smart Cities: A Comprehensive Review of Applications and Opportunities

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***Abstract*—The smart city concept originated a few years ago as a combination of ideas about how information and communication technologies can improve urban life. With the advent of the digital revolution, many cities globally are investing heavily in designing and implementing smart city solutions and projects. Machine Learning (ML) has evolved into a powerful tool within the smart city sector, enabling efficient resource management, improved infrastructure, and enhanced urban services. This paper discusses the diverse ML algorithms and their potential applications in smart cities, including Artificial Intelligence (AI) and Intelligent Transportation Systems (ITS). The key challenges, opportunities, and directions for adopting ML to make cities smarter and more sustainable are outlined.**

***Keywords*—Smart city; machine learning; artificial intelligence; intelligent transportation system; smart grids**

I. Introduction

A. Background

According to the reports [1], by 2050, the global urban population is expected to reach 70%. This surge in urbanization will drastically impact cities' environment, management, and security. To efficiently handle the meteoric growth in urbanization, many countries have proposed the concept of smart cities to manage resources and optimize energy consumption effectively [2]. Smart city projects can precisely ensure a green environment by developing and adopting low-carbon emission technologies. Urbanization has witnessed unprecedented growth in recent decades, with an increasing number of people migrating to cities for better opportunities and improved quality of life [3]. This rapid urban expansion brings numerous challenges, such as increased energy consumption, traffic congestion, inadequate infrastructure, and environmental degradation [4]. In response, smart cities have emerged as a transformative approach to incorporate advanced Information and Communication Technology (ICT) based hardware and software in urban planning [5]. The smart city utilizes ICT to enhance 'citizens' quality of life, foster the economy, facilitate a process to resolve transport and traffic problems through proper management, encourage a clean and sustainable environment, and provide accessible interaction with the relevant authority of the government [6]. The increased urban expansion and innovations in urban planning and ICT have encouraged planners to focus on promoting the smart city's concept, which considers the well-being of the urban population by focusing on a combination of human, environmental, social, cultural, energy, information access and usage, and other technological advances [7]. Moreover, as urbanization continues to surge, efficient and sustainable urban public transportation becomes increasingly vital. Association rule mining, a key data analysis technique, plays a crucial role in optimizing public transportation systems by uncovering valuable insights from large datasets. These insights enable cities to enhance transportation efficiency, reduce congestion, and improve overall mobility. The quality of urban public transportation directly impacts the daily lives of millions, affecting everything from commute times to air quality. By harnessing the power of data analytics, cities can provide residents with reliable, accessible, and eco-friendly transportation options, ultimately contributing to improved urban well-being and reduced environmental impact [8].

The proliferation of digital sensors, Internet of Things (IoT) devices, and the availability of vast amounts of data has created new possibilities for harnessing information to optimize urban systems and services [9, 10]. Machine Learning (ML), a branch of Artificial Intelligence (AI), has emerged as a key technology within the smart city context. It enables cities to analyze and extract valuable insights from the vast amounts of data generated by various sources, including sensors, social media, and municipal databases [11]. ML techniques can uncover patterns, correlations, and trends that may go unnoticed, enabling more informed decision-making and proactive interventions [12]. By applying ML algorithms to urban data, cities can gain actionable insights and predictive capabilities in energy management, transportation planning, waste management, public safety, and citizen engagement. These ML-driven applications have the potential to transform traditional urban systems into intelligent, adaptive networks that optimize resource utilization, improve service delivery, and enhance the overall quality of life for residents [13, 14]. However, deploying ML in the complex and dynamic urban environment comes with challenges, ranging from data privacy and security to ensuring ethical and fair AI practices. Addressing these challenges is crucial to realizing the full potential of ML for smart cities and creating sustainable urban ecosystems that meet the evolving needs of residents [15-17].

B. Literature Review

The emergence of smart cities represents a pivotal response to the challenges posed by rapid urbanization and the increasing demand for improved urban infrastructure and services. As cities grow and evolve, the need to optimize resource management, enhance citizen well-being, and ensure environmental sustainability has become paramount. This paradigm shift towards smart urbanization is deeply intertwined with the advancements in Information and Communication Technology (ICT) and, more notably, the integration of ML and Artificial Intelligence (AI) into urban planning and governance. In the realm of ML and AI, an extensive body of research has explored their applications across diverse domains, from healthcare to finance and beyond. Within the context of smart cities, these technologies offer unparalleled opportunities for data-driven decision-making, predictive analytics, and automation of urban processes. Studies have demonstrated the potential of ML algorithms in optimizing energy consumption, streamlining transportation systems, enhancing public safety, and promoting sustainable environmental practices. Moreover, ML-driven citizen engagement strategies have shown promise in fostering community collaboration and tailoring services to individual needs [18].

In addition to these technological advancements, the rise of ML in smart cities aligns with broader societal trends, such as the increasing importance of sustainability and the demand for efficient public services. Policymakers, urban planners, and researchers recognize the potential of ML to address the complex and interconnected challenges of modern urban environments [19]. However, the adoption of ML in the urban context is not without its hurdles. Privacy concerns, data quality, ethical considerations, and the need for scalable and interpretable ML models are among the critical issues that warrant careful consideration. This literature review establishes the significance of the research question by highlighting the transformative potential of ML in smart cities, drawing upon existing research and the broader context of urban development. It underscores the need for comprehensive exploration of ML applications, challenges, and opportunities within the smart city framework, which serves as the core focus of this paper.

C. Objectives

This review paper aims to provide a comprehensive overview of the applications of ML in the context of smart cities. We aim to explore the various ML techniques employed, their impact on urban life, and the challenges and opportunities associated with their implementation. By examining the current state of ML applications in smart cities, we can identify key trends, gaps, and potential future directions for research and development.

D. Structure of the Review

This paper is organized into several sections to provide a structured analysis of ML applications for smart cities. Section II introduces the foundations of smart cities and ML, highlighting their integration and the potential benefits they offer when combined. Section III explores a range of applications where ML has been successfully applied in smart cities, such as smart energy management, intelligent transportation systems, urban planning and development, public safety and security, waste management and environmental monitoring, healthcare and well-being, and citizen engagement and participation. Section IV highlights future directions and research trends in ML for smart cities, such as explainable AI, edge computing and distributed ML, federated learning for privacy preservation, IoT integration, and the emergence of urban data marketplaces and governance. Finally, Section V concludes the review by summarizing the key findings, implications, and recommendations for adopting ML in building smarter and more sustainable cities.

II. Foundations of ML in Smart Cities

This section provides a solid foundation by introducing the key concepts and principles underlying smart cities and ML. It offers an overview of the fundamental elements of smart cities, including their objectives, characteristics, and the integration of technology and data-driven approaches. Furthermore, this section explores the core principles and techniques of ML, emphasizing their relevance and applicability within the context of smart cities.

A. Overview of Smart Cities

Smart cities represent a paradigm shift in urban development, driven by the rapid advancement of technology and the need to address the complex challenges faced by growing urban populations. At its core, a smart city leverages innovative technologies, data analytics, and connectivity to transform urban environments into intelligent, efficient, and sustainable ecosystems. The objectives of smart cities are centered around improving the quality of life for citizens and enhancing the overall efficiency of urban systems [20]. By integrating technology and data, smart cities aim to optimize resource allocation, enhance infrastructure and services, and enable effective decision-making. These objectives are achieved through various domains and initiatives, such as smart governance, smart mobility, smart energy management, smart buildings, and smart healthcare [21, 22].

Smart cities rely on a robust digital infrastructure that supports collecting, storing, and analyzing data from diverse sources [23]. This includes sensors, IoT devices, and communication networks that enable the seamless integration of urban systems. The proliferation of connected devices and the availability of real-time data empower city administrators and residents to make informed decisions and respond quickly to changing circumstances [24]. Moreover, smart cities emphasize citizen-centric approaches, prioritizing the needs and preferences of residents. Through digital platforms and services, citizens can actively participate in decision-making processes, provide feedback and access information about urban services. This promotes community engagement and collaboration, creating more inclusive and responsive urban environments [25]. Smart cities ' sustainability is a key pillar as they strive to minimize environmental impact and optimize resource management. This includes initiatives such as smart energy grids, waste management systems, and promoting green and eco-friendly practices. Smart cities aim to reduce carbon emissions, conserve resources, and create a more sustainable future by integrating renewable energy sources, optimizing transportation systems, and implementing efficient waste management strategies [26].

B. ML Fundamentals

ML is a powerful branch of AI that enables systems to automatically learn from data and make predictions or decisions without explicit programming. Understanding the fundamentals of ML is essential for comprehending its integration and impact within the context of smart cities [27]. ML algorithms can be categorized into three main types: supervised, unsupervised, and reinforcement learning [28]. In supervised learning, models are trained using labeled data, where the algorithm learns to map input features to corresponding output labels. This approach is commonly used for tasks such as classification and regression [29].

On the other hand, unsupervised learning involves exploring unlabeled data to discover hidden patterns and structures. Clustering and dimensionality reduction are typical applications of unsupervised learning. Reinforcement learning focuses on training an agent to interact with an environment and learn optimal actions based on rewards and feedback. This technique is employed in scenarios where the agent must make sequential decisions [30].

As shown in Fig. 1, the general process of machine learning involves the following key stages. During training, the model learns from a portion of the data by optimizing its internal parameters to minimize prediction errors. The trained model is then evaluated using the testing data to assess its performance and generalization capabilities. Model evaluation metrics, such as accuracy, precision, recall, and F1 score, quantify the model's performance [31]. Feature engineering is a critical aspect of ML, where relevant input features are selected and transformed to improve model performance. This process involves understanding the data, identifying informative features, handling missing values, scaling features, and encoding categorical variables. Ensemble learning techniques, such as bagging and boosting, combine multiple models to make predictions. Transfer learning is another important technique that leverages knowledge gained from one task or domain to improve performance on another related task or domain, reducing the need for extensive training data [32].

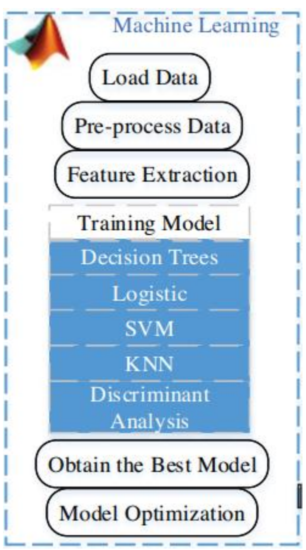

Fig. 1. The general process of ML.

C. Integration of ML in Smart Cities

Integrating ML techniques within the context of smart cities can revolutionize urban development and enhance residents' efficiency, sustainability, and quality of life. This subsection explores how ML can be applied in smart cities and the benefits it offers [33]. One key application of ML in smart cities is urban planning and infrastructure management. ML algorithms can analyze vast amounts of data from diverse sources, such as sensor networks, social media, and municipal databases, to gain insights into urban patterns, land use, and transportation flows. These insights enable urban planners to make informed decisions regarding infrastructure development, zoning regulations, and transportation optimization, leading to more efficient and well-designed cities. ML also plays a crucial role in energy management and sustainability within smart cities. By leveraging data from smart grids, energy consumption patterns, and weather forecasts, ML algorithms can optimize energy distribution, predict energy demands, and identify opportunities for energy conservation. This enables cities to reduce energy waste, lower carbon emissions, and promote the integration of renewable energy sources, ultimately contributing to a greener and more sustainable urban environment.

Another important application is in the realm of smart mobility and transportation. ML techniques can analyze real-time data from various sources, including GPS data, traffic cameras, and transportation networks, to predict traffic congestion, optimize route planning, and improve public transportation systems. This leads to reduced congestion, shorter travel times, and enhanced mobility options for citizens. ML also contributes to public safety and security in smart cities. By analyzing data from surveillance systems, social media, and emergency calls, ML algorithms can detect patterns and anomalies, aiding in identifying potential security threats, crime hotspots, and emergency response optimization. This improves the safety and well-being of citizens and enables law enforcement agencies to address security challenges proactively.

Moreover, ML enhances citizen engagement and participation in smart cities. ML algorithms can capture public sentiment, identify community needs, and provide personalized services by analyzing data from social media platforms and citizen feedback. This promotes a sense of inclusion and empowerment among citizens, enabling them to participate in decision-making processes and co-create the urban environment actively. Integrating ML in smart cities brings numerous benefits, including improved urban planning, optimized energy management, enhanced mobility, increased safety, and citizen-centric services. However, challenges such as data privacy, security, ethical considerations, and ensuring fairness in AI algorithms must be addressed to harness the potential of ML in smart cities fully. By overcoming these challenges, cities can leverage the power of ML to create smarter, more sustainable, and livable urban environments.

III. ML Applications in Smart Cities

This section presents a clear and comprehensible trend of ML applications in smart cities. As specified in Fig. 2, the potential applications are categorized into seven main categories, including smart city, home automation, and smart healthcare. Tables I to VII summarize the obtained results from reviewing the models.

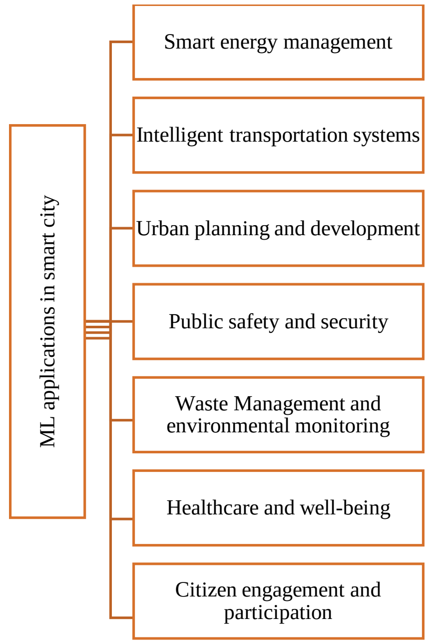

Fig. 2. ML applications in smart cities.

A. Smart Energy Management

Smart energy management is critical to creating sustainable and efficient smart cities. ML techniques have been successfully applied in various energy management aspects, revolutionizing how energy is generated, distributed, and consumed. In this subsection, we discuss the applications of ML in smart energy management and their impact on creating greener and more efficient urban environments.

- Energy demand prediction: ML algorithms, such as regression models and artificial neural networks, are employed to predict energy demand accurately. By analyzing historical energy consumption data, weather patterns, and other relevant factors, these models can accurately forecast future energy demand. This information enables utility providers to optimize energy production and distribution, ensuring a reliable and efficient energy supply while minimizing waste.

- Energy load forecasting: ML techniques are used to forecast energy load patterns in real-time. By analyzing data from smart meters, weather conditions, and historical load profiles, algorithms can predict future load patterns. This information aids in managing peak demand, optimizing energy distribution, and facilitating the integrating of renewable energy sources into the grid. Load forecasting helps utilities balance supply and demand, reduce costs, and improve the overall reliability and stability of the energy grid.

- Energy optimization and control: ML algorithms optimize energy consumption within smart buildings and homes. By leveraging data from sensors, occupancy patterns, and weather conditions, algorithms can learn and adapt to energy usage patterns. They can automatically adjust heating, cooling, and lighting systems to optimize energy efficiency while maintaining occupant comfort. Energy optimization algorithms help reduce energy waste, lower utility bills, and promote sustainable energy consumption practices.

- Energy theft detection: The ML techniques aid in detecting energy theft and unauthorized usage within the energy grid. By analyzing consumption patterns and identifying anomalies, algorithms can flag suspicious activities that indicate potential theft or tampering. This helps utility companies prevent revenue loss and ensure fair distribution of energy resources.

- Renewable energy integration: ML is crucial in integrating renewable energy sources into the energy grid. Algorithms can analyze weather data, historical renewable energy generation, and demand patterns to optimize the utilization and management of renewable energy resources. This enables effective grid integration, reduces reliance on fossil fuels, and promotes the transition to a greener, more sustainable energy infrastructure.

ML applications in smart energy management offer significant benefits such as improved energy efficiency, cost savings, reduced carbon emissions, and enhanced grid reliability. However, data quality, privacy, and algorithmic transparency challenges need to be addressed to ensure the responsible and effective deployment of ML techniques in smart cities' energy systems.

TABLE I. ML APPLICATIONS IN SMART ENERGY MANAGEMENT

Approach	ML type	Objective	Achievement	Challenges	References
Energy demand prediction	Supervised	Predict future energy demand accurately using ML algorithms	Accurate forecasting enables the optimization of energy distribution, cost reduction, and efficient load balancing	Relies on historical data and assumptions and may not account for sudden changes or events that deviate from historical patterns Requires continuous updating and validation to account for evolving energy consumption patterns	[34-40]
Energy load forecasting	Supervised	Forecast real-time energy load patterns based on data from smart meters and weather conditions	Enables efficient energy distribution, demand management, and integration of renewable energy sources Helps balance supply and demand, improve grid stability, and optimize resource allocation	Relies on accurate and timely data from smart meters and weather sensors Uncertainty in weather conditions and unforeseen events can impact the accuracy of load forecasts Requires robust data management and monitoring systems to ensure data quality and reliability	[41-48]
Energy optimization and control	Supervised	Optimize energy consumption in smart buildings and homes through ML algorithms.	Maximizes energy efficiency, reduces waste, and lowers utility bills Improves occupant comfort by dynamically adjusting heating, cooling, and lighting systems Enables demand response strategies and load balancing	Requires integration with smart devices and sensors for real-time data collection Dependency on accurate data and system feedback Potential privacy concerns related to the collection and usage of personal data Optimization algorithms may face challenges in highly dynamic environments and require continuous adaptation to changing conditions.	[49-53]
Energy theft detection	Supervised	Detect and flag potential energy theft or unauthorized usage within the energy grid using ML.	Helps prevent revenue loss and ensure fair energy distribution Improves the financial sustainability of utility providers Identifies anomalies and patterns indicative of energy theft or tampering	Relies on data quality and availability. False positives or false negatives may occur, requiring human intervention for verification May face challenges in identifying sophisticated or evolving techniques used for energy theft	[54-60]
Renewable energy integration	Supervised	Optimize the integration of renewable energy sources into the energy grid through ML algorithms.	Enables efficient utilization of renewable energy, reduces reliance on fossil fuels, and lowers carbon emissions Optimizes resource allocation based on weather patterns, demand, and grid conditions	Relies on accurate weather data and renewable energy generation forecasts. Uncertainty in weather patterns The intermittent nature of renewable sources can pose challenges in balancing supply and demand. Integrating diverse renewable sources and their variability may require advanced modeling and management strategies.	[61-64]

B. *Intelligent Transportation Systems*

Intelligent Transportation System (ITS) plays a crucial role in enhancing urban transportation's efficiency, safety, and sustainability. ML techniques have been widely applied in various aspects of ITS to optimize traffic management, improve transportation infrastructure, and provide intelligent decision-making capabilities. In this subsection, we discuss the applications of ML in ITS and their impact on creating smarter and more efficient urban mobility.

- Traffic prediction and management: ML algorithms predict and manage traffic flow in real-time. These algorithms can forecast traffic patterns and congestion levels by analyzing historical traffic data, weather, and other relevant factors. This information aids in proactive traffic management, optimizing signal timings, rerouting strategies, and providing real-time traffic updates to drivers and traffic management authorities. ML-based traffic prediction and management systems improve traffic flow, reduce congestion, and enhance overall transportation efficiency.
- Intelligent routing and navigation: ML techniques enable intelligent routing and navigation systems considering real-time traffic conditions, road incidents, and user preferences. These systems use ML algorithms to analyze historical and real-time data, such as traffic flow, accidents, and road closures, to provide optimal routes to drivers. By considering dynamic factors, ML-based routing and navigation systems help reduce travel time, fuel consumption, and environmental impact, improving overall transportation efficiency.

- Vehicle and pedestrian safety: ML algorithms contribute to improving vehicle and pedestrian safety in smart cities. Combined with ML, computer vision techniques enable intelligent video surveillance systems to detect and analyze traffic violations, identify potential safety risks, and provide early warning alerts. ML algorithms can also analyze vehicle sensor data to predict and prevent accidents by detecting anomalies, identifying aggressive driving behavior, and supporting advanced driver assistance systems (ADAS). These applications enhance road safety, reduce accidents, and improve transportation security.

- Public transportation optimization: ML techniques optimize public transportation systems, including bus and train schedules, route planning, and fleet management. ML algorithms can optimize public transportation services, improve reliability, reduce waiting times, and enhance passenger satisfaction by analyzing historical ridership data, weather conditions, and other factors. ML algorithms can also support demand-responsive transportation systems, enabling adaptive routing and scheduling based on real-time demand and passenger preferences.

- Smart parking management: ML algorithms are used to optimize parking management in smart cities. By analyzing data from sensors, historical occupancy patterns, and real-time information, ML-based parking systems can provide accurate parking availability predictions, guide drivers to available parking spaces, and optimize parking space utilization. These applications reduce traffic congestion, lower vehicle emissions, and improve the overall efficiency of parking operations.

- ML applications in ITS offer significant benefits, including improved traffic flow, enhanced transportation efficiency, increased safety, and reduced environmental impact. However, data privacy, scalability, and algorithmic transparency must be addressed to ensure the responsible and effective deployment of ML techniques in smart city transportation systems. Ongoing research and development efforts aim to overcome these challenges and unlock the full potential of ML in shaping the future of urban mobility.

C. *Urban Planning and Development*

Urban planning and development play a vital role in shaping cities' physical and social infrastructure. ML techniques have emerged as powerful tools for analyzing vast data and extracting valuable insights to support urban planning and development decisions [86]. In this subsection, we discuss the applications of ML in smart cities' urban planning and development and how they contribute to creating sustainable, livable, and efficient urban environments.

TABLE II. ML APPLICATIONS IN ITS

Approach	ML type	Objective	Achievement	Challenges	References
Traffic prediction and management	Supervised	ML algorithms predict and manage traffic flow in real-time, optimizing signal timings and providing updates.	Improved traffic flow Reduced congestion Proactive management.	Relies on accurate and up-to-date data, challenges in data integration and availability Limited control over external factors like accidents or road works	[65-71]
Intelligent routing and navigation	Supervised	ML enables intelligent routing systems to consider real-time traffic conditions, incidents, and user preferences.	Reduced travel time, fuel consumption, and environmental impact Improved navigation and route optimization	Dependency on accurate and real-time data, challenges in integrating multiple data sources Potential biases in data can lead to suboptimal route recommendations	[72-75]
Vehicle and pedestrian safety	Supervised	ML-based surveillance systems detect traffic violations, identify risks, and support driver assistance systems	Improved road safety Early warning alerts Accident prevention	Challenges in real-time detection accuracy Potential privacy concerns related to surveillance systems limitations in detecting complex traffic scenarios or unpredictable pedestrian behavior	[76-78]
Public transportation optimization	Supervised	ML optimizes public transportation systems, schedules, and route planning based on demand and historical data.	Enhanced public transportation services Improved reliability and passenger satisfaction	Data integration challenges Limited effectiveness during unexpected events or disruptions, dependency on accurate and up-to-date ridership data	[79-81]
Smart parking management	Supervised	ML algorithms optimize parking space utilization and guide drivers to available parking spaces.	Reduced traffic congestion Improved parking efficiency Lower vehicle emissions.	Dependence on accurate and real-time parking occupancy data Challenges in sensor deployment and maintenance Limited effectiveness in highly congested areas.	[82-85]

- Land use and zoning optimization: ML algorithms analyze various data sources, such as satellite imagery, demographic data, and economic indicators, to optimize land use and zoning regulations. By identifying patterns and relationships in data, ML can assist urban planners in determining the most suitable locations for residential, commercial, and industrial zones. These insights enable more efficient land use planning, balanced development, and the promotion of mixed-use neighborhoods.

- Transportation infrastructure planning: ML techniques aid in transportation infrastructure planning by analyzing data on population distribution, commuting patterns, and transportation demand. These algorithms can identify optimal locations for transportation hubs, such as bus stops, metro stations, or bike-sharing stations, based on demand and accessibility factors. ML-based transportation planning improves connectivity, reduces travel time, and enhances transportation efficiency.

- Environmental impact assessment: ML algorithms are employed to assess the environmental impact of urban development projects. These algorithms can predict the potential impact of proposed projects by analyzing air quality, noise levels, water resources, and biodiversity. This information assists in making informed decisions, ensuring sustainable development practices, and minimizing negative environmental effects.

- Urban mobility and traffic management: ML techniques optimize urban mobility and traffic management by analyzing data from various sources, including sensors, GPS devices, and social media feeds. These algorithms can identify traffic patterns, predict congestion, and optimize transportation routes and signals. ML-based traffic management systems enhance traffic flow, reduce congestion, and improve the overall efficiency of urban transportation.

- Infrastructure maintenance and management: ML algorithms contribute to maintaining and managing urban infrastructure, such as roads, bridges, and utilities. These algorithms analyze sensor data, maintenance records, and historical patterns to predict infrastructure deterioration and schedule maintenance activities. ML-based systems help ensure urban infrastructure reliability, safety, and longevity by optimizing maintenance efforts.

ML applications in urban planning and development provide significant benefits, including optimized land use, improved transportation infrastructure, sustainable development practices, and efficient management of urban assets. However, challenges such as data quality, data integration, and interpretability of ML models must be addressed to ensure the effective and responsible application of ML techniques in urban planning processes. Ongoing research and collaboration between urban planners and data scientists aim to overcome these challenges and leverage the full potential of ML in shaping smarter and more sustainable cities.

TABLE III. ML APPLICATIONS IN URBAN PLANNING AND DEVELOPMENT

Approach	ML type	Objective	Achievement	Challenges	References
Land use and zoning optimization	Supervised	Data is analyzed to optimize land use and zoning regulations for sustainable development.	Efficient land use planning Promotion of mixed-use neighborhoods Optimized resource allocation	Relies on accurate and comprehensive data Challenges in integrating various data sources Potential biases in data affecting zoning decisions	[87, 88]
Transportation infrastructure planning	Supervised	Transportation infrastructure is optimized by identifying optimal locations for hubs and facilities.	Enhanced connectivity Reduced travel time Improved transportation efficiency	Dependency on accurate and up-to-date data Challenges in integrating different transportation modes Potential biases in data affecting planning decisions	[89, 90]
Environmental impact assessment	Supervised	The environmental impact of development projects is assessed based on various data sources.	Informed decision-making Promotion of sustainable development practices Reduced environmental impact	Relies on accurate and comprehensive environmental data Challenges in quantifying long-term environmental impacts Potential biases in data affecting assessments	[91-93]
Urban mobility and traffic management	Supervised	Urban mobility and traffic management are optimized by analyzing data from various sources.	Improved traffic flow Reduced congestion Enhanced transportation efficiency	Dependency on accurate and real-time data Challenges in data integration and processing Potential biases in data affecting traffic management decisions	[94-96]
Infrastructure maintenance and management	Supervised	Infrastructure deterioration and maintenance activities are predicted	Enhanced infrastructure reliability Optimized maintenance scheduling Improved asset management	Relies on accurate infrastructure data Challenges in integrating maintenance records Potential biases in data affecting maintenance decisions	[97-99]

D. Public Safety and Security

Ensuring public safety and security is a critical aspect of smart city initiatives. ML techniques have emerged as powerful tools in analyzing large volumes of data and extracting meaningful insights to enhance public safety measures and security systems. In this subsection, we discuss the applications of ML in smart cities' public safety and security domains and how they contribute to creating safer and more secure urban environments.

- Video surveillance and monitoring: ML algorithms enable intelligent video surveillance systems that can analyze real-time video feeds from cameras across the city. These algorithms can automatically detect and track suspicious activities, identify objects of interest, and raise alerts for potential security threats. ML-based video surveillance enhances situational awareness, improves incident response, and aids in crime prevention and detection.

- Predictive policing: ML techniques are employed to predict and prevent crime by analyzing historical crime data, socio-economic indicators, and other relevant factors. These algorithms can identify patterns, hotspots, and trends, enabling law enforcement agencies to deploy resources strategically and proactively. ML-based predictive policing helps reduce crime rates, improve resource allocation, and enhance public safety.

- Emergency response optimization: ML algorithms optimize emergency response systems by analyzing emergency call records, traffic conditions, and geographical information. These algorithms can identify the optimal deployment of emergency vehicles, predict response times, and dynamically allocate resources based on real-time incidents. ML-based emergency response systems improve response efficiency, minimize response times, and save lives in critical situations.

- Cybersecurity and threat detection: ML techniques aid in cybersecurity and threat detection by analyzing network traffic, user behavior, and system logs to detect anomalies and potential security breaches. These algorithms can identify patterns of malicious activity, classify threats, and provide early warnings to prevent cyber-attacks. ML-based cybersecurity systems protect critical infrastructure, sensitive data, and digital services.

- Disaster management and resilience: ML algorithms contribute to disaster management and resilience by analyzing data from various sources, such as weather forecasts, sensor networks, and social media feeds. These algorithms can predict and model the impact of natural disasters, aid in evacuation planning, and assist in resource allocation during emergencies. ML-based disaster management systems enhance preparedness, response, and recovery capabilities.

TABLE IV. ML APPLICATIONS IN PUBLIC SAFETY AND SECURITY

Approach	ML type	Objective	Achievement	Challenges	References
Video surveillance and monitoring	Supervised	Real-time video feeds are analyzed to detect and track suspicious activities and objects.	Enhanced situational awareness Improved incident response Crime prevention and detection	Dependency on accurate and high-quality video feeds Potential biases in the algorithmic analysis Privacy concerns related to extensive video surveillance	[100-102]
Predictive policing	Supervised	Crime is predicted and prevented by analyzing historical data and relevant socio-economic factors.	Proactive resource allocation Reduced crime rates Improved law enforcement strategies	Relies on accurate and comprehensive data Potential biases in data affecting predictions Ethical concerns related to algorithmic profiling	[103, 104]
Emergency response optimization	Supervised	Emergency response systems are optimized by predicting response times and resource allocation.	Efficient resource allocation Reduced response times Improved emergency management	Dependency on accurate and real-time data Challenges integrating multiple data sources Potential biases in algorithmic predictions	[105-107]
Cybersecurity and threat detection	Supervised	Network traffic and user behavior are analyzed to detect and prevent cyber threats and breaches.	Early detection of anomalies Improved threat prevention Enhanced critical infrastructure protection	Evolving nature of cyber threats Challenges in identifying new and sophisticated attack patterns Potential biases in algorithmic analysis	[108-110]
Disaster management and resilience	Supervised	Data is analyzed to predict and manage the impact of natural disasters and aid in recovery efforts.	Improved preparedness and response Enhanced resource allocation Efficient evacuation planning	Dependency on accurate and comprehensive data Challenges integrating various data sources Potential biases in algorithmic predictions related to complex disaster scenarios	[111-113]

ML applications in smart cities' public safety and security domains offer significant benefits, including improved situational awareness, proactive crime prevention, efficient emergency response, enhanced cybersecurity, and better disaster management. However, challenges such as data privacy, algorithmic biases, and ethical considerations need to be addressed to ensure the responsible and effective deployment of ML techniques in public safety and security systems. Ongoing research and collaboration between law enforcement agencies, security experts, and data scientists aim to overcome these challenges and leverage the full potential of ML in creating safer and more secure smart cities.

E. Waste Management and Environmental Monitoring

Effective waste management and environmental monitoring are essential for smart city initiatives to create sustainable, eco-friendly urban environments. ML techniques have revolutionized these areas by enabling the analysis of large-scale data sets and extracting valuable insights for optimizing waste management processes and monitoring environmental conditions. In this subsection, we discuss the applications of ML in smart cities' waste management and environmental monitoring and how they contribute to achieving efficient resource utilization and environmental sustainability.

- Waste sorting and recycling: ML algorithms play a crucial role in waste sorting and recycling by automating the identification and segregation of different waste materials. Using computer vision and image recognition techniques, these algorithms can analyze images of waste and classify them into specific categories, such as plastic, paper, glass, or organic waste. ML-based waste sorting systems enhance recycling efforts, reduce landfill waste, and promote a circular economy.

- Predictive waste collection: ML techniques optimize waste collection routes and schedules based on predictive analysis. By analyzing historical data on waste generation patterns, population density, and other relevant factors, these algorithms can predict the optimal time and location for waste collection. ML-based waste collection systems reduce operational costs, minimize environmental impact, and improve efficiency.

- Environmental quality monitoring: ML algorithms analyze data from environmental sensors and monitoring devices to assess air quality, water quality, noise levels, and other environmental parameters. These algorithms can detect patterns, identify pollution sources, and predict environmental risks. ML-based environmental monitoring systems facilitate early detection of pollution events, enable targeted interventions, and promote healthier and cleaner urban environments.

- Energy optimization and conservation: ML techniques optimize energy consumption and promote energy conservation in smart cities. These algorithms analyze data on energy usage patterns, weather conditions, and building characteristics to identify opportunities for energy savings. ML-based energy management systems can dynamically adjust energy usage, optimize building operations, and promote sustainable energy practices.

TABLE V. ML APPLICATIONS IN WASTE MANAGEMENT AND ENVIRONMENTAL MONITORING

Approach	ML type	Objective	Achievement	Challenges	References
Waste sorting and recycling	Supervised	The identification and sorting of waste materials are automated for recycling.	Improved recycling efforts Reduced landfill waste Promoting a circular economy	Dependency on accurate and comprehensive waste data Challenges in integrating waste sorting systems Potential biases in algorithmic classification	[114-117]
Predictive waste collection	Supervised	Waste collection routes and schedules are optimized based on predictive analysis.	Reduced operational costs Minimized environmental impact Improved waste management efficiency	Dependency on accurate waste generation data Challenges in integrating real-time data Potential biases in algorithmic predictions	[118]
Environmental quality monitoring	Supervised	Data is analyzed from environmental sensors to assess air quality, water quality, and noise levels.	Early detection of pollution events Targeted interventions Promotion of healthier urban environments	Relies on accurate and comprehensive environmental data, sensor deployment, maintenance challenges Potential biases in algorithmic analysis.	[119]
Energy optimization and conservation	Supervised	Energy consumption is optimized, and energy conservation is promoted in smart cities.	Reduced energy usage Improved energy management Promoted sustainable energy practices	Dependency on accurate and real-time energy data Challenges in integrating heterogeneous data sources Potential biases in algorithmic optimization	[120, 121]
Green spaces management	Supervised	ML algorithms optimize the management of green spaces by analyzing data on soil moisture and plant health.	Efficient resource management, water conservation, and promotion of healthy urban ecosystems	Relies on accurate and comprehensive data on soil and plant conditions, data collection, and maintenance challenges Potential biases in algorithmic analysis.	[122]

- Green spaces management: ML algorithms contribute to efficiently managing green spaces, such as parks and gardens, by analyzing data on soil moisture, weather conditions, and plant health. These algorithms can optimize irrigation schedules, detect plant disease outbreaks, and support precision agriculture techniques. ML-based green space management systems enhance resource efficiency, conserve water, and promote healthy urban ecosystems.

ML applications in waste management and environmental monitoring offer significant benefits, including improved waste sorting and recycling, optimized waste collection processes, enhanced environmental quality monitoring, energy conservation, and efficient management of green spaces. However, challenges such as data quality, integration of heterogeneous data sources, and interpretability of ML models need to be addressed to ensure the effective and responsible deployment of ML techniques in these domains. Ongoing research and collaboration between waste management experts, environmental scientists, and data scientists aim to overcome these challenges and leverage the full potential of ML in creating sustainable and environmentally conscious smart cities.

F. *Healthcare and Well-being*

The application of ML in the healthcare and well-being domain of smart cities has the potential to revolutionize the delivery of healthcare services, improve patient outcomes, and enhance overall well-being. ML techniques enable the analysis of large volumes of healthcare data, including patient records, medical images, and sensor data, to extract valuable insights and support personalized and proactive healthcare interventions. In this subsection, we discuss the applications of ML in smart cities' healthcare and well-being domains and how they contribute to creating healthier and more resilient urban communities.

- Disease diagnosis and predictive analytics: ML algorithms can analyze patient data, such as symptoms, medical history, and test results, to aid disease diagnosis and prediction. These algorithms can identify patterns, detect anomalies, and provide early disease warnings, enabling timely interventions and personalized treatment plans. ML-based diagnostic systems improve accuracy, reduce misdiagnosis, and enhance patient care.

- Remote patient monitoring: ML techniques enable remote monitoring of patients' health conditions using wearable devices and sensors. These algorithms can analyze real-time data, such as heart rate, blood pressure, and activity levels, to detect deviations from normal patterns and alert healthcare providers. ML-based remote monitoring systems facilitate proactive interventions, reduce hospitalizations, and enhance patient convenience and comfort.

- Health risk assessment and prevention: ML algorithms analyze various data sources, including lifestyle data, environmental factors, and genetic information, to assess individuals' health risks and provide personalized recommendations for prevention. These algorithms can identify risk factors, predict susceptibility to diseases, and suggest healthy lifestyle interventions. ML-based health risk assessment systems empower individuals to make informed decisions, promote preventive care, and reduce healthcare costs.

- Health resource optimization: ML techniques optimize the allocation of healthcare resources, such as hospital beds, medical staff, and equipment. These algorithms can analyze patient data, bed occupancy rates, and historical trends to predict future demand and facilitate resource planning. ML-based resource optimization systems improve operational efficiency, reduce waiting times, and ensure better utilization of healthcare resources.

- Mental health support: ML algorithms contribute to mental health support by analyzing data from various sources, such as social media posts, wearable devices, and electronic health records. These algorithms can detect patterns indicative of mental health conditions, provide personalized recommendations, and offer virtual counseling and support. ML-based mental health support systems enhance access to care, reduce stigma, and improve mental well-being in smart cities.

The applications of ML in the healthcare and well-being domains of smart cities offer significant benefits, including improved disease diagnosis, proactive healthcare interventions, personalized treatment plans, optimized resource allocation, and enhanced mental health support. However, challenges such as data privacy and security, ethical considerations, and biases in algorithmic analysis need to be addressed to ensure the responsible and effective deployment of ML techniques in these domains. Ongoing research and collaboration between healthcare professionals, data scientists, and policymakers aim to overcome these challenges and harness the full potential of ML in creating healthier and more resilient smart cities.

G. *Citizen Engagement and Participation*

Citizen engagement and participation are key components of smart cities, aiming to involve residents in decision-making processes and improve the quality of urban life. ML techniques significantly facilitate citizen engagement by analyzing large amounts of data and enabling personalized interactions between citizens and city authorities. In this subsection, we discuss the applications of ML in smart cities' citizen engagement and participation domains, highlighting how they enhance residents' communication, collaboration, and empowerment.

- Sentiment analysis and feedback processing: ML algorithms analyze public sentiment by mining social media posts, online reviews, and citizen feedback. These algorithms can automatically classify sentiments as positive, negative, or neutral, providing valuable insights into public opinions about various aspects of urban life. Sentiment analysis helps city authorities understand citizen concerns, identify areas for improvement, and tailor policies and services accordingly.

TABLE VI. ML APPLICATIONS IN HEALTHCARE AND WELL-BEING

Approach	ML type	Objective	Achievement	Challenges	References
Disease diagnosis and predictive analytics	Supervised	Patients' data are analyzed to aid in disease diagnosis and prediction	Improved accuracy Early detection of diseases Personalized treatment plans	Dependency on accurate and comprehensive patient data Potential biases in algorithmic analysis Challenges in interpretability	[123-126]
Remote patient monitoring	Supervised	Remote monitoring of patients' health conditions using wearable devices and sensors	Proactive interventions Reduced hospitalizations Improved convenience for patients	Reliability and accuracy of sensor data Potential privacy concerns Challenges in data integration.	[127-129]
Health risk assessment and prevention	Supervised	Individuals' health risks are assessed, and personalized recommendations are provided for prevention.	Personalized recommendations for preventive care, Reduced healthcare costs	Reliance on accurate and diverse data sources Potential biases in algorithmic analysis Ethical considerations	[130-132]
Health resource optimization	Supervised	The allocation of healthcare resources is optimized based on patient data and demand predictions.	Improved resource utilization Reduced waiting times Efficient resource planning	Data accuracy and quality Challenges in integrating multiple data sources Potential biases in demand predictions	[133, 134]
Mental health support	Supervised	Various data sources are analyzed to provide mental health support and virtual counseling.	Enhanced access to care Reduced stigma Personalized support for mental well-being	Privacy and security concerns related to sensitive mental health data Potential biases in algorithmic analysis	[135, 136]

- Participatory decision-making: ML techniques enable participatory decision-making by providing platforms for citizens to express their opinions, vote on proposals, and contribute to policy development. These algorithms can aggregate and analyze citizen inputs, allowing city authorities to make informed decisions that reflect the preferences and priorities of the community. Participatory decision-making enhances transparency, accountability, and democratic processes in smart cities.

- Personalized citizen services: ML algorithms personalize citizen services by leveraging data on individual preferences, behaviors, and needs. These algorithms can recommend relevant information, services, and events based on citizens' profiles and historical interactions. Personalization enhances citizen experience, increases engagement, and fosters a sense of belonging in the community.

- Urban analytics and planning: ML techniques analyze data from various sources, including sensors, traffic patterns, and citizen-generated data, to generate urban planning and development insights. These algorithms can identify usage patterns, predict future trends, and optimize urban infrastructure and services. Urban analytics and planning empower city authorities to make data-driven decisions, improve resource allocation, and create more livable and sustainable cities.

- Community empowerment and collaboration: ML algorithms facilitate community empowerment and collaboration by connecting citizens with similar interests and promoting collective action. These algorithms can identify common goals, facilitate collaboration platforms, and support grassroots initiatives. Community empowerment enhances social cohesion, fosters civic engagement, and encourages residents to actively participate in shaping their neighborhoods.

ML applications in citizen engagement and participation domains of smart cities offer significant benefits, including improved communication between citizens and city authorities, participatory decision-making, personalized citizen services, data-driven urban planning, and community empowerment. However, challenges such as data privacy, the digital divide, biases in algorithmic analysis, and ensuring inclusive participation need to be addressed to ensure equitable and meaningful engagement of all residents. Ongoing research and collaboration between data scientists, urban planners, and policymakers aim to overcome these challenges and leverage the full potential of ML in enhancing citizen engagement and building inclusive smart cities.

TABLE VII. ML APPLICATIONS IN CITIZEN ENGAGEMENT AND PARTICIPATION

Approach	ML type	Objective	Achievement	Challenges	References
Sentiment analysis and feedback processing		Public sentiment and citizen feedback are analyzed to gain insights into public opinions and concerns.	Understand citizen sentiments: Sentiment analysis allows for the comprehension of public sentiments and concerns, aiding policymakers in making informed decisions Identify areas for improvement: By processing citizen feedback, areas for policy improvement can be pinpointed, leading to more effective governance Tailor policies accordingly: Tailoring policies to address specific citizen sentiments enhances public satisfaction and engagement.	Biases in sentiment analysis: Ensuring the accuracy and impartiality of sentiment analysis remains a challenge Challenges in handling unstructured data: Managing and extracting insights from unstructured data, such as text and social media content, require advanced techniques Potential privacy concerns related to data mining: Ethical considerations surrounding data mining must be addressed to protect citizen privacy.	[137-140]
Participatory decision-making		Enable citizens to participate in decision-making processes and contribute to policy development actively.	Increased transparency, accountability, and democratic processes: Involving citizens in decision-making enhances government transparency and accountability Representation of citizen preferences and priorities: Decision-making reflects the diverse preferences and priorities of the community, leading to more inclusive policies.	Digital divide: Ensuring equitable access to participation platforms and overcoming the digital divide is essential for meaningful engagement Potential biases in algorithmic analysis, ensuring inclusivity and diversity in participation: Care must be taken to mitigate algorithmic biases and encourage diverse citizen participation.	[141, 142]
Personalized citizen services		Citizen services are personalized by recommending relevant information, events, and services based on profiles.	Enhanced citizen experience: Personalization improves the user experience and increases citizen engagement Increased engagement: Tailored recommendations encourage citizens to interact more with available services Tailored services: Citizens receive services that match their specific needs and interests.	Privacy concerns related to data collection and profiling: Safeguarding citizen privacy in data collection and profiling processes is critical Potential biases in personalization algorithms: Ensuring that personalization algorithms do not reinforce biases is an ongoing challenge.	[143, 144]
Urban analytics and planning		Urban data is analyzed to generate insights for urban planning, infrastructure optimization, and resource allocation.	Data-driven decision-making: Urban analytics facilitates data-driven decision-making, leading to more efficient resource allocation and planning. Optimized resource allocation: Through data analysis, cities can allocate resources more effectively, reducing waste Improved urban infrastructure and services: Data-driven insights enhance the quality of urban services and infrastructure.	Data quality and integration: Ensuring the accuracy and integration of data from various sources is vital for meaningful analysis Interpretability of ML models: Understanding how ML models arrive at conclusions is crucial for decision-makers Biases in data and algorithms: Identifying and addressing biases in data and algorithms is essential to avoid unintended consequences.	[145-147]
Community empowerment and collaboration		Community empowerment and collaboration by connecting citizens and supporting collective action	Foster social cohesion: Connecting citizens fosters social cohesion and a sense of community Encourage civic engagement: Empowering citizens to take action encourages active civic participation. Support grassroots initiatives: ML algorithms can connect citizens with grassroots initiatives that align with their interests.	Ensuring inclusive participation: Efforts must be made to ensure that all segments of the population have opportunities to engage. Potential biases in algorithmic matchmaking: Algorithms must be designed to avoid excluding certain groups inadvertently. Challenges sustaining community engagement and collaboration: Sustaining long-term community engagement requires ongoing effort and commitment.	[148]

IV. FUTURE DIRECTIONS AND RESEARCH TRENDS

ML applications in smart cities are constantly evolving, and several future directions and research trends hold promise for advancing the capabilities and impact of smart city technologies. In this subsection, we discuss some key areas likely to shape the future of ML in smart cities.

- Explainability and transparency: As ML algorithms become more complex and pervasive in smart cities, there is a growing need for explainability and transparency. Researchers are exploring techniques to make ML models more interpretable, allowing stakeholders to understand the reasoning behind algorithmic decisions. Ensuring transparency not only builds trust but also helps in identifying potential biases and addressing ethical concerns.

- Privacy and security: With the increasing use of data in smart city environments, preserving privacy and ensuring data security are critical research areas. Future work aims to develop robust privacy-preserving ML techniques for data analysis while protecting sensitive information. Additionally, efforts are focused on enhancing the security of ML models to prevent adversarial attacks and unauthorized access to data.

- Federated learning and edge computing: Federated learning, a distributed learning approach, is gaining attention in the context of smart cities. It allows training ML models on decentralized data sources while preserving data privacy. Furthermore, integrating ML with edge computing enables real-time data processing and decision-making at the network's edge, reducing latency and dependence on cloud infrastructure.

- Human-centered ML: The future of ML in smart cities lies in designing algorithms and systems that are more human-centered. This includes considering user needs, preferences, and values in developing ML models. Human-centric approaches aim to ensure that ML technologies serve the well-being and inclusivity of all citizens, addressing biases, fairness, and ethical considerations.

- Integration of multiple data sources: To unlock the full potential of ML in smart cities, there is a need to integrate diverse data sources from various domains. This includes combining data from IoT devices, social media, urban sensing networks, and administrative records. Future research focuses on developing techniques for effective data integration, data fusion, and handling heterogeneity and spatiotemporal dynamics in smart city data.

- Autonomous systems and reinforcement learning: Advancements in autonomous systems, such as self-driving vehicles and intelligent infrastructure, present new opportunities for ML. Reinforcement learning techniques can enable autonomous systems to learn from their interactions with the environment and make optimal decisions. Future research aims to develop robust and safe reinforcement learning algorithms for autonomous systems in smart city contexts.

- Ethical and legal implications: As ML becomes deeply embedded in smart city applications; there is a need to address ethical and legal implications. Researchers are investigating frameworks for responsible AI deployment, considering issues such as algorithmic fairness, accountability, and legal regulations. Ensuring that ML in smart cities aligns with ethical guidelines and legal requirements is crucial for building trust and avoiding unintended negative consequences.

- Transfer learning and generalization: Transfer learning, which leverages knowledge gained from one task to improve performance on another, holds promise for smart cities. Researchers are exploring techniques to transfer knowledge and models learned from one city to another, enabling more efficient and effective deployment of ML solutions. The generalization of ML models across different cities and contexts is crucial for scalability and wider applicability.

- Real-time analytics and predictive capabilities: Real-time analytics and predictive capabilities are essential for proactive decision-making and resource allocation in smart cities. Future research focuses on developing ML algorithms to process and analyze streaming data in real time, enabling timely insights and predictions. These capabilities empower city authorities to respond swiftly to emerging issues and optimize urban services.

- Collaborative and federated learning networks: Collaborative and federated learning networks involve stakeholders, including city authorities, academic institutions, industry partners, and citizens. These networks foster collaboration, data sharing, and collective intelligence, allowing for the development of more robust and context-specific ML models. Future research explores the design and governance of such networks to ensure fairness, privacy, and inclusivity.

- Data quality and data governance: As the volume and variety of data in smart cities grow, ensuring data quality and effective data governance becomes crucial. Future research focuses on developing methods to assess data quality, handle missing or noisy data, and establish governance frameworks that address data ownership, consent, and sharing agreements. Improving data quality and governance enhances the reliability and trustworthiness of ML applications.

- Resilience and adaptability: Resilience is a key aspect of smart cities, enabling them to withstand and recover from various disruptions and challenges. ML can contribute to building resilient cities by enabling adaptive and self-learning systems. Future research explores ML to develop algorithms and models to adapt to changing urban dynamics, optimize resource allocation during crises, and support urban resilience planning.

- Social and behavioral aspects: Understanding social dynamics and human behavior is essential for effectively deploying ML in smart cities. Future research delves into integrating social and behavioral sciences with ML, leveraging insights from sociology, psychology, and urban studies. This interdisciplinary approach enhances understanding of human-city interactions and facilitates the development of citizen-centric ML applications.

- Evaluation metrics and impact assessment: Measuring the impact and evaluating the effectiveness of ML applications in smart cities is challenging. Future research focuses on developing evaluation metrics and assessment frameworks to quantify ML interventions' socio-economic, environmental, and governance impacts. Robust evaluation methods are crucial for evidence-based decision-making and ensuring the alignment of smart city initiatives with desired outcomes.

V. Conclusion

Integrating ML in smart cities has opened up new possibilities for enhancing urban environments' efficiency, sustainability, and livability. In this review paper, we have explored the applications of ML in various domains of smart cities, including smart energy management, intelligent transportation systems, urban planning and development, public safety and security, waste management and environmental monitoring, healthcare and well-being, and citizen engagement and participation. ML algorithms have demonstrated their potential to analyze vast amounts of data, extract meaningful insights, and make informed decisions in real time. ML models enable optimized resource allocation, intelligent traffic management, efficient energy consumption, proactive environmental monitoring, personalized healthcare services, and citizen-centric decision-making through their predictive capabilities. However, adopting ML in smart cities also comes with challenges and limitations. Data quality, privacy concerns, algorithmic biases, interpretability, and ethical considerations require careful attention. Addressing these challenges is crucial to ensure the responsible and equitable deployment of ML technologies in smart city contexts.

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