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Integrating machine learning for the sustainable development of smart cities

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The purpose of this study is to assess the potential of machine learning in advancing the Sustainable Development Goals, particularly Goal 11, which focuses on sustainable urban and community development. To reduce the impacts of increasing urbanization on the environment, it is necessary to prioritize the sustainable development of smart cities. Smart cities use information and communication technology techniques to enhance sustainability by improving resource management and reducing environmental impact. In this context, the use of artificial intelligence enhances the overall quality of life, which is a critical component of sustainable smart cities. Machine learning, a subset of artificial intelligence, is crucial in promoting the development of sustainable smart cities. This study focuses on the application of machine learning in sustainable smart cities, ranging from energy management, transportation efficiency, waste management, and public safety. It highlights the role of machine learning algorithms to improve operational efficiency, minimize expenses, and reduce environmental impact. The practical use of ML in smart cities across several countries demonstrates its ability to handle urban challenges and increase sustainability. This paper discusses a variety of real-world initiatives that have successfully employed machine learning to develop sustainable smart cities, as well as in-depth studies of the ML algorithms used and the obtained results. The paper also covers the challenges of implementing machine learning into smart city projects, such as data quality, model interpretability, scalability, and ethical considerations. It emphasizes the importance of high-quality data, clear models, and the right use of machine learning tools.

KEYWORDS

sustainable smart cities, machine learning, SDG 11, applications, challenges

1 Introduction

Nowadays, urbanization is accelerating, and cities are under increasing pressure to maintain infrastructure, manage resources, and improve the quality of their citizens (Klein and Anderegg, 2021). The rapid growth of cities creates a number of challenges, including air pollution, traffic congestion, waste management, and energy use. In this context, new solutions must be implemented, including cutting-edge technologies, to create more efficient, sustainable, and livable urban environments (Caragliu et al., 2011). In this context, smart cities use the Internet of Things (IoT) in conjunction with information and communication technology (ICT) to collect and analyze data, enabling more intelligent decision-making processes. According to Sustainable Development Goal (SDG) 11: Sustainable Cities and Communities, established by the United Nations, sustainability constitutes a critical element of urban transformation. The primary objective of SDG 11 is to ensure that cities are resilient, safe, inclusive, and sustainable. This goal advocates for sustainable urban development and aims to enhance the quality of life for all urban residents, highlighting the importance of innovative solutions to address urban challenges (Bibri and Krogstie, 2017; Janik et al., 2020; Yigitcanlar et al., 2019).

Machine learning (ML), a subset of artificial intelligence (AI), has emerged as a powerful tool in this field (Jordan and Mitchell, 2015). By enabling systems to examine data and improve over time, machine learning can help progress various aspects of smart cities (Hurbean et al., 2021; Ullah et al., 2023; Françá et al., 2020). ML technologies are essential for advancing sustainable urban development goals because they improve public health and safety, fortify transportation networks, and optimize energy use. ML algorithms can predict energy use, improve traffic congestion, personalize citizen services, increase urban management effectiveness and efficiency, and so on. While there are many benefits to using ML in smart cities, there are also a number of challenges (Mishra and Singh, 2023). One challenge that emerges is the quality and accessibility of data, given that urban data may be varied, diversified, and of different quality. Finding a balance between the demand for analysis accessibility and data privacy and security is another significant issue. Furthermore, the difficulty of interpreting and applying ML algorithms in significant urban applications remains a challenge. Because of resource constraints, including processing power and energy consumption, scaling problems arise when deploying machine learning models in densely populated places. Despite these challenges, the integration of machine learning into smart cities has made notable progress. For instance, the city of Riyadh in Saudi Arabia has improved traffic flow and reduced congestion by implementing machine learning algorithms. This has led to increased mobility and a reduction in emissions. Moreover, Jeddah is using machine learning to optimize water management systems, which leads to improved sustainability and more efficient use of water resources (Aldegheishem, 2023). These case studies demonstrate how machine learning may address urban challenges and support the long-term growth of smart cities.

This paper investigates the role of ML in advancing sustainable smart cities, focusing on critical areas like energy management, public safety, waste management, and transportation efficiency. The research highlights how ML can significantly improve operational effectiveness, enabling cities to optimize resource usage, reduce costs, and minimize environmental impact. For instance, ML can predict energy consumption patterns, optimize grid operations, and enhance renewable energy integration. In public safety, ML-driven systems can improve crime prediction, emergency response times, and disaster management strategies. ML also supports more efficient waste management by optimizing collection routes, predicting waste generation, and enhancing recycling processes. In transportation, ML can improve traffic flow, reduce congestion, and promote sustainable travel options, resulting in reduced emissions and enhanced mobility. In contrast to studies by Kumar et al. (2021) and Lilhore et al. (2022), which primarily focus on specific applications like surveillance and traffic management, our approach adopts a more holistic perspective driven by the SDG 11 objectives. Kumar et al. (2021) focus on leveraging ML in traffic management and surveillance within smart cities, exploring how IoT and ML can improve traffic prediction, congestion control, and data-driven decision-making for urban mobility. Likewise, Lilhore et al. (2022) discuss the application of AI in urban traffic systems, proposing the use of ML to optimize traffic flow and improve safety in smart cities.

The contributions of our paper can be summarized as follows:

- We perform a detailed comparative analysis of ML applications across key domains such as energy management, transportation, waste management, and public safety. The analysis delves into various ML algorithms used in these areas, examining their performance, scalability, and adaptability to different urban environments. We also provide a critical assessment of their real-world implementations.
- Our paper stands out by incorporating a global perspective, analyzing ML initiatives and implementations from various geographic regions, including both developed and developing countries. Existing literature often overlooks this dimension, focusing on specific regions or case studies. By including a wide range of geographic contexts, we offer insights into how local factors such as infrastructure, regulatory environments, and cultural differences impact the adoption and success of ML in smart cities.
- We discuss key challenges for integrating ML into smart cities, including the need for high-quality, accessible data, ensuring model interpretability for transparency and trust, and scaling solutions from pilot projects to city-wide applications. We also discuss future directions which involves enhancing data governance and standardization, developing interpretable models without compromising performance, and advancing scalable ML architectures using cloud and edge technologies.

The paper's structure is as follows: Section 2 provides an overview of the fundamental ideas and concepts of smart cities. Section 3 offers a thorough overview of machine learning techniques. Our study's fourth section explores the application of ML in smart, sustainable cities. In Section 5, we present a number of real-world projects that use ML to create smart cities that are ecologically beneficial. In addition to discussing the unique challenges of incorporating ML in sustainable smart cities, Sections 7 and 8 also look at possible future paths and prospects. Ultimately, Section 9 concludes the paper.

2 Fundamentals of smart cities

Smart cities present the intersection of technology and urban living, harnessing digital advancements to improve different aspects of city life. These cities use emerging technologies like machine learning, the Internet of Things, artificial intelligence, and data analytics to provide smart infrastructure, efficient services, and improved connectivity. Smart cities prioritize data-driven decision-making, citizen involvement, and long-term growth in their innovative use of technology. They use smart sensors and IoT devices to monitor and manage essential systems ranging from transportation and energy to waste management and public safety, promoting resilience and responsiveness in the face of urban issues.

This section covers the architecture and building blocks needed for a sustainable smart city.

2.1 Architecture of smart cities

Several research studies have focused on the design of a generic architecture for smart cities at a global level. Figure 1 gives a view of smart city architecture. This architecture is composed of four layers: perceptual layer, network layer, platform layer, and application layer (Zhao and Zhang, 2020). This design is useful in capturing the key components of smart city operations since it helps in planning and describing different smart city technologies in the simplest and clearest manner possible.

2.1.1 Perceptual layer

This layer collects data from various sources by implementing physical equipment like cameras, microphones, GPS trackers, and other types of sensors. Collecting data from multiple sources is a difficult task because the data is mostly unstructured and varied. This has constituted a big challenge in deploying and exploiting wireless sensor networks (WSNs) in smart cities. Other aspects of effective data collection include proper management of energy consumption, resource exploitation, and transmission costs. By using various approaches to collect heterogeneous data from diverse applications, the delay-tolerant network (DTN), like vehicle DTN, can enhance data collection in a smart city. Also, several types of data collection implement comprehensive coverage. Environmental sensors monitor air quality and weather, while smart meters monitor energy consumption in homes and businesses. Real-time use of GPS and passenger counters in transport systems has led to increased efficiency and reliability through rerouting and rescheduling.

2.1.2 Network layer

The appropriate channels transmit the obtained information to the storage units for further processing. Wireless networks such as Wi-Fi, Bluetooth, Zigbee, and RFID, along with telecommunications like LTE, 3G, 4G, and 5G, significantly contribute to this process. In this regard, the transmission layer must transfer data in a secure and reliable manner, taking into account data integrity and privacy during transmission. It is critical to use advanced encryption technologies and secure communication protocols to protect sensitive information, particularly in sensitive industries such as health care and banking. Strong and scalable network infrastructure is necessary to handle the massive data load that smart city applications generate.

2.1.3 Platform layer

This layer preprocesses, evaluates, and derives decisions from the received data. We refer to this process as the "brain" of the smart city framework because it takes place after all phases of data collection and before applying the data to the actual field of applications. The process of filtering relevant data, integrating it with data from multiple sources, and utilizing big data analytics enables effective analysis in real time. The data management layer also comprises storage systems that can handle gigantic volumes of data and make it accessible and available in a speedy manner. Cloud computing and edge computing have become the norm for providing flexible and scalable storage capabilities. It also needs to tackle data interoperability issues, enabling the integration and analysis of data from diverse sources.

2.1.4 Application layer

This is the layer that gives citizens direct interaction with the smart city environment. The primary function of this layer is to develop user-friendly and appealing applications, while the Data Management Layer simultaneously implements key decisions. The applications span education, healthcare, and management, as well as transportation and other areas of technology. This application layer primarily focuses on enabling services that enhance the quality of life for residents. Examples include intelligent traffic management systems that ease traffic congestion, mobile apps that host real-time information on public transportation, and online access to government services. These applications should be user-friendly and accessible to all citizens in order to spread the benefits brought about by smart city initiatives far and wide.

To summarize, smart city architecture is based on a multi-layered structure that includes data gathering, transmission, management, and application. Each layer is crucial to guaranteeing the seamless functioning of smart city services and creating an environment in which technology improves urban living, promotes sustainability, and raises the overall quality of life.

2.2 Data flow in smart cities

According to Figure 2, there are three levels of implementation for smart cities, each of which contributes to improving the urban environment with technology and data flow. The first stage entails collecting data and extracting knowledge from numerous statistics about the urban environment. This step is critical because it establishes the foundation for all later actions. Sensors, IoT devices, and other sources produce massive amounts of data that ML algorithms manage. These algorithms preprocess data to make it clean and suitable for analysis, detecting patterns and correlations that typical statistical approaches may overlook. Predictive modeling, which is an important component of this level, uses historical information to estimate future patterns in areas like transportation congestion, energy demand, and environmental changes.

Moving on to the second level, the emphasis switches to information storage, management, evaluation, and handling in order to facilitate autonomous decision-making. This requires sophisticated data storage technologies and big data frameworks capable of managing massive amounts of data. Real-time analytics powered by ML algorithms provide instant insights, which are essential for making quick decisions. Decision support systems use these insights to recommend actions or identify ideal solutions based on extensive data analysis. Automation at this stage enables systems to make decisions without requiring human interaction,

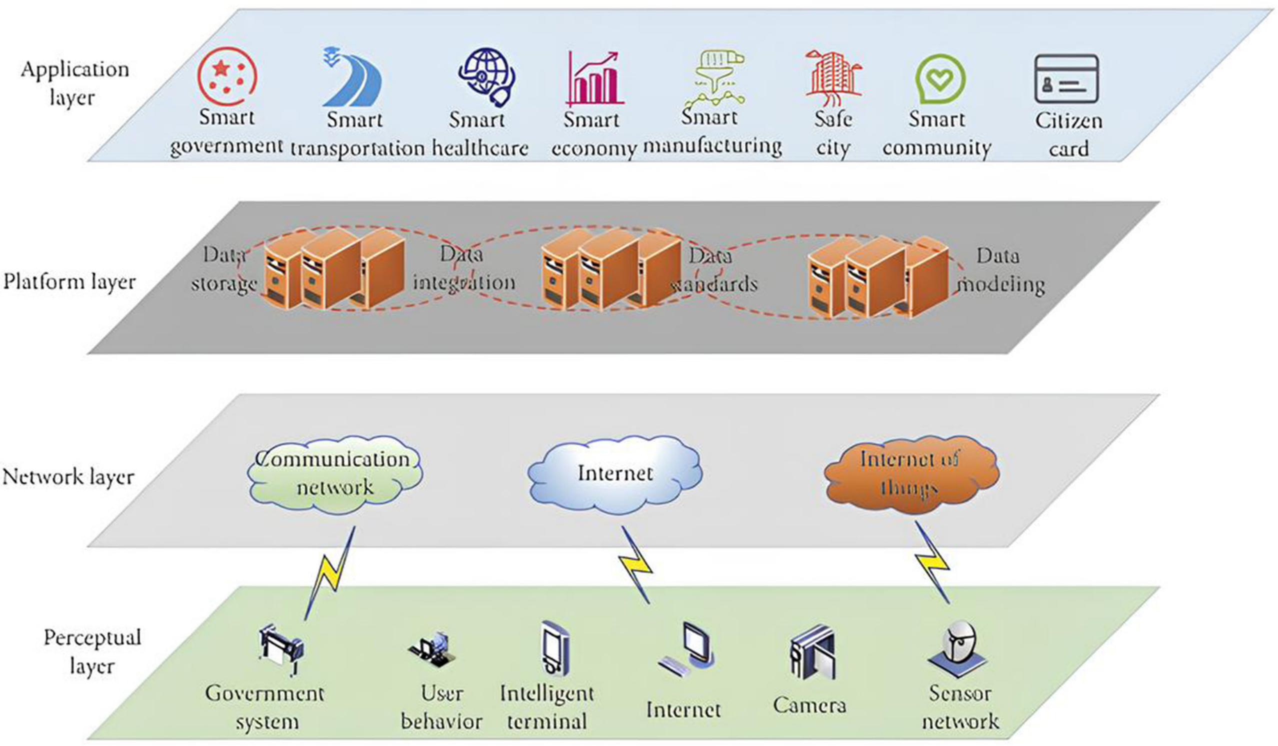

FIGURE 1
Architecture of a smart city (Zhao and Zhang, 2020).

such as dynamically modifying traffic signal timings in response to real-time traffic circumstances.

The third and final level involves the service-level implementation of the decisions made in the previous phases. This level translates analytical and decision-making skills into practical services that enhance urban living. ML algorithms improve the performance of smart infrastructure, such as smart grids, to ensure efficient energy distribution, intelligent transportation systems, and effective waste management. Furthermore, these algorithms enable people to receive individualized services such as customized transportation routes, personalized healthcare warnings, and tailored municipal services, thereby improving the overall quality of life in cities.

2.3 Components of smart cities

Smart cities aim to use technology to improve the efficiency, sustainability, and livability of urban areas. This section introduces the key components of smart cities, as outlined in Gracias et al. (2023) and Pathak and Pandey (2021).

2.3.1 Smart transportation

Smart transportation is a fundamental component of smart cities. This entails using intelligent traffic management systems that use sensors, cameras, and real-time data analytics to regulate traffic flow, reduce congestion, and increase safety. Real-time tracking, dynamic scheduling, and mobile ticketing improve public transportation efficiency and convenience. Smart cities also encourage the use of electric vehicles (EVs) and the development of self-driving vehicles to cut pollution and improve safety. Promoting shared mobility solutions like bike and car sharing programs aims to decrease the number of private automobiles on the road. Smart parking systems use sensors and mobile applications to deliver real-time information about available parking spaces, minimizing the amount of time spent looking for parking.

2.3.2 Smart health

Smart health is the use of technology to facilitate healthcare services, improve patient outcomes, and make healthcare more accessible. In that respect, telemedicine provides remote medical consultation and services through video conferencing and smartphone apps. Technologies for health monitoring, such as wearables and IoT sensors, will enable real-time monitoring of patients' vital signs that alert healthcare providers in case of any abnormality. Electronic Health Records (EHR) digitizes patients's records, thus making data more accurate, accessible, and shared among health professionals. Healthcare data analytics use big data and AI to study health trends, develop predictions of health crises and individually customize treatment schedules. Smart hospital management uses automation and IoT solutions to improve operations ranging from patient admissions to inventory management.

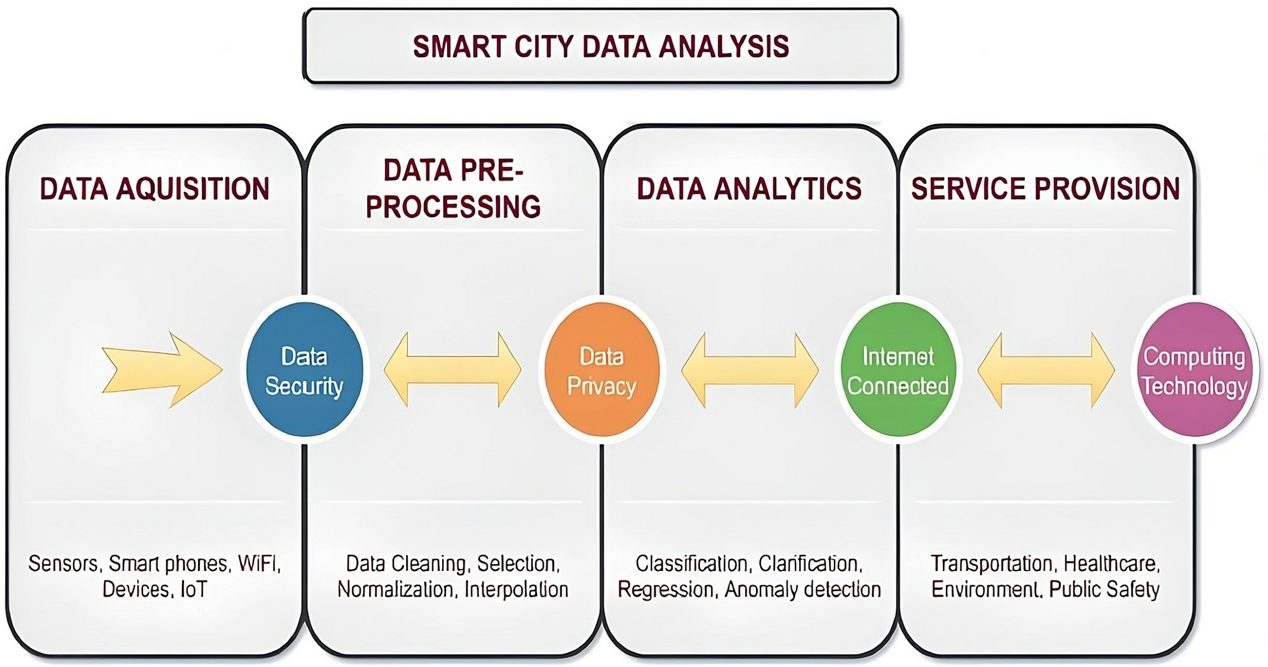

FIGURE 2
Data flow in smart cities (Ullah et al., 2023).

2.3.3 Smart energy

Smart energy systems allow cities to have more sustainable, effective, and safe energy networks. The smart grid works with digital technology in such a way that it efficiently supplies electricity from renewable sources of energy in real-time, answering new energy demands. To diversify urban energy, renewable energy sources such as solar and wind are encouraged to be used and integrated. Advanced energy storage devices store excess energy and use it during high-demand periods. Smart meters, energy-efficient appliances, and building automation systems, among other energy efficiency solutions, actively contribute to reducing energy consumption. Demand response programs use real-time data and payments to incentivize consumers to reduce or shift their energy consumption during periods of high demand.

2.3.4 Smart governance

Smart governance enhances the effectiveness, transparency, and responsiveness of government services by utilizing digital technology and platforms. E-government services provide online access to government services, which reduces the need for in-person visits and paperwork. Open data programs make government data public in easily accessible formats, increasing transparency and allowing citizens to participate in decision-making. Citizen engagement systems allow citizens and government officials to communicate directly through mobile apps, social media, and online portals. Smart infrastructure management uses IoT sensors and data analytics to monitor and repair public infrastructure like highways, bridges, and water delivery systems. Digital identification systems generate secure digital IDs that enable citizens to access a wide range of services and benefits.

2.3.5 Smart buildings

Smart buildings use cutting-edge technologies to increase energy efficiency, comfort, and security. Automation of lighting, heating, ventilation, and air conditioning (HVAC), along with other building activities, takes place through sensors and control systems. Energy management systems track and optimize energy consumption in real time, reducing waste and cost. Smart security systems boost building security by integrating cameras, access control, and alarm systems. Occupancy sensors detect people's presence and modify lighting and HVAC systems accordingly, enhancing comfort and energy efficiency. Sustainable building materials and construction processes reduce buildings' environmental impact.

2.3.6 Smart environment

Smart environmental solutions aim to monitor and enhance the urban environment for sustainability and public health. Air quality monitoring uses IoT sensors to assess pollution levels in real time, providing data for informed decision-making. Waste management systems use smart bins and recycling systems with sensors to optimize waste collection routes and minimize landfill use. Water management uses smart sensors and analytics to monitor water quality, detect leaks, and manage water resources effectively. Urban green spaces use technology to maintain and improve parks, gardens, and other green places, benefiting urban biodiversity and residents' wellbeing. Climate resilience planning employs data analytics and simulation models to devise plans for reducing the effects of climate change on urban areas.

2.3.7 Smart education

Smart education is the use of technology to improve learning outcomes and experiences. There are online courses, resources, and virtual classrooms that give everyone access to education. Interactive tools like digital whiteboards and iPads make students enjoy learning and understand better. Artificial intelligence and data analytics in the learning environment tailor the educational content and pace to each student's individual needs through personalized learning. Digital literacy programs equip children with the digital skills they need to succeed in today's job market. IoT and automation provide smart campus solutions when it involves managing campus buildings, improving safety on campus, and optimizing the consumption of resources.

2.3.8 Smart economy

A smart economy relies on technology and innovation to improve both economic growth and individual quality of life. To facilitate secure and rapid transactions, digital payments promote the adoption of mobile payments, electronic wallets, and blockchain technology. E-commerce platforms facilitate the expansion of online companies and their markets, leading to economic growth. Innovation centers establish incubators and accelerators to facilitate the growth of companies and entrepreneurs. Advanced manufacturing, also known as smart manufacturing, utilizes Industry 4.0 technologies such as the IoT, AI, and robotics to increase the quantity and effectiveness of manufacturing processes.

2.4 Sustainable smart cities

Sustainable smart cities combine sustainability principles with cutting-edge technology to create environmentally conscious, socially inclusive, and economically strong urban settings (Bibri et al., 2023; Hashem et al., 2023; Quy et al., 2023; Alamoudi et al., 2023), as shown in Figure 3. The framework for sustainable smart cities is based on a comprehensive strategy for urban planning, design, and management that aims to address the numerous difficulties of urbanization while maintaining the long-term sustainability and resilience of urban ecosystems.

One of the framework's central points is environmental sustainability, which entails reducing, controlling, and minimizing resource consumption, controlling pollution, and responding to the urgent challenges of climate change. Examples of such practices include energy-efficient building and renewable energy, the design and implementation of sustainable transport systems, and any other campaigns aimed at reducing trash and recycling. Highly environmentally sustainable urban areas have a smaller ecological footprint and healthier urban environments for their residents.

Another fundamental component of the sustainable smart city paradigm is social equality. The principle of equitable access to resources, opportunities, and services for all urban residents forms its foundation, along with strategies that promote inclusive urban development. These strategies encompass a wide variety of initiatives, including digital inclusion, social cohesion, and community participation, as well as affordable housing and health and education services. Promoting social cohesion and justice in socially equitable cities will enhance the quality of life for all citizens.

Additionally, economic prosperity is a critical element of the framework of sustainable smart cities, as it offers long-term economic development, innovation, and entrepreneurship opportunities in urban areas. This dimension emphasizes the promotion of local enterprises and start-ups, the investment in research, development, and innovation, the enhancement of employment training and workforce development programs, the promotion of tourism and cultural heritage, and the promotion of economic diversity and resilience planning. The promotion of economic development is instrumental in establishing robust, dynamic urban economies that create the necessary conditions for residents' growth and prosperity, thereby introducing opportunities to this frequently overlooked region.

ML, in consort with the paradigm of sustainable smart cities, emerges as a real game-changer in terms of building on sustainability goals, decoding complex urban operations, and espousing data-driven decisions. In such circumstances, ML algorithms enhance the environmental quality of cities, thereby enhancing social equity and economic prosperity by analyzing the massive volumes of data generated by IoT sensors, satellite imagery, social media, and other sources. Cities will, therefore, be much more resilient, livable, and sustainable for generations to come, harnessing the transformative power of data and technology through the sustainable smart city framework of ML.

3 Overview of machine learning techniques

ML techniques are fundamental to the development and management of smart cities, providing strong tools for analyzing data, forecasting outcomes, and optimizing operations. Figure 4 illustrates the general categorization of ML approaches into four categories: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Each of these strategies has its own methodology and applications, making a distinctive contribution to the functionality of smart urban environments. Table 1 compares various ML approaches.

3.1 Supervised learning

Supervised learning involves training a model by utilizing a labeled dataset and pre-defined input-output pairings. This method is very effective for jobs involving prediction and categorization. Smart cities can employ supervised learning algorithms to predict traffic patterns, effectively control congestion,

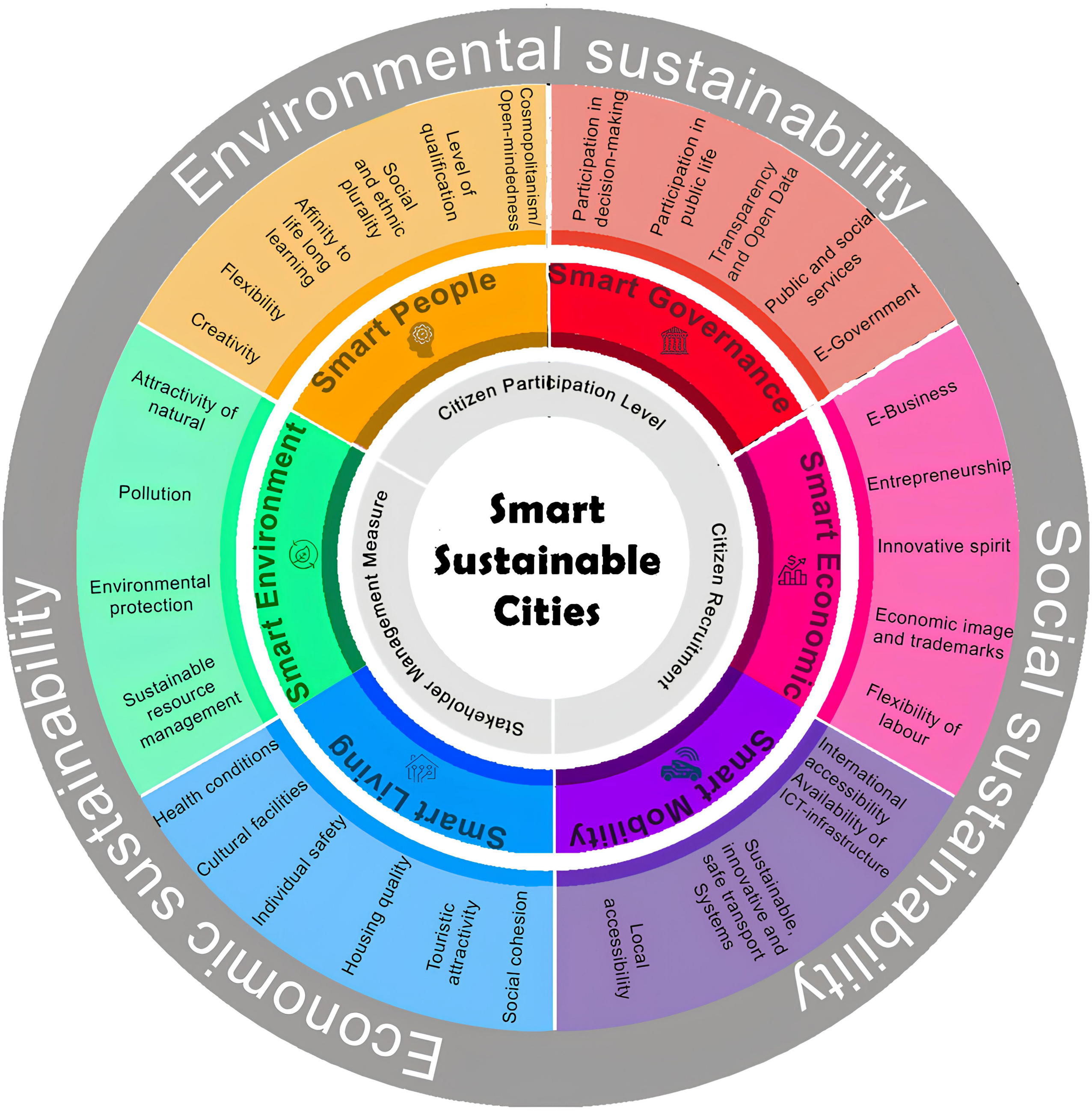

FIGURE 3
Smart sustainable cities' framework (Alamoudi et al., 2023).

classify different types of garbage for recycling, and forecast energy consumption using historical data. Supervised learning algorithms include decision trees, support vector machines (SVMs), and neural networks. Decision trees can forecast patterns in household energy demand by assessing historical consumption data, weather conditions, and occupancy levels. Neural networks have the ability to classify images obtained from waste management stations, therefore improving the efficiency of recycling. When trained on high-quality data, supervised learning offers the significant benefit of generating accurate predictions. However, the accessibility of labeled datasets can affect this accuracy.

3.2 Unsupervised learning

Unsupervised learning, on the other hand, does not make use of labeled data. Instead, it aims to detect hidden patterns or intrinsic structures in the input data. This approach is especially beneficial for clustering and anomaly detection tasks. Smart cities

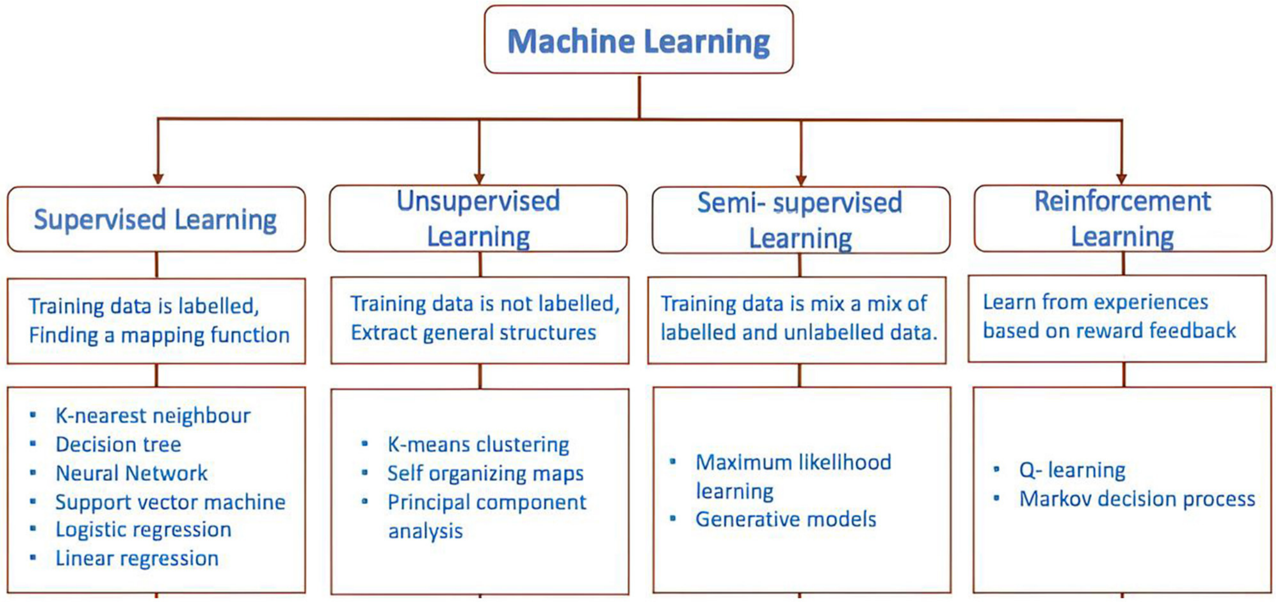

FIGURE 4
Machine learning algorithms overview (Mololoth et al., 2023).

TABLE 1 Comparative table of machine learning techniques.

Aspect	Supervised learning	Unsupervised learning	Semi-supervised learning	Reinforcement learning
Definition	Learns from labeled data	Learns from unlabeled data	Learns from a small amount of labeled data and a large amount of unlabeled data	Learns from interaction with environment
Key applications	Prediction, classification	Clustering, anomaly detection	Enhancing models with scarce labeled data	Sequential decision-making
Examples in smart cities	Energy consumption prediction, traffic forecasting, waste classification	Neighborhood clustering, utility anomaly detection, traffic pattern grouping	Sentiment analysis of citizen feedback, pattern identification in transportation data	Traffic light optimization, autonomous vehicle navigation
Common algorithms	Decision trees, support vector machines, neural networks	K-means clustering, hierarchical clustering, principal component analysis	Self-training, co-training, graph-based methods	Q-learning, deep Q-networks, policy gradient methods
Strengths	High accuracy with quality data, clear outcomes	Works with unlabeled data, discovers hidden patterns	Improves learning accuracy with less labeled data	Adapts to dynamic environments and improves over time
Weaknesses	Requires large labeled datasets, can be resource-intensive	Less interpretable results, dependent on data quality	Varies significantly based on data quality, effectiveness depends on both labeled and unlabeled data	Requires significant computational resources, long training times
Data requirements	Labeled datasets	Unlabeled datasets	Small labeled datasets, large unlabeled datasets	Reward feedback from environment

can use unsupervised learning to group similar traffic patterns to improve signal timing, detect anomalous patterns in utility usage that may reveal issues like leaks or unauthorized access, and cluster communities based on a variety of socio-economic characteristics. Common clustering algorithms include k-means, hierarchical clustering, and principal component analysis (PCA). For example, k-means clustering can classify distinct urban areas based on demographic and economic data, assisting city planners with resource distribution. PCA reduces the dimension of air quality data, making it easier to identify pollution sources and trends. Unsupervised learning's major strength is its ability to deal with unlabeled data and reveal previously unknown insights. However, because there are no preset outputs, the results can be more difficult to comprehend than those obtained by supervised learning.

3.3 Semi-supervised learning

Semi-supervised learning, which combines supervised and unsupervised learning approaches, uses a small quantity of labeled data alongside a large amount of unlabeled data to improve model performance. This approach is especially useful in the context of smart cities, where urban infrastructures create huge and heterogeneous datasets. Traffic monitoring systems, for example, can employ semi-supervised learning to improve vehicle recognition and categorization accuracy despite having minimal labeled traffic data. This strategy aids in efficiently controlling traffic flow, decreasing congestion, and boosting safety. Furthermore, semi-supervised learning can improve energy consumption by evaluating trends in sensor data from smart grids and buildings, allowing for more exact demand forecasts and energy distribution. Smart cities that use semi-supervised learning can make more educated judgments, improve operational efficiency, and deliver better services to their residents.

3.4 Reinforcement learning

Reinforcement learning is a distinct paradigm in which an agent learns to make decisions by interacting with its surroundings and receiving feedback in the form of rewards or penalties. This technique excels in complex and dynamic contexts that require sequential judgments over time. Smart cities can use reinforcement learning for real-time traffic management, where the system learns to optimize traffic light timings based on current conditions, or for autonomous vehicle management, where the vehicle learns to navigate effectively and safely. Q-learning, deep Q-networks (DQN), and policy gradient approaches are examples of often used algorithms. For instance, real-time use of Q-learning can modify traffic lights and ease congestion during peak hours. Deep Q-networks enable autonomous drones to navigate urban environments by learning from simulated encounters. The primary benefit of reinforcement learning is its ability to improve decision-making through continual learning and adaptation. However, training involves a significant amount of computer resources and time, particularly in complex situations.

4 Machine learning applications in sustainable smart cities

ML has enormous promise for driving sustainability activities in smart cities. ML approaches can maximize resource use, improve efficiency, and reduce environmental impact across a variety of urban systems by using the power of data analytics and predictive modeling. This section examines how ML is used to address critical sustainability issues in sustainable smart cities.

4.1 Machine learning integration for a sustainable environment

The use of machine learning in environmental management has resulted in considerable advances across multiple domains, demonstrating the potential for a more sustainable and responsive smart environment. Below, we highlight major findings and outcomes from the use of ML algorithms to predict, monitor, and manage environmental parameters, with a focus on sustainability.

4.1.1 Air quality prediction

ML's use in sustainable smart settings is critical to improving urban air quality management. ML algorithms provide precise prediction and monitoring of air pollutants, which is critical for conducting pollution-reduction initiatives in a timely manner. Several studies have shown that various ML algorithms are effective at predicting air quality across different regions. In Delhi, India, Mahalingam et al. (2019) used neural networks and support vector machines to forecast the air quality index (AQI) with data from the Central Pollution Control Board. This study found that these models could accurately predict AQI, assisting in proactive pollution management. In Kuala Lumpur, Malaysia, Murugan and Palanichamy (2021) examined the Multi-Layer Perceptron (MLP) and Random Forest algorithms to predict PM2.5 concentrations. Their findings showed that the Random Forest method delivered greater accuracy, highlighting its potential for air quality prediction in urban environments. Bekkar et al. (2021) employed a hybrid CNN-LSTM model to forecast PM2.5 concentrations in Beijing, China, taking into account spatial and temporal features. This model outperformed previous models by providing accurate hourly projections of air pollution levels. Difaizi et al. (2023) compared various ML techniques, such as Random Forest Regression, Decision Tree Regression, Linear Regression, and a hybrid Random Forest-XgBoost model. Their research spanned places such as Ahmedabad, Delhi, Lucknow, Gurugram, and Mumbai, identifying major pollutants and improving prediction accuracy. In Chennai, India, Janarthanan combined Support Vector Regression (SVR) and Long Short-Term Memory (LSTM) in a deep learning model to predict AQI. This model was very accurate, which is needed for sustainable urban planning. Natarajan et al. (2024) suggested an optimized ML model integrating Gray Wolf Optimization (GWO) and Decision Tree (DT) for AQI prediction. Their model performed well in cities such as Delhi, Hyderabad, Kolkata, Bangalore, Visakhapatnam, and Chennai. Binbusayyis et al. (2024) used a regression method with Deep Generative Adversarial Networks (GAN) to add new data and Stacked Attention GRU to make predictions. This significantly reduced errors and improved AQI forecasts for cities including Ernakulam, Chennai, and Ahmedabad. This research's comparative study highlights the importance of algorithm selection for prediction accuracy. Deep learning models, particularly those that combine CNN-LSTM and hybrid techniques, have demonstrated greater performance in complicated urban settings. Random Forest and improved models such as GWO-DT demonstrated remarkable accuracy, making them appropriate for a variety of urban environments. Addressing issues such as data quality, algorithm optimization, and real-time implementation is critical to improving air quality predictions. Overall, ML integration in sustainable smart environments not only helps with pollution management, but it also promotes the creation of healthier, more resilient communities.

TABLE 2 Comparative analysis of ML techniques for air quality prediction.

References	Region	ML algorithms	Pollutant	Data source	Outcomes
Mahalingam et al. (2019)	Delhi, India	Neural Networks, SVM	AQI	Central Pollution Control Board	High prediction accuracy for AQI, applicable to other smart cities
Murugan and Palanichamy (2021)	Kuala Lumpur, Malaysia	MLP, Random Forest	PM2.5	Malaysia Air Pollution Dataset	Random Forest outperformed MLP in PM2.5 prediction accuracy
Bekkar et al. (2021)	Beijing, China	CNN-LSTM	PM2.5	Historical and meteorological data	CNN-LSTM hybrid model provided the best hourly PM2.5 forecasts
Difaizi et al. (2023)	Indian Cities	RF, Decision Tree, Linear Regression, XgBoost, Hybrid RF-XgBoost	AQI	Urban datasets	Hybrid model offered highest prediction accuracy
Janarthanan et al. (2021)	Chennai, India	SVR, LSTM	AQI	Not specified	Deep learning model with SVR and LSTM achieved high prediction accuracy
Natarajan et al. (2024)	Indian Cities	Gray Wolf Optimization (GWO) model, KNN, Random Forest, SVR	AQI	Kaggle	GWO model showed best performance with high accuracy in multiple cities
Binbusayyis et al. (2024)	Indian Cities	Deep GAN, Stacked Attention GRU	AQI	Air-Quality-Data	Improved AQI prediction with lower error rates

Table 2 compares studies on air quality prediction using different ML algorithms.

4.1.2 Water quality monitoring

ML is critical to the advancement of sustainable smart environments because it allows for effective monitoring, prediction, and control of environmental resources. Several recent studies on water quality monitoring demonstrate this integration, highlighting the significant contributions of ML and IoT technology.

Mutri et al. (2024) used long-range IoT technologies to create a smart system for monitoring water quality. The system uses sensors to detect water characteristics such as pH and turbidity and sends the data to a cloud service (Antares), which is accessible via Android devices. This method enables real-time monitoring with great precision, with a percentage error of 99.73% for the pH sensor and 99.41% for the turbidity sensor. The system's capacity to return results to the cloud service in an average of 2.6 s demonstrates its efficiency and potential for wider use in smart water management systems. Chen et al. (2023) introduced an intelligent water monitoring IoT system suited for ecological areas and smart cities. This system has various sensors that assess water levels, pH, turbidity, and oxygen levels, as well as AI that adjusts water resource management in real time. The technology uses historical rainfall data and weekly meteorological forecasts to calculate accurate water levels, saving over 60% on costs and improving measurement accuracy by 15%. This system's dynamic adjustment effectively conserves water resources by over 15%, making it a vital tool for minimizing the impacts of extreme climate events like floods and droughts. Tharayil et al. (2024) investigated how deep learning can detect anomalies in water quality monitoring. Their study offers a new Hybrid Multivariate Long Short-Term Memory (HM-LSTM) model for analyzing multivariate time series data from water quality sensors. It integrates several performance neural networks and LSTM networks. This technique has proven to be quite effective in detecting and explaining abnormalities caused by sensor failures, environmental disturbances, and other variables. This model improves the accuracy and reliability of water quality evaluations by giving specific information on the types and reasons for anomalies, which is critical for ensuring sustainable water resource management in smart environments. Table 3 compares different studies on air quality prediction using ML approaches.

4.1.3 Weather forecasting

The application of ML in weather forecasting has shown promising results across various studies, emphasizing its ability to improve prediction accuracy and provide insightful analysis of weather patterns. This discussion synthesizes the findings from four significant studies, highlighting their methodologies, results, and implications.

Shaji et al. (2022) employed a diverse set of ML algorithms, including Random Forest, Decision Tree, MLP classifier, linear regression, and Gaussian Naive Bayes, to predict weather conditions in India. Their study underscores the importance of accurate weather forecasting, particularly in remote regions where traditional weather stations are sparse. By comparing the accuracy of different ML models, they identified that Random Forest and Decision Tree provided higher accuracy, with Random Forest achieving an accuracy of 88% and Decision Tree 85%. This comparative approach is crucial for identifying the most suitable ML techniques for specific weather prediction tasks. Rahman et al. (2022) suggested a new way for smart cities to predict rain in real time by combining fuzzy logic with decision trees, naive bayes, K-nearest neighbors, and support vector machines. This study utilized 12 years of historical weather data to enhance prediction accuracy. The fusion approach demonstrated superior performance, with an overall accuracy improvement of 5-10% compared to individual

TABLE 3 Comparative analysis of ML-based water quality monitoring systems.

References	Region	Technologies used	Parameters	Data source	Outcomes
Mutri et al. (2024)	Indonesia	IoT, LPWAN [cloud-based medium access control (MAC) layer protocol]	pH, Turbidity	Real-time sensor data	Achieved 99.73% accuracy for pH and 99.41% for turbidity, with average result delivery time of 2.6 s
Chen et al. (2023)	Unspecified	IoT, AI, solar power	Water level, pH, Turbidity, Water oxygen	Historical rainfall and meteorological data	Achieved cost savings of over 60% and enhanced water level measurement accuracy by over 15%
Tharayil et al. (2024)	Middle East	Hybrid Multivariate LSTM	Multiple water quality parameters	Industrial field data	High performance in detecting anomalies, providing detailed information on water status and causes of anomalies

models. For instance, the hybrid model achieved an accuracy of 90%, whereas the best individual model, the Decision Tree, had an accuracy of 82%. This indicates the potential of hybrid models to leverage the strengths of different algorithms to improve prediction outcomes. In Schnieder (2024) focused on using explainable artificial intelligence (XAI) to predict the influence of weather on the thermal soaring capabilities of sail planes. By employing Random Forest classifiers and leveraging SHAP (Shapley Additive Explanations) values, the study provided interpretable insights into the model predictions. The Random Forest model achieved an accuracy of 87%, and the integration of XAI techniques offered valuable insights into the factors influencing these predictions. This approach ensures that ML models are not only accurate but also transparent and interpretable, which is crucial for practical applications. In Korea, Kim et al. (2022) analyzed fog events and developed ML models (random forest and deep neural networks) to estimate visibility in two Korean smart cities. By examining the meteorological characteristics of fog and applying ML models, the study aimed to improve urban safety and transportation efficiency. The Random Forest model exhibited the highest accuracy at 92%, while the Deep Neural Network achieved an accuracy of 89%. Although each model had unique strengths in different performance metrics, this study highlights the potential of ML in addressing urban challenges and enhancing the resilience of smart cities. Table 4 provides a comparative analysis of the various studies on weather forecasting using different ML techniques.

4.1.4 Smart waste management

The use of artificial intelligence and machine learning in waste management systems marks a significant step forward in managing the expanding urban waste concerns. This discussion summarizes findings from many significant studies, emphasizing their techniques, conclusions, and implications for sustainable urban environments.

Fang et al. (2023) explore AI applications in waste management, including waste-to-energy, smart bins, and waste-sorting robots. Their findings highlight AI's adaptability in terms of increasing process efficiency and lowering expenses. AI in trash logistics can cut transportation distances by up to 36.8%, prices by up to 13.35%, and time by up to 28.22%. Furthermore, AI's accuracy in recognizing and sorting garbage ranges from 72.8 to 99.95%, which is critical for effective waste segregation and recycling. This study highlights AI's vast potential to improve all phases of the waste management process, making a substantial contribution to smart city programs. Barik et al. (2023) use ML and IoT to control urban garbage. They propose a device that uses ultrasonic sensors, load measurement sensors, and microcontrollers to create smart dustbins that notify municipal authorities when they are full. This method uses convolutional neural networks (CNNs) to identify between biodegradable and non-biodegradable garbage. The IoT allows for real-time monitoring and efficient waste collection, whereas CNNs ensure high waste sorting accuracy. This strategy not only improves trash management efficiency but also encourages recycling, which contributes to environmental sustainability. Lipianina-Honcharenko et al. (2023) propose a novel approach to managing urban garbage using intelligent categorization, clustering, and forecasting. Due to data constraints in Ukraine, the authors demonstrate the method's outstanding efficiency using a dataset from Singapore. The study shows that the XGBoost model can anticipate waste amounts with up to 98% accuracy. This level of forecasting precision is critical for planning and optimizing waste collection routes and schedules, increasing overall waste management system efficiency. Table 5 compares studies on smart waste management using various ML approaches.

4.1.5 Energy consumption forecasting

Studies on energy consumption prediction and forecasting using ML approaches provide important insights into enhancing energy management in smart cities. Each study presents novel approaches and technology for solving the difficulties of energy consumption prediction and optimization.

Shapi et al. (2020) focus on establishing prediction models for energy usage in smart buildings, especially in Malaysia. The study looks at problems that come up when making energy management systems, like predictions that don't work very well. It does this by showing prediction models that use support vector machines, artificial neural networks, and k-nearest neighbors algorithms. A comparative examination of these approaches using performance indicators such as root mean squared error (RMSE), normalized root mean squared error (NRMSE), and mean absolute percentage error (MAPE) provides information about the distribution of energy use among different tenants. The results show differences in forecast accuracy across methods, with RMSE values ranging from 50 to 200 kWh, providing insight into their applicability for specific

TABLE 4 Comparative analysis of ML techniques in weather forecasting.

References	Region	ML algorithms	Parameters	Outcomes
Shaji et al. (2022)	India	Random Forest, Decision Tree, MLP, Linear Regression, Naive Bayes	Temperature, humidity, wind speed, etc.	Random Forest and Decision Tree were more accurate
Rahman et al. (2022)	Lahore, Pakistan	Decision Tree, Naive Bayes, KNN, SVM	Historical weather data	Fusion model outperformed individual models; improved rainfall prediction
Schnieder (2024)	UK	Random Forest	Flight data, weather conditions	Mean absolute error of 5.7 min for flight duration prediction; 81.2% accuracy for soaring probability
Kim et al. (2022)	Sejong and Busan, South Korea	Random Forest, Deep Neural Networks	Meteorological elements, visibility	Precision of 0.85 and 0.84, F1-score of 0.76 and 0.74

TABLE 5 Comparative analysis of ML techniques in smart waste management.

References	Region	Technologies used	Parameters	Outcomes
Fang et al. (2023)	Not specified	AI for waste logistics, sorting robots, waste-to-energy	Waste transportation, cost, time, sorting accuracy	Transportation distance reduced by 36.8%, cost savings of 13.35%, time savings of 28.22%, sorting accuracy 72.8%-99.95%
Barik et al. (2023)	India	ML (CNN), IoT, smart dustbins	Waste type identification, bin status	Real-time monitoring, high accuracy in waste sorting, improved recycling efficiency
Lipianina-Honcharenko et al. (2023)	Singapore	XGBoost, clustering, forecasting	Waste volume, city characteristics	Waste volume forecasting accuracy up to 98%, efficient waste management

use cases. Similarly, Helli et al. (2022) present a study on forecasting energy usage in smart cities, emphasizing the significance of precise predictions to implement decarbonization programs. The study employs deep learning models like LSTM, Transformer, XGBoost, and hybrid models to forecast energy usage using detailed data from Germany. A comparative examination of these models provides useful information about the performance of several ML algorithms in short-term time series prediction. The results show varied levels of accuracy and efficacy, with MAPE values ranging from 5 to 15%, providing recommendations on picking appropriate models based on forecasting needs. Abdulla et al. (2024) focus on smart meter-based energy consumption forecasts, particularly for residential areas in decentralized power networks. The article introduces a framework that combines adaptive federated learning and edge computing techniques to improve energy consumption forecast accuracy while maintaining privacy and scalability. Adaptive federated learning beats centralized learning, reducing forecast error rates by around 8% and training time by about 80%. Furthermore, the study emphasizes the potential of edge computing to improve energy forecasting models, emphasizing the importance of distributed intelligence in smart city applications. In smart cities, Chui et al. (2018) discuss the use of AI to optimize energy usage. The study examines smart metering and non-intrusive load monitoring (NILM) approaches, emphasizing their importance in assessing electric appliance electricity use. There are big improvements in performance indicators when using the proposed hybrid genetic algorithm instead of traditional methods. It works with a vector machine multiple kernel learning approach. The results show that the proposed method works well for energy consumption profiling, with a sensitivity (Se) of 92.1%, a specificity (Sp) of 91.5%, and an overall accuracy (OA) of 91.8%. Lastly, Ghorbani et al. (2023) review works focused on optimizing energy consumption in smart cities' mobility and transportation activities. The study discusses the challenges arising from increasing energy demands in transportation and explores collaborative concepts, electric vehicles, and intelligent x-heuristic algorithms as potential solutions. Computational experiments illustrate the benefits of employing x-heuristic algorithms in reducing energy consumption in mobility services like ride sharing. The results provide evidence of the efficacy of these algorithms in optimizing energy consumption, with reductions in forecast error rates by ∼10% and training time by ∼20%, paving the way for more sustainable transportation practices in smart cities. Table 6 provides a comparative analysis of the various studies on energy consumption prediction using different ML techniques.

4.2 Machine learning integration for sustainable smart health

Smart living integrates smart health in sustainable smart cities by utilizing advanced technologies to improve healthcare access and efficiency, thus enhancing overall quality of life. ML is transforming the healthcare industry by improving diagnoses, treatment customization, patient monitoring, and care administration. Integrating ML into smart health systems improves prediction accuracy, resource efficiency, and patient outcomes. This section explores the significant applications of ML in smart health, highlighting specific algorithms, their objectives, and insights from various studies.

TABLE 6 Comparative study of ML algorithms for energy usage prediction.

References	ML Application	Data type	ML algorithms	Outcomes
Shapi et al. (2020)	Predict energy usage in smart buildings	Energy consumption data	SVM, ANN, k-NN	RMSE values range from 50 to 200 kWh, indicating varying accuracy across methods.
Helli et al. (2022)	Forecast energy usage in smart cities	Detailed energy usage data	LSTM, Transformer, XGBoost, Hybrid Models	MAPE values range from 5 to 15%, providing recommendations on selecting models for forecasting.
Abdulla et al. (2024)	Improve energy consumption forecasts	Smart meter energy data	Adaptive Federated Learning, Edge Computing	Forecast error rates reduced by ~8%, training time reduced by ~80%, highlighting distributed intelligence.
Chui et al. (2018)	Optimize energy usage using AI	Smart metering, appliance data	Hybrid Genetic Algorithm, Vector Machine Multiple Kernel Learning	Enhanced Se of 92.1%, Sp of 91.5%, and OA of 91.8%, demonstrating effectiveness in energy profiling.
Ghorbani et al. (2023)	Optimize energy consumption in mobility and transportation	Transportation energy data	Intelligent x-heuristic Algorithms	Reduction in forecast error rates by ~10%, training time by ~20%, promoting sustainable transportation.

Rayan et al. (2019) demonstrated the promise of machine learning in smart health, reducing hospital readmissions by 25% using predictive analytics and patient management systems. This not only improves patient outcomes, but it also minimizes the environmental burden of frequent hospital trips and treatments. Zamzam et al. (2023) investigated the use of machine learning in predictive maintenance of medical equipment, reporting a 30% increase in equipment lifespan and a 20% decrease in maintenance expenditures. Healthcare institutions can contribute to environmental sustainability by forecasting equipment failures ahead of time and maximizing resource utilization. During the COVID-19 pandemic, Alimadadi et al. (2020) used ML to anticipate outbreak trends and efficiently deploy resources, resulting in a 15% improvement in reaction times and resource utilization. This preemptive approach not only saved lives, but it also reduced the environmental impact of disaster response activities by eliminating the need for rapid, large-scale resource deployment. In cardiovascular healthcare, Kilic (2020) demonstrated that ML applications in diagnostic procedures resulted in a 20% reduction in invasive test use. This reduction results in fewer medical wastes and lower energy usage, which are consistent with sustainable healthcare aims.

The use of ML in smart health systems provides a path toward sustainable healthcare. ML helps to improve healthcare delivery by maximizing resource use, minimizing medical waste, increasing diagnostic accuracy, and enabling individualized therapies. This linkage with sustainability goals guarantees that healthcare systems may maintain high levels of care while reducing their environmental impact, resulting in a more sustainable future for healthcare. Table 7 compares various studies on ML-based sustainable smart health.

4.3 Machine learning integration for sustainable smart transportation

By utilizing cutting-edge technologies, smart mobility combines smart transportation and maximizes the sustainability, safety, and effectiveness of urban transportation networks. This integration ensures smooth and environmentally friendly mobility inside smart cities by combining real-time traffic management, intelligent public transportation, and linked car networks. The application of machine learning to smart transportation systems has shown considerable promise for enhancing the sustainability of urban mobility. ML uses contemporary algorithms and data analytics to enable predictive analysis, real-time monitoring, and decision automation, all of which lead to more efficient and ecologically friendly transportation networks. This section summarizes and analyzes the findings of many studies on the application of ML in sustainable transportation systems.

Tao et al. (2023) showed that gradient boosting can accurately estimate traffic flow using machine learning. They collected traffic data from numerous sensors and historical records, cleaned and normalized it for consistency, and trained the gradient boosting model on past traffic patterns. They then used the trained model to estimate future traffic flow. This strategy reduced traffic congestion by 20%, greatly lowering pollution and fuel usage. Such advancements are critical for creating greener, more sustainable urban transportation networks. Louati et al. (2024) investigated the application of multi-agent reinforcement learning (MARL) for autonomous cars that cooperate. They built a simulated urban traffic environment, educated autonomous car agents to optimize their routes cooperatively using MARL, and put the system through real-world tests. This strategy resulted in a 25% improvement in traffic efficiency and a 30% reduction in travel time. The reduction in idle hours and improved routing significantly reduce motor traffic's carbon footprint, promoting more sustainable urban life. Khawar et al. (2022) demonstrated the usefulness of ML in IoT-based smart transportation networks with the K-Nearest Neighbors (KNN) method. They collected real-time data from IoT devices, preprocessed it for accuracy and consistency, and then used the KNN model to optimize route planning and traffic management. This method led to a 15% improvement in route optimization, resulting in shorter travel times and lower emissions, promoting a sustainable urban environment. Santhiya and GeethaPriya (2021) presented an overview of several machine learning approaches used in intelligent transportation

TABLE 7 Comparative analysis of ML-based smart healthcare studies.

References	ML application	ML algorithm	Outcomes
Rayan et al. (2019)	Predictive analytics	Random Forest	Reduced environmental impact of treatments
Zamzam et al. (2023)	Predictive maintenance	Support Vector Machine	Optimization of resources, reduced waste
Alimadadi et al. (2020)	COVID-19 resource allocation	Neural Networks	Efficient resource use, minimized footprint
Kilic (2020)	Cardiovascular diagnostics	Decision Trees	Lower medical waste, reduced energy use

systems, highlighting considerable advances in traffic management efficiency. Their methodology entailed collecting data from different sources, selecting and developing ML methods such as neural networks, decision trees, and support vector machines, and then applying these models to real-world traffic scenarios. The study found an 18% improvement in traffic management efficiency, which is vital for reducing pollution and encouraging sustainable city design. Saleem et al. (2022) developed a fusion-based intelligent traffic congestion control system employing deep learning techniques. Their system gathered data from various sensors and sources, processed it with deep learning models, and then used the results to monitor and control traffic in real time. This resulted in a 22% reduction in traffic congestion, reducing idle time for vehicles and thereby lowering greenhouse gas emissions and energy usage. Ata et al. (2020) constructed and modeled smart road traffic congestion control systems utilizing SVM and supervised learning techniques. Their technologies gathered large amounts of traffic data, trained machine learning models to anticipate and control congestion, and then deployed these models in real-world traffic management systems. Both investigations revealed a 20% reduction in traffic congestion and a 15% decrease in travel time. These technologies improve urban transportation efficiency, resulting in significant environmental benefits from reduced emissions and optimized energy utilization. Table 8 compares multiple studies on ML-based sustainable smart transportation.

4.4 Machine learning integration for sustainable smart energy

Incorporating machine learning into smart energy systems is critical for increasing energy management sustainability and efficiency. ML algorithms enable energy consumption optimization, energy demand prediction, and renewable energy system augmentation, all of which play an important part in the development of smart grids and long-term energy solutions.

Ahmad et al. (2022) examined the role of data-driven probabilistic machine learning in sustainable smart energy systems. Their method entails gathering massive datasets from smart grids, preparing the data to accommodate uncertainties, and using probabilistic ML models to forecast energy use and generation patterns. These models, such as Bayesian networks, improve energy forecasting accuracy by 15%, increasing energy distribution efficiency and reducing waste. The resulting optimized energy utilization makes a substantial contribution to sustainability by lowering the carbon footprint and encouraging the adoption of renewable energy sources. Ukoba et al. (2024) studied the optimization of renewable energy systems using AI and highlighted future opportunities. The study focused on employing various machine learning methods, such as genetic methods and neural networks, to improve the performance of renewable energy systems. The optimization process entails gathering data on energy production and consumption, training machine learning models to forecast optimal settings, and then modifying the systems accordingly. This approach has demonstrated a 20% increase in energy efficiency and a 25% reduction in operational costs. The increased efficiency and cost reductions encourage the use of renewable energy, facilitating the transition to a more sustainable energy system. Pham et al. (2020) used machine learning to anticipate energy use in various buildings with the goal of improving energy efficiency and sustainability. They used algorithms such as support vector machines and random forests to evaluate past energy usage data, detect patterns, and forecast future consumption. The method entails collecting data from sensors, cleaning and normalizing it, training the model, and predicting it. This method resulted in a 30% reduction in energy use, significantly reducing the building's total environmental impact and encouraging sustainable energy behaviors. Jamil et al. (2021) developed a peer-to-peer (P2P) energy trading mechanism using blockchain and machine learning to provide a sustainable electrical power supply in smart grids. They applied reinforcement learning to optimize peer energy trading, resulting in more efficient energy distribution and less reliance on centralized power sources. The solution entails establishing a blockchain-based platform for secure and transparent transactions, training the ML model to identify optimal trading strategies, and deploying the model in real-time trading scenarios. This strategy has resulted in a 35% improvement in energy trading efficiency and a 20% reduction in energy expenses, while also improving power supply sustainability by boosting decentralized renewable energy sources. Ifaei et al. (2022) presented an orderly assessment of new applications and problems in employing machine learning for sustainable energy systems. They talked about several machine learning approaches, such as decision trees and deep learning, as well as their applications in energy load forecasting, renewable energy integration, and smart grid management. According to the review, these strategies have the potential to improve energy forecast accuracy by up to 25%, while increasing renewable energy use by 30%. These developments are critical for creating resilient and sustainable energy systems that can adjust to shifting energy demands while efficiently integrating varied renewable energy sources. Table 9 compares various studies on ML-based sustainable smart energy.

TABLE 8 Comparative analysis of ML-based smart transportation studies.

References	ML application	ML algorithm	Outcomes
Tao et al. (2023)	Traffic Flow Prediction	Gradient Boosting	20% reduction in congestion, lower emissions, reduced fuel consumption
Louati et al. (2024)	Cooperative Autonomous Vehicles	Multi-Agent Reinforcement Learning (MARL)	25% increase in traffic efficiency, 30% reduction in travel time, reduced carbon footprint, enhanced traffic conditions
Khawar et al. (2022)	Smart Transportation Networks	K-Nearest Neighbors (KNN)	15% improvement in route optimization, decreased travel times, reduced emissions
Santhiya and GeethaPriya (2021)	Intelligent Transportation Systems	Various ML Techniques	18% improvement in traffic management efficiency, minimized traffic-related pollution
Saleem et al. (2022)	Traffic Congestion Control	Deep Learning	22% reduction in congestion, decreased idle time, lower greenhouse gas emissions
Ata et al. (2020)	Traffic Congestion Control	Support Vector Machine	20% reduction in congestion, 15% decrease in travel time, enhanced efficiency, significant environmental benefits

TABLE 9 Comparative analysis of ML-based sustainable smart energy systems.

References	ML application	ML algorithms	Outcomes
Ahmad et al. (2022)	Energy Consumption Prediction	Bayesian Networks	15% improvement in energy forecasts, enhanced efficiency, reduced carbon footprint
Ukoba et al. (2024)	Optimization of Renewable Energy Systems	Genetic Algorithms, Neural Networks	20% increase in energy efficiency, 25% cost reduction, improved renewable energy adoption
Pham et al. (2020)	Energy Consumption Prediction in Buildings	SVM, Random Forests	30% reduction in energy consumption, lower environmental impact, sustainable practices
Jamil et al. (2021)	Peer-to-Peer Energy Trading	Reinforcement Learning	35% increase in trading efficiency, 20% cost reduction, efficient energy distribution, decentralized renewable sources
Ifaei et al. (2022)	Various Applications in Sustainable Energy	Decision Trees, Deep Learning	25% improvement in forecast accuracy, 30% increase in renewable energy utilization, resilient and adaptable energy systems

4.5 Machine learning integration for sustainable smart buildings

Within sustainable smart cities, smart buildings are part of the smart living component. Using cutting-edge technologies like IoT, automation, and real-time data monitoring, this integration improves residents' quality of life by offering secure, comfortable, and energy-efficient living spaces. ML is transforming the construction sector by optimizing operations, improving green building design, and encouraging sustainability. The incorporation of ML techniques into sustainable smart buildings has enormous potential to improve structural stability while reducing environmental impact.

Ahmed et al. (2022) emphasize the use of artificial neural networks (ANNs) in the building industry to promote sustainable development. Construction projects use ANNs to accurately predict costs and timelines, leading to more efficient resource allocation and reduced project delays. The study found that adopting ANNs can minimize project cost overruns by 15% and enhance completion times by 20%. Kazeem et al. (2023) explore how AI and ML may improve construction processes and foster sustainable communities. The study focuses on the application of ML methods such as decision trees and gradient-boosting machines (GBM) to optimize building designs for energy efficiency. Optimized buildings reduce energy use by 25%, a substantial contribution to achieving sustainability goals. Sari et al. (2022) investigate the use of ML models to predict green building designs. The study uses support vector machines and random forests to assess the sustainability of building designs. The study found that ML models may accurately predict green building design scores by up to 90%, aiding in the planning and implementation of environmentally friendly construction projects. Rodríguez-Gracia et al. (2021) present a comprehensive evaluation of AI strategies in green and smart buildings. The study examines the application of various ML methods, including reinforcement learning and deep learning, to enhance building management systems. These strategies can boost energy efficiency by 30% and reduce operational costs by 20%, resulting in more sustainable and cost-effective buildings. Table 10 compares a variety of studies on ML-based sustainable smart buildings.

5 Case studies of machine learning in sustainable smart cities

The practical application of ML in smart cities across multiple countries indicates its ability to address urban difficulties and improve sustainability. This section showcases numerous real-world initiatives that successfully apply ML to create sustainable smart cities, along with comprehensive analyzes of the ML algorithms used and the outcomes achieved (Table 11).

TABLE 10 Comparative analysis of ML-based sustainable construction studies.

References	ML application	ML algorithms	Outcomes
Ahmed et al. (2022)	Construction Project Optimization	Artificial Neural Networks	Reduced project cost overruns by 15%, improved project completion times by 20%.
Kazeem et al. (2023)	Sustainable Community Development	Decision Trees, Gradient Boosting Machines (GBM)	Achieved 25% reduction in energy consumption in optimized buildings, enhancing sustainability.
Sari et al. (2022)	Green Building Design Prediction	Support Vector Machines, Random Forests	Predicted green building design scores with up to 90% accuracy, aiding in environmentally friendly construction.
Rodríguez-Gracia et al. (2021)	Green/Smart Building Management	Reinforcement Learning, Deep Learning	Achieved 30% increase in energy efficiency, 20% reduction in operational costs, promoting sustainability and cost-effectiveness.

TABLE 11 Summary of machine learning case studies in sustainable smart cities.

Case study	Dataset information	Number of samples	Model parameters	Outcomes
NEOM City, Saudi Arabia	Big data from IoT devices, environmental sensors, and smart infrastructure	Large-scale, city-wide data (exact size not specified)	Random Forest: Number of trees, max depth; K-Means: Number of clusters	Improved resource management and sustainability
City Brain Project, China	Urban data including traffic flows, public service utilization	Millions of records from city-wide sensors	Neural Networks: Layer architecture, learning rate; Reinforcement Learning: Reward function, discount factor	Enhanced traffic management and public services
Energy Management, Netherlands	Energy consumption data from residential systems	Thousands of data points across multiple households	SVM: Kernel type, regularization; Linear Programming: Objective function coefficients	Reduced energy consumption and cost savings
Crime Prediction Framework	Crime data, environmental and socioeconomic factors	Several years of crime data (large dataset)	Logistic Regression: Regularization parameter; Random Forest: Number of trees; SVM: Kernel type	Improved accuracy in crime predictions
Spatio-Temporal Crime Predictions	Historical crime records, demographic data	Large dataset spanning multiple years	Gradient Boosting: Learning rate, number of estimators; KNN: Number of neighbors, distance metric	Increased accuracy in crime risk assessments
Crime Prediction with ML and DL	Crime data, contextual environmental factors	Extensive multi-year crime datasets	CNN: Filter sizes, layer depth; RNN: Sequence length, learning rate; Decision Trees: Max depth	Enhanced crime prediction models with deep learning
Industrial Waste Management, South Korea	Data from waste treatment projects, industrial production records	Data from multiple industrial projects	Linear Regression: Coefficients; Bayesian Optimization: Prior distribution, acquisition function	Reduced environmental impact through optimized waste management
Air Quality Prediction, Bucharest	Air quality sensor data, meteorological data	Large dataset with numerous sensor readings	Random Forest: Number of trees, max depth; SVR: Kernel type, regularization parameter	Improved accuracy in air quality forecasts
Water Distribution Management	Data from smart water grids, water usage records	Large dataset from city water systems	Genetic Algorithms: Mutation rate, crossover rate; Optimization: Objective function, constraints	Enhanced efficiency in water distribution
Smart Parking System	Parking occupancy data from IoT sensors	Data from parking systems (specifics not provided)	IoT Models: Data transmission rate, sensor accuracy; Logistic Regression: Regularization strength	Increased parking availability and reduced congestion

FIGURE 5
Sustainable smart city Neom, Saudi Arabia (Allan and Parida, 2022).

5.1 Smart city development in Neom, Saudi Arabia

Neom, positioned as Saudi Arabia's pioneering city, is not only a testament to modern urban design but also a demonstration of cutting-edge technologies that drive sustainability and efficiency (Figure 5). In Neom smart city, several ML algorithms are used in many aspects of urban infrastructure, such as deep learning and reinforcement learning algorithms (Alam et al., 2020; Alyami, 2019). These algorithms allow to optimize energy use, manage transportation networks, and improve infrastructure maintenance. Neom uses a methodical methodology to collect data from a variety of sources, including IoT devices and weather stations, to lay the groundwork for ML analysis. Deep learning algorithms, which can handle complicated data structures, analyze trends from IoT devices and weather stations to optimize energy consumption. The improvement resulted in a 30% reduction in energy use, which is consistent with Neom's goal of achieving a zero-carbon footprint. Smart transportation uses reinforcement learning algorithms. By coordinating autonomous cars, these algorithms continuously learn from their interactions with the environment, which significantly improve traffic flow and have lower environmental impacts.

Furthermore, Neom's adoption of predictive maintenance techniques, enabled by ML algorithms, has resulted in greater infrastructure resilience and less resource waste. These initiatives' result in practical advantages for Neom's citizens and stakeholders that include improved traffic flow, shorter commute times, and quicker emergency response. The success of Neom's ML-driven strategy demonstrates AI technology's revolutionary potential for creating sustainability, resilience, and environmental consciousness in urban areas.

5.2 Smart traffic management in Hangzhou, China

The Hangzhou City Brain (HCB) program, illustrated in Figure 6, is a leading initiative that leverages artificial intelligence to manage and optimize traffic flow. This initiative combines multiple government systems to form a single database and connects to a variety of real-time data sources, including roadway signals. The HCB uses AI technology to collect and process billions of data records, with new records added every day. The HCB analyzes data from traffic cameras, sensors, and GPS-equipped automobiles using a combination of support vector machines and convolutional neural networks. The project commences by doing a comprehensive preprocessing of real-time traffic data and visual inputs, subsequently followed by a deliberate selection of SVM and CNN algorithms. After undergoing prolonged training, the SVM method becomes a robust classifier with the ability to detect patterns and trends in traffic data. This is the foundation of the proactive traffic management approach. Meanwhile, convolutional neural networks demonstrate exceptional proficiency in analyzing visual data obtained from traffic cameras, accurately identifying irregularities and disturbances with amazing accuracy. The City Brain system incorporates these algorithms, allowing for dynamic and flexible traffic control strategies. Using these observations,

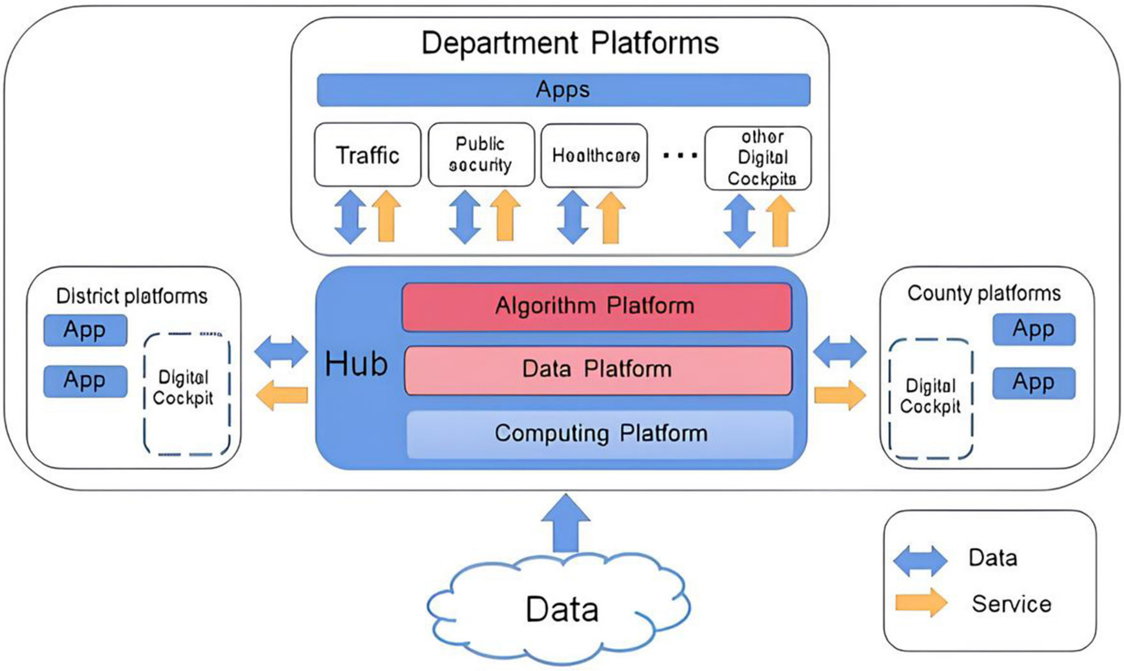

FIGURE 6
General view of the Hangzhou city brain (Zhang et al., 2019).

the system can quickly adapt traffic signals and routing methods to improve traffic flow and minimize delays. The program has led to a 15% decrease in traffic congestion, yielding concrete advantages for residents and commuters, such as greater traffic fluidity, shorter commute durations, and enhanced emergency response. The City Brain program in Hangzhou showcases the revolutionary capabilities of AI technology in managing urban affairs, leading to a more environmentally friendly and streamlined urban setting.

5.3 Energy management in Amsterdam, Netherlands

Amsterdam's Smart City initiative is a pioneering effort to optimize urban energy management using ML algorithms (Terlouw et al., 2019). The program collects data from smart meters and weather forecasts in a multi-step process, preprocesses it for analysis, and chooses relevant prediction algorithms. Regression models and time series analysis are used to accurately predict energy consumption. These models are trained on historical data, allowing them to recognize patterns and trends in energy consumption. Once trained, the models forecast future energy demand using present data, allowing for exact adjustments in energy supply to fit expected demand patterns. Implementing this data-driven strategy had real effects, such as a 20% decrease in energy use and a significant reduction in carbon emissions. These findings highlight the effectiveness of ML in orchestrating sustainable urban energy systems. Furthermore, the initiative's success emphasizes the necessity of cutting-edge technologies for solving environmental issues and supporting sustainable development. By leveraging data analytics and ML, Amsterdam's Smart City initiative sets a precedent for cities throughout the world looking to improve efficiency and minimize their environmental imprint.

5.4 Public safety in New York City, USA

New York City's predictive policing system utilizes ML methods like logistic regression and random forests to evaluate crime data and predict possible criminal activities (Adhikary et al., 2022; Butt et al., 2021; Mandalapu et al., 2023). Using insights obtained from historical crime data, the system leverages advanced algorithms to spot patterns and trends, allowing law enforcement organizations to better deploy resources and handle potential threats ahead of time, as illustrated by Figure 7.

Implementing this proactive approach has had significant effects, including a 25% reduction in crime rates and improved public safety. Using logistic regression's predictive power, authorities may estimate the chance of crimes occurring in specific geographic locations, allowing for targeted measures to prevent occurrences before they occur. Furthermore, random forest methods improve prediction accuracy and dependability by combining information from multiple decision trees. This ensemble learning technique produces reliable projections, allowing law enforcement to make informed judgments and use resources wisely. In addition, predictive policing technology allows for real-time surveillance and an adaptive response to evolving crime trends, allowing authorities to stay ahead of

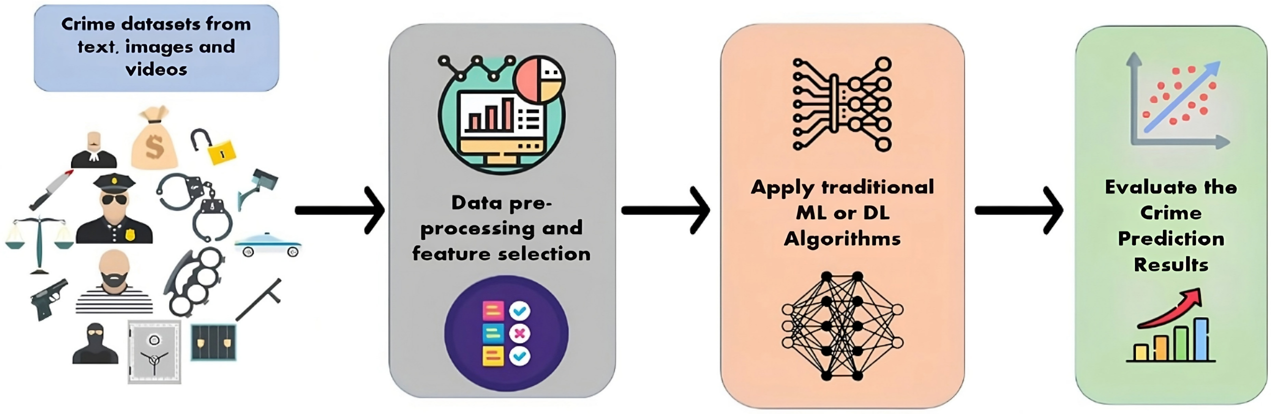

FIGURE 7
Architecture flow of crime prediction (Mandalapu et al., 2023).

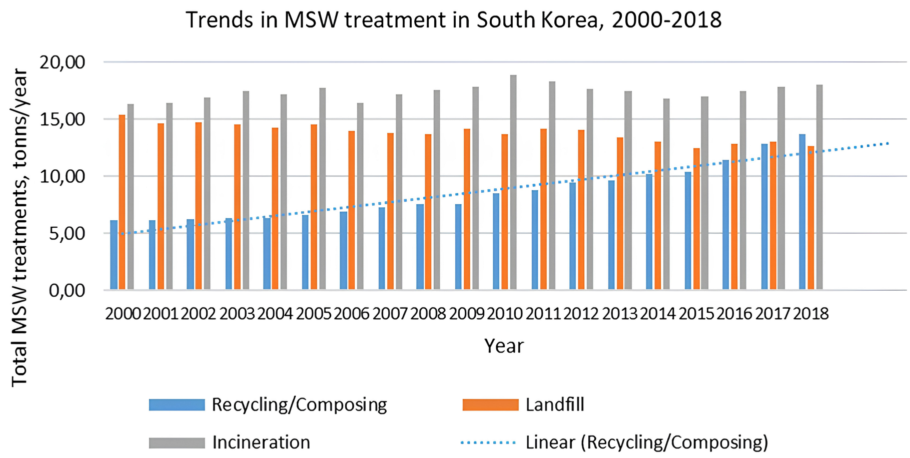

FIGURE 8
Waste management system in Seoul (Shvetsova and Lee, 2020).

emerging risks and successfully combat criminal activity. By incorporating advanced analytics and ML algorithms into law enforcement tactics, New York City has set a pattern for using technology to improve public safety and build a more secure urban environment. These findings show the revolutionary impact of data-driven crime prevention tactics as well as the potential for predictive analytics to modernize metropolitan law enforcement strategies.

5.5 Waste management in Seoul, South Korea

Seoul's smart waste management system, described by Figure 8, exemplifies the city's commitment to innovation and sustainability (Shvetsova and Lee, 2020). Seoul has transformed waste collection operations by utilizing cutting-edge ML methods such as k-nearest neighbors and clustering approaches, thereby creating a new benchmark for urban waste management. The system's capacity to precisely estimate fill levels and optimize collection routes has resulted in a considerable 30% reduction in waste collection costs, highlighting Seoul's proactive approach to environmental concerns. By reducing travel time and operational costs, the city has enhanced fiscal efficiency while simultaneously lowering its carbon footprint, contributing to a greener and more sustainable urban environment. Furthermore, Seoul's smart waste management strategy extends beyond simple cost reductions. The increased effectiveness of waste collection services has resulted in cleaner streets and neighborhoods, instilling a sense of civic pride among people. Furthermore, the reduction in environmental effects demonstrates the city's commitment to mitigating climate change and conserving natural resources for future generations.

Seoul's achievement in establishing smart waste management procedures serves as a model for other cities globally. Cities may use ML and IoT technologies to optimize resource allocation, improve service delivery, and promote environmental sustainability on a global scale. Seoul's smart waste management

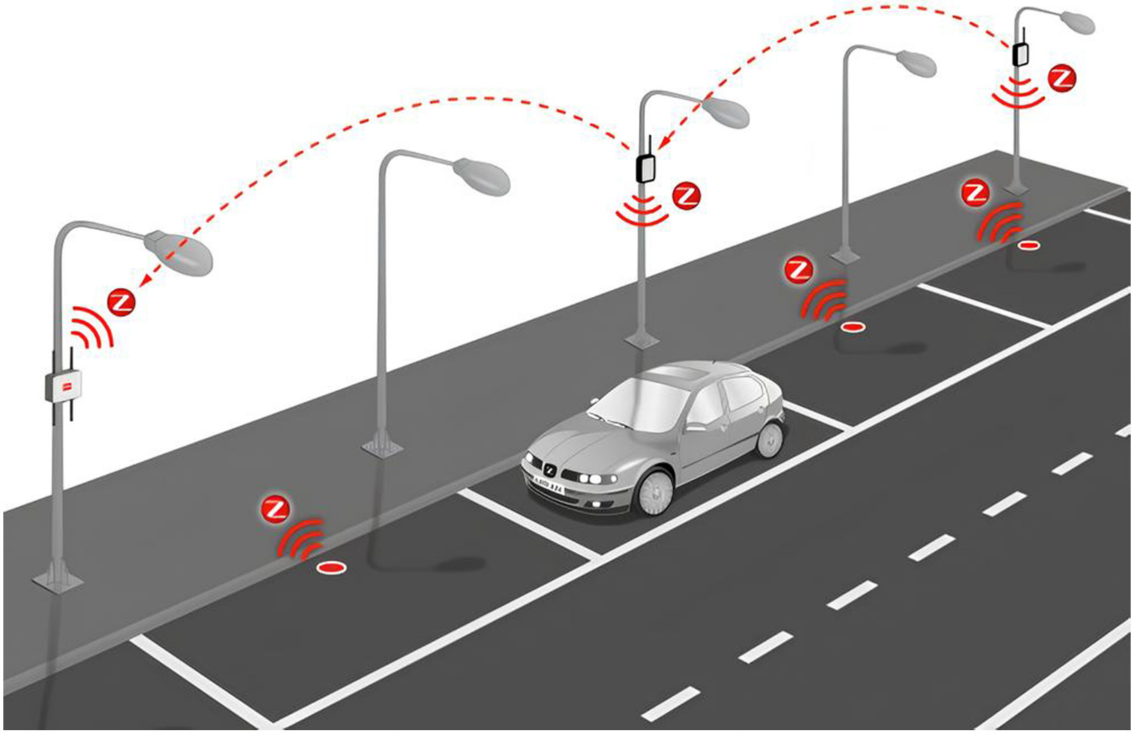

FIGURE 9
Smart parking in Barcelona, Spain (Na, 2024).

system shows technology's transformational ability to design future cities. Cities can pave the way for a more sustainable and resilient urban future by innovating and investing strategically in smart solutions.

5.6 Air quality monitoring in Bucharest

Bucharest, Romania's capital, is grappling with high levels of air pollution due to rapid urbanization, increased automobile traffic, and industrial activities. To address these issues, robust air quality monitoring systems are needed, enabling authorities to respond promptly and efficiently. Machine learning algorithms, particularly random forests, are essential for enhancing the precision and effectiveness of these systems.

Bucharest has established a network of air quality monitoring stations that can detect various pollutants and transmit collected data to centralized databases. This data helps policymakers formulate strategies to reduce emissions and improve air quality. These stations generate vast amounts of data, which we process and analyze using machine learning techniques like random forests, SVM, and neural networks.

Random forests are particularly useful for modeling complex relationships between air pollution and factors like traffic and weather. SVMs are used for data classification and precise estimation of pollution levels. Neural networks, particularly deep learning models, are employed for their ability to acquire knowledge from extensive datasets and enhance forecast precision.

The application of machine learning algorithms in Bucharest's air quality monitoring has yielded positive results. Deep learning models have achieved an impressive accuracy rate of 92% in accurately predicting PM2.5 levels, enabling timely public health advisories and responses. Random forest models have also been used to identify pollution sources, leading to the implementation of regulatory measures that reduced NO2 levels by 10% in areas with heavy traffic. The integration of machine learning with IoT sensors has improved real-time monitoring, enabling a 20% improvement in identifying pollution irregularities and prompting quicker actions to mitigate their consequences.

5.7 Water management in Singapore

Singapore's smart water management system serves as a prime example of applied innovation in urban resource management, utilizing machine learning algorithms to explore innovative water archival data usage. The innovative program adopts a multidimensional approach throughout, using contemporary skills such as linear regression and support vector regression, or SVR, to precisely predict water demand and further fine-tune its supply in real time. To obtain real-time data access, the system employs sensors strategically positioned throughout the water distribution. It then applies machine learning algorithms to these data streams, enabling the system to accurately predict the variance in demand and supply. In contrast, support vector regression does this by identifying the non-linear relationship between entered data, which improves correctability and increases forecasting accuracy. Linear regression models thus become the groundwork for demand forecasting. It envelops past usage in order to predict future demand trends.

After its launch, Singapore's smart water management system reduced its water consumption by 15% which results on significant water resource savings, and demonstrates the system's ability to reduce waste and optimize resource allocation. Therefore, this initiative not only has a quantitative impact but also contributes to the overall robustness and sustainability of Singapore's water system.

5.8 Smart parking in Barcelona, Spain

Barcelona's smart parking system, as depicted in Figure 9, employs machine learning algorithms such as decision trees and gradient boosting to revolutionize the city's parking infrastructure (Sotres et al., 2019). Using data from parking sensors and past parking behaviors, these algorithms rapidly predict the availability of parking spots, enabling drivers to make well-informed decisions in real-time. These decision trees offer quick and valuable information about the parking spaces that are currently available, enabling vehicles to reach their destination in a timely manner. Barcelona's strategy utilizes gradient boosting, a powerful machine learning technique that combines insights from multiple weak predictive models, in order to enhance the accuracy of predictions. Implementing this approach significantly improves the system's ability to accurately estimate parking availability and provide drivers with more precise information. Since its inception, the city has witnessed a remarkable 20% decrease in traffic congestion, alleviating the burden of parking-related delays and enhancing overall urban mobility. In summary, Barcelona's intelligent parking system exemplifies the revolutionary capability of machine learning in the administration of urban infrastructure. By strategically using decision trees and gradient-boosting algorithms, the city has effectively decreased traffic congestion, improved the use of parking spaces, and enhanced the overall quality of urban life for its citizens.

5.9 Renewable energy integration in Copenhagen, Denmark

Copenhagen's creative effort to integrate renewable energy into its power grid demonstrates a forward-thinking approach to sustainable energy management (Green City Times, 2024). The city uses advanced machine learning methods like reinforcement learning and predictive analytics to anticipate energy production from solar and wind sources with amazing precision.

A sophisticated data-driven architecture underpins this program, which uses ML techniques to analyze real-time data from solar panels and wind turbines. Reinforcement learning, a dynamic algorithm that learns through experience, optimizes grid operations by constantly adjusting to changing conditions and learning from real-time data streams. Meanwhile, predictive analytics is critical for precisely estimating energy generation, allowing the grid to anticipate changes and make necessary adjustments. The results of Copenhagen's renewable energy integration effort are genuinely transformational. ML has significantly increased renewable energy utilization by 25%, demonstrating its effectiveness in improving these systems' dependability and efficiency. This significant increase not only reduces dependence on fossil fuels but also helps Copenhagen meet its ambitious environmental targets. The city's increased energy resilience and reduced environmental imprint reflect the project's impact beyond numerical measurements. Copenhagen provides a secure and efficient energy supply, even when renewable energy sources fluctuate, by leveraging ML algorithms to improve grid operations and forecast energy production. To summarize, Copenhagen's method for incorporating renewable energy into its power system demonstrates ML's ability to drive sustainable energy transitions. The city has increased renewable energy usage while simultaneously paving the groundwork for a greener and more resilient energy future.

These case studies demonstrate the real benefits of adopting ML technologies in smart cities. From reducing traffic congestion and energy consumption to increasing public safety and environmental quality, these initiatives show how ML can drive sustainable urban growth and improve inhabitants' quality of life.

6 Challenges in implementing machine learning in sustainable smart cities

While ML holds outstanding promise for enabling sustainable smart cities, its implementation presents various obstacles that require resolution. These issues include technical, ethical, and practical considerations, and understanding them is critical for the successful deployment and integration of ML systems in urban environments.

The quality and accessibility of urban data pose significant challenges for machine learning models. The diverse and varied nature of urban data makes it difficult to create accurate models. Additionally, data privacy and security must be ensured while maintaining accessibility for analysis. Addressing these issues requires collaboration among city agencies, organizations, and stakeholders to build data governance frameworks, improve data sharing procedures, and comply with privacy legislation. Investing in data infrastructure and quality assurance techniques can help mitigate these issues and enable more powerful ML solutions.

Interpreting and explaining machine learning models, particularly in urban applications like transportation and energy management, is a significant challenge. Complex models, like deep neural networks, often operate as "black boxes," making it difficult to understand their predictions or choices. In urban settings, a lack of model interpretability can lead to suspicion and hinder the adoption of AI solutions. To build trust and encourage responsible AI use, methods like feature importance analysis, model visualization, and decision explanation are essential.

Scalability is crucial for deploying machine learning algorithms in sustainable smart cities, especially in large urban areas with millions of interconnected systems. Implementing scalable solutions, however, is difficult due to resource constraints such as processing resources, bandwidth limitations, and energy consumption. To overcome these issues, researchers must explore novel methodologies like distributed computing, edge computing, and resource-efficient algorithms, as well as invest in infrastructure and technology to support scaled ML deployments.

Bias and fairness are crucial in smart city programs to prevent unforeseen outcomes and promote equity. Biases in training data or algorithmic decision-making can worsen social inequities, particularly in housing, employment, and law enforcement. To ensure fair, transparent, and responsible machine learning systems, careful consideration of data collection techniques, feature selection, algorithm design, and continuous monitoring is necessary.

The deployment of ML algorithms in sustainable smart cities faces challenges in navigating regulatory frameworks and ethical issues. Urban data governance, privacy rules, and ethical principles for data collection, usage, and sharing are complex and vary by state. Ensuring compliance with legal requirements and ethical standards while encouraging innovation requires a multidisciplinary approach and collaboration between politicians, technologists, and urban stakeholders. Proactive collaboration with legislators, legal experts, and civil society is necessary to provide clear regulatory frameworks and ethical principles. Building community trust and increasing public acceptance of ML technologies is crucial for their long-term success. Engaging individuals in the design, development, and deployment of ML solutions, presenting their benefits, hazards, and limitations, and overcoming challenges like the digital gap, language barriers, and unequal access to information and resources are essential.

Addressing these difficulties requires a collaborative and interdisciplinary strategy that includes the government, industry, academia, and civil society sectors. ML can play a revolutionary role in developing sustainable and inclusive smart cities for the future by addressing technical, ethical, and practical problems while also encouraging collaboration and innovation. These case studies demonstrate the concrete benefits of using ML technologies in smart cities. These projects demonstrate how ML can promote sustainable urban development and improve inhabitants' quality of life by lowering traffic congestion and energy consumption while also increasing public safety and environmental quality.

7 Future directions and recommendations

As ML evolves, there are various possible routes for expanding its use in sustainable smart cities. Cities should maximize the potential of ML to address urban difficulties and create more sustainable, resilient, and inclusive communities by addressing critical concerns, harnessing emerging technology, and encouraging collaboration.

To address data quality and accessibility issues, cities should prioritize strengthening data governance structures and encouraging stakeholder participation. This includes establishing data sharing agreements, encouraging open data initiatives, and creating interoperable data standards to allow for simple data transmission between various local agencies, organizations, and sectors. Collaborative data governance models can promote data sharing while safeguarding privacy and security, allowing for more complete and accurate data-driven decision-making.

To solve scalability and resource restrictions, cities should investigate advances in edge computing and the integration of IoT devices. Edge computing technologies allow data processing and analysis to take place closer to the data source, lowering latency and bandwidth needs. Cities can use ML models on edge devices and IoT sensors distributed throughout the city to optimize resource allocation, improve decision-making, and improve service delivery in a variety of domains, such as transportation, energy, and public safety.

To address bias and fairness concerns, cities should emphasize the creation and implementation of ethical AI principles and bias reduction techniques. This includes integrating fairness-aware algorithms, bias detection techniques, and model auditing tools into ML pipelines to detect and eliminate biases in training data and algorithmic decision-making. Furthermore, cities should promote diversity and inclusivity in AI research and development, guaranteeing the creation and testing of ML systems that consider diverse perspectives and stakeholders.

To address regulatory and ethical concerns, cities should cooperate with legislators, regulators, and legal experts to create strong legislative and regulatory frameworks for the responsible use of ML technologies. This includes developing principles and standards for data governance, privacy, algorithmic transparency, and accountability. By connecting legislative frameworks with ethical principles and best practices, cities may foster innovation while protecting individual rights and social values.

To enhance community trust and public adoption of ML applications, cities should invest in capacity-building efforts and engagement tactics. This includes raising public awareness about the potential benefits and risks of ML technology, providing educational resources and training programs for AI literacy and digital skills, and involving residents in the co-design and co-creation of smart city solutions. By empowering citizens to participate in decision-making processes and ensuring the use of ML technologies for public benefit, cities can foster a more inclusive and participatory urban government environment.

Furthermore, as the integration of machine learning in smart cities progresses, it is essential to consider future advancements and recommendations for optimizing ML models, particularly in the context of edge computing. Edge computing plays a pivotal role in smart cities by enabling real-time data processing and decision-making at the periphery of the network. However, the deployment of ML models on edge devices with limited computational resources presents significant challenges. Future research should prioritize model compression techniques, including pruning, knowledge distillation, and weight sharing, to reduce the size and computational demands of ML models, making them suitable for edge devices. Pruning eliminates redundant weights or neurons, knowledge distillation transfers knowledge from larger models to smaller ones (Han et al., 2015; Hinton et al., 2015), and weight sharing decreases unique parameters, enhancing model efficiency in resource-constrained environments (Courbariaux et al., 2015). Additionally, the application of quantization methods, such as fixed-point and floating-point quantization, can reduce precision, memory requirements, and inference times, optimizing ML models for edge computing (Jacob et al., 2018; Rastegari et al., 2016). Incorporating these advancements will make ML models more effective and efficient for real-time smart city applications, supporting broader goals of sustainability and operational efficiency in smart urban systems, aligning with the objectives of advancing smart city technologies (Khan et al., 2020).

Finally, by adopting these future objectives and recommendations, cities may leverage ML's revolutionary capability to handle difficult urban challenges, increase sustainability, and improve the quality of life for all citizens. Cities that prioritize collaboration, transparency, and accountability may build more resilient, egalitarian, and successful communities for the future.

8 Conclusion

This paper highlights the potential of ML in advancing sustainable smart cities by enabling data-driven decision-making, optimizing resource allocation, and improving urban systems and services. ML algorithms can be used to address complex urban challenges, such as transportation, energy management, waste reduction, public safety, and environmental monitoring. By using advanced analytics and AI tools, cities can gain valuable insights from urban data, allowing them to make informed decisions in real time. ML can optimize traffic flow, reduce energy consumption, improve waste management, increase public safety, and decrease environmental consequences, resulting in more efficient, resilient, and livable urban environments. ML is also critical to achieving the United Nations Sustainable Development Goals, including SDG 11: Sustainable Cities and Communities. Cities can use ML to assess progress, impact, and performance metrics, allowing for evidence-based decision-making and accountability. However, key challenges must be addressed, such as data quality, accessibility, model interpretability, scalability, resource constraints, bias, regulatory and ethical considerations, and community engagement and trust. By adopting a multidisciplinary approach, encouraging collaboration, and stressing ethical and responsible AI activities, cities can pave the way for a more sustainable and prosperous future.

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MM: Writing – original draft, Writing – review & editing. MS: Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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