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## **REAL-TIME APPLICATIONS OF MACHINE LEARNING IN SMART CITIES: A REVIEW**

***Abstract:** With the rate of urbanization, cities worldwide are seeking innovative solutions to enhance their lives to be more efficient, sustainable, and livable. One of the most groundbreaking technologies that enable this change is machine learning (ML), an artificial intelligence subfield that enables systems to learn from data and make smart decisions without being specifically coded. This review discusses the critical role of real-time machine learning in the development of smart cities, whose applications cut across diverse sectors such as transportation, energy, public safety, environmental monitoring, and health. While these innovations promise to make urban processes more efficient, they come with challenges. Concerns related to data privacy, infrastructural constraints, algorithmic bias, and policy deficits persist in keeping ML's full potential in real-time urban contexts from being realized. This paper discusses these challenges and sets out the future directions for the integration of intelligent systems in contemporary urban governance.*

***Keywords:** machine learning, artificial intelligence, smart cities, sustainable, integration, intelligent system*

### **1. Introduction**

The smart city system has emerged as an inclusive framework for responsive and is in increasing demands of urban lifestyles supported with digital technology. A technology at the heart of this version of digital disruption is machine learning, which enables systems to respond to immense amounts of real-time data collected from sensors, mobile phones, traffic cameras, utility meters, and social media. Algorithmic learning from an array of real-time data allows cities to innovate compared to traditional systems that are based on the application of static rules. For example, where a conventional system remains fixed

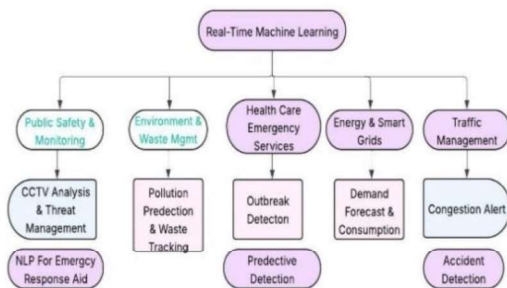
using preset vulnerability parameters in order to understand what happened through a controlled historical lens, machine learning continuously learns from historical activity to make predictive and prescriptive inferences about the real-time circumstances experienced through the lens of the causal schematic and impact it deems relevant. In doing so, smart cities are changing from a reactionary posture to a proactive and even autonomously informed posture. From predicting traffic congestion, to optimizing energy grids, machine learning augments the efficacy of the functions within cities, making them more responsive, efficient and sustainable. As operational intelligence increases, so have the actions smart cities

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can implement to increase citizen quality of life. The proliferation of data availability, improved computing power, and the global growth of IoT devices has made machine-learning solutions increasingly feasible and scalable within real-world city environment.

## 2. Applications of Real-Time Machine Learning in Smart Cities

One of the most influential real-time uses of machine learning in smart cities is in traffic management and smart transportation systems. Machine Learning (ML) algorithms can process data from Global Positioning System (GPS) signals, road sensors, and traffic cameras to forecast congestion, detect accidents, and improve traffic signal timing. This not only reduces travel time and fuel usage but also helps in decreasing urban levels of pollution. Adaptive traffic control systems through the use of reinforcement learning models have been implemented in a number of cities to control traffic dynamically in relation to current conditions. In the field of energy efficiency, ML plays an important role in how smart grids work and manage the energy. Predictive models help in the use to anticipate energy demand, identify unusual in patterns of consumption, and



**Figure 1.** Uses of machine learning in smart cities

match supply with actual demand in real time. Such information helps service provider save energy from waste, enhance big distribution, and helps the integration of renewable resources. Smart buildings based with machine learning auto-process can also adjust the heating, cooling, and lighting in real time, further helps in enhancing energy efficiency.

Public monitoring and safety also gain very high from machine learning. Real-time video analysis through deep learning models and helped it to allow authorities to identify unusual activity, detect dangerous objects, or detect individuals who have bad intention in crowded areas. Natural language processing (NLP) it helps to improves emergency response systems by allowing intelligent call routing and the detection of urgent incidents based on both voice and text analysis. But these systems also pose a danger issues of monitoring and privacy of person's personal interest, which point towards the need for ethical deployment of Artificial Intelligence.

Environmental sustainability is also another area where machine learning is proving to be important. Real-time air quality monitoring, noise, and waste pollution levels helps cities to react in a timely manner to environmental issues. Machine learning algorithms can detect problem related in pollution, locate sources of contamination, and suggest measures to decrease the level of damage. Intelligent waste management systems, supported by IoT sensors and predictive algorithms, can plan collection schedules for maximum efficiency, thus minimizing fuel consumption and maintaining hygiene.

Both medical care and emergency services in smart cities are further being revolutionized by real-time machine learning implementations. Public health records and wearable body monitors are fed continuously into a system that observes early indicators of outbreaks or healthcare anomalies. The emergency response crews are aided by predictive dispatch programs that take account of hospital loads, traffic situation,

and gravity of incidents before dispatching aid. All such technologies lead to quicker response time and better usage of medical services, saving precious lives in the process.

### 3. Review of literature

(Taloma et al., 2025) This paper discusses applying smart meters and machine learning to better manage water. It states that smart meters are able to gather a great deal of data that can be used to locate leaks, learn how much water citizens consume, and test whether the water is pure. The essay discusses three primary applications: inspecting the health of water pipes, knowing the utilization of water, and monitoring water purity. It also discusses new concepts such as sharing data without transferring it, simplifying computer decisions so that they are easier to understand, and employing imitation data to protect real data. It also mentions that there are still some issues such as lacking sufficient good data and maintaining people's information confidential.

(Huotari, Malhi, and Främling 2024) This paper "Machine Learning Applications for Smart Building Energy Utilization: A Survey" discusses how machine learning (ML) can be used to save energy in buildings. The more energy consumed; the article describes how machine learning can improve energy consumption. It examines four primary areas: smart grids, energy management, building maintenance, and personalizing energy consumption. The paper describes some of the ML techniques, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), which assist in managing the use of energy. The paper discusses issues such as bad data, privacy concerns, and integrating ML into existing systems. The paper proposes means to better this, such as utilizing better data, more sophisticated ML techniques, and getting everything to work together better. Briefly, it describes how ML can optimize energy savings in buildings and what needs

to be done to improve it.

(Alrashdi, 2024) This paper presents a brilliant and efficient framework for real-time pandemic disease detection and monitoring, such as COVID-19, especially in smart cities. This system relies on the combination of Artificial Intelligence (AI) and the Internet of Things (IoT) and is dubbed as Internet of Things (IoT) for medical data analysis that is received from different hospitals and devices. One of the biggest issues when it comes to handling such data is that they come from varying sources with varying machines and setups so that all of them are difficult to process collectively. For solving this, researchers created a deep learning model, which is termed as a multi-decoder segmentation network that has the ability to detect COVID-19 infections within CT scans even if data belongs to various hospitals or areas. To enhance the feasibility and speed of this system, they used fog computing, which calculates data close to where it is collected (as compared to relying on faraway cloud servers). This removes delay and improves response time. The system, PANDFOG, was tested with real-world CT scan data and proved to be very accurate for infection detection. It was also efficient in speed, energy usage, and adaptability, making it a viable answer to improving healthcare in smart cities under the scenarios of pandemics.

(Ullah et al., 2024) This paper examines in detail how intelligent cities are evolving with the assistance of emerging technologies such as the Internet of Things (IoT) and machine learning. It discusses how cities are leveraging these technologies to gather and analyze vast amounts of data to make more informed decisions in sectors such as transport, waste, energy, and health. The writers present actual examples of how smart health services, parking systems, and streetlights are improving due to connected devices and intelligent programs. However, the paper also mentions some challenges, such as safeguarding data, requiring skilled

labor, and adapting to insert such systems in pre-existing city environments. The report leaves no doubt that though such technologies can greatly enhance city life, we need to carefully think ahead and consider what's moral and equitable. Generally, it's a useful analysis of the expansion of smart cities and the work yet to be accomplished.

(Jagatheesaperumal et al. 2023) This paper discusses one smart method for monitoring road condition with sound. The researchers built a small piece of equipment to fit on the wheel of an automobile. The device has a microphone and sensor to detect depth of cracks. When the vehicle is in motion, the equipment hears the road and transfers sound information to the computer system. They employed machine learning to know what type of road the vehicle is on—such as smooth, rough, slippery, or grassy. They experimented with various algorithms and discovered that the MLP (Multilayer Perceptron) algorithm performed best with an accuracy level of about 99%.

The most wonderful thing about it is that if the road is too bad or has cracks that are deep, the system can alert the road authorities to repair it. This can prevent accidents and ensure roads are safer, particularly in smart cities. It's more affordable and faster than other techniques because it does not require cameras or many individuals inspecting the roads.

(Quasim et al., 2023) This paper discusses an intelligent system to prevent individuals from stealing electricity in smart cities. In smart cities, there are special electric meters that gather information and transmit it over the internet. However, these meters cannot identify whether a person is stealing electricity. To address this, the researchers developed a system known as ETPS (Energy Theft Prevention System). It employs smart technology and machine learning (a type of AI) to determine when and where electricity is being pilfered. The system monitors the electricity usage data from time to time and

searches for anything unusual or out of place. They implemented some intelligent computer models such as GRU, GWO, DRCNN, and LSTM for theft detection and prediction. The system implements another method termed as SMA (Simple Moving Average) for abnormal energy consumption spot. After being tested, this system surpassed previous practices. It detected theft sooner, with lower energy, and higher precision. The system aids in power-saving, lower cost, and safe and more efficient smart cities.

(Prawiyogi et al., 2022) This paper “Integrating Machine Learning techniques with large Internet of Things” generated datasets allow city infrastructures to learn, improve, and make real-time decision-making more effective. Key uses are smart traffic management, energy efficiency, optimization of water supply, waste disposal, and improved public security. These technologies reinforce one another to improve efficiency in service provision, reduce costs, and enhance the quality of life for inhabitants. The literature overviews some Machine Learning algorithms—supervised, unsupervised, and reinforcement learning—that help to analyze and predict urban behaviour, enabling proactive intervention. Internet of Things devices constantly capture data through sensors built into infrastructure, which is fed into Machine learning models powering automation and optimization. However, in the areas of data privacy, cybersecurity, and platform interoperability. The review stresses the need for creating scalable and secure architectures and invites governments, industries, and academia to integrate. Overall, Machine Learning and Internet of Things are the base technologies in building sustainable, responsive, and intelligent cities, representing a significant paradigm shift in the functioning of cities and their services.

(Bhattacharya et al., 2022) This paper is about how deep learning (DL) technologies are transforming the development of future smart cities. As ICTs are evolving at a very

fast rate, cities are adopting smart infrastructures rapidly with a vision to enhance the quality of urban living. Deep learning, being an artificial intelligence discipline, is leading the way by providing solutions to urban challenges with data-driven intelligence. The article talks about different deep learning models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Belief Networks (DBNs) and their application in smart city use cases like traffic management, energy efficiency, waste management, healthcare, and public safety. For example, CNNs have ubiquitous application in surveillance and traffic monitoring, and RNNs in forecasting energy usage patterns and transportation requirements.

(Haque et al., 2022) The occupant-centric class comprises ML (machine learning) techniques that work to enhance occupant experience through occupancy detection, activity recognition, and behavioral or preference modeling. These techniques employ sensors and past information to infer presence, monitor activities like sleeping or cooking, and learn personal comfort habits to customize environmental conditions like temperature and lighting. Machine learning is a algorithms like Support Vector Machines (SVM), Decision Trees (DT), Artificial Neural Networks (ANN), and clustering algorithms are employed in these applications.

By comparison, the device/energy-centered solutions utilize the application of ML for energy use management and optimization, appliance failure detection, as well as amplification of sensor data interpretation. The methods apply in predicting demand for energy, usage profiling, and the automated application of energy-saving measures. The paper additionally delves into advanced ML concepts including reinforcement learning and deep learning in predictive control and intelligent decision-making. One major strength of this review lies in its attention to ML insights, as compared to previous

reviews that focused essentially on architectural or technical concerns related to constructing BMS. The writers worries that the consideration of user comfort and behavior habits in facilitating smart technology adoption. They also found out the major challenges like data privacy, the lack of structured data, and the adaptability of ML models in dynamic settings.

(Srihith et al. 2022) This paper "Future of Smart Cities: The Role of Machine Learning and Decision Making in Urban Informatics" speaks about how machine learning (ML) is changing the face of urban planning and management in smart cities. It refers to the increasing volume of urban data generated by IoT sensors and devices and how ML techniques can handle the data to make city services effective, improve infrastructure, and give the people good experience. The authors describe the fields of application of ML in traffic control, energy efficiency, public safety, and environmental monitoring. They mention predictive analytics and real-time decision-making as essential for making city systems responsive to dynamic conditions. The paper also mentions the challenges to smart cities like data privacy, ethics, algorithmic bias, and the need for robust infrastructure. One of the most significant themes is the combination of decision science and machine learning to facilitate data-driven city planning and collaborative governance. Interdisciplinary collaboration between data scientists, policymakers, citizens, and urban planners in facilitating equal, sustainable, and inclusive access to smart technologies is also encouraged. In general, the study defines smart cities as not only technologically smart but also inclusive, efficient, and people-oriented by virtue of machine learning capacity.

(Sharma et al., 2021) The authors propose an AI-blockchain (AI-BC) multi-layered architecture designed into four platforms of intelligence: device, edge, fog, and cloud. Each of the platforms deals with particular tasks in handling data so that intelligent city

infrastructures are able to gather, process, and safeguard data at different levels. Real-time data processing is done with the help of AI-based analytics by the architecture, while providing secure, tamper-proof transactions through blockchain smart contracts. Some of the prime characteristics of the system are decentralized storage of data, cryptographic verification, and dynamic decision-making capability. The paper also details two perspectives in the integration model: AI-oriented Blockchain and Blockchain-oriented AI. In the first case, AI enhances blockchain's efficiency by predicting resource needs and improving decision-making. In the second, blockchain addresses AI's limitations by improving data security, transparency, and trustworthiness. This dual-layered integration enables robust real-time applications such as smart healthcare, transportation, agriculture, and energy management. In order to analyze performance, the authors performed simulations based on Ethereum and NS3 simulator platforms. From their experiments, they found better accuracy, less latency, enhanced privacy, and improved energy efficiency on all four platforms. For example, fog computing gives in maximum accuracy (92%) and minimum latency. The suggested model was superior to other frameworks with regard to computational complexity, energy expenditure, and scalability.

(Sharma, Haque, and Blaabjerg 2021) This paper presents an extensive survey of integrating edge intelligence within Internet of Things (IoT) networks, with emphasis on the use of artificial intelligence (AI) methodologies being more and more utilized at the network edge instead of on centralized cloud servers. The move towards edge intelligence seeks to address major limitations of the conventional IoT architectures, which include high latency, bandwidth limitations, and privacy concerns. The review classifies edge intelligence into three broad approaches: edge learning (Executing AI tasks on edge devices), edge

inference (Executing model inference on edge), and collaborative edge-cloud systems. It discusses the enabling technologies, such as lightweight deep learning models, hardware accelerators, and federated learning frameworks. It also touches upon various uses, ranging from smart cities and autonomous cars to industrial IoT and health care, showcasing the advantages of real-time processing and localized decision-making. Some of the challenges are emphasized, including resource limitations of edge devices, security threats, and the intricacy of deploying and managing AI models across distributed environments. Lastly, the authors outline future areas of research emphasizing model optimization, adaptive learning, and enhanced edge-cloud collaboration.

(Ghazal et al., 2021) It highlights how technological innovation can significantly enhance urban living, especially for healthcare services. The study reviews several IoT applications such as wearable sensors, smart pills, and remote patient monitoring, which produce large amounts of health-related data. Machine learning algorithms such as supervised, unsupervised, and reinforcement learning are critical in processing the data to enhance diagnostics, treatment customization, and operational effectiveness. The paper also reflects on the application of wireless sensor networks (WSNs), blockchain for secure data storage, and AI-based decision support systems in optimizing medical treatments. The paper, however, also identifies issues such as cybersecurity attacks and urban fragmentation. The review presents an all-encompassing overview of existing literature and technologies, identifying gaps and proposing directions for future research integrating AI and IoT into sustainable, secure, and efficient smart healthcare systems. Overall, it is a starting point study for understanding the application of smart technologies in urban healthcare infrastructure in modern cities.

(Panesar, 2019) Machine learning and Artificial Intelligence for healthcare It plays

a crucial role in this day, which improved health outcomes that explain how AI and ML are reshaping healthcare through big data. With the help of AI, ML, and data science, those technologies are used for disease prediction, personalized treatment, etc. In this paper it includes real-world case studies, such as diabetes management and medical imaging, to show practical benefits, but there are certain challenges to face, such as data privacy, bias, and ethical concerns. Looking ahead, it envisions a future where smart technology and AI-driven decisions improve care while stressing the need for responsible data use.

(Ameer et al., 2019) This paper titled “Comparative Analysis of Machine Learning Techniques for Predicting Air Quality in Smart Cities” studies the application of machine learning (ML) techniques on improving air quality forecasting in smart cities. Along with urbanization, comes pollution and cities are facing intense challenges related to the management of air quality. This study features the implementation of four regression techniques: Decision Tree, Random Forest, Gradient Boosting, and Multi-layer Perceptron on the dataset of five cities in China. These models were evaluated on several parameters: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) and were validated for accuracy, processing time, and implementation feasibility using Apache Spark for real-time applications. Results indicate that Random Forest regression outperformed other models across diverse datasets, offering the best accuracy in minimal time and error. The study also notes the relationships between the concentrations of PM2.5 and certain meteorological factors, with special focus on temperature and wind speed. Smart city data collection, management and prediction is achieved in real-time through the application of IoT sensors, big data platforms, and by proposed sophisticated four-layer architecture. The paper's remaining conclusion states that although all the

models are good, Random Forest stands out as the most balanced in providing accuracy while minimizing error.

(Mohammadi et al., 2018) This paper "Semi-supervised Deep Reinforcement Learning in Support of IoT and Smart City Services" proposes a new paradigm that extends deep reinforcement learning (DRL) to the semi-supervised learning paradigm to address challenges in smart city solutions, especially where little labeled data exists. The authors combine DRL with Variational Autoencoders (VAE) to leverage both labeled and unlabeled data. The approach enhances optimal policy learning, especially in use cases such as smart buildings that rely significantly on indoor positioning systems. As a case study, the model is instantiated with BLE-based indoor localization in a smart campus environment. Experimental results from actual deployment at a university library indicate that the semi-supervised DRL model greatly enhances localization accuracy and learning efficiency. Particularly, it enhances target location proximity by 23% and gains at least 67% more rewards compared with a supervised DRL model. This paper demonstrates the potential of semi-supervised DRL in scalable and efficient data IoT deployment, citing its applicability in practical smart city deployments where there is a large amount of unlabeled data and labeling manually is not possible.

(Mohammadi et al., n.d.) The authors contend that the swift implementation of smart cities creates enormous amounts of data, most of which is not utilized because there are no efficient analytic mechanisms and standardization. They highlight the under-exploitation of unlabeled data and introduce a new semi-supervised deep reinforcement learning (DRL) framework to tackle this problem. The primary contribution of the paper is presenting a hierarchical, three-level learning architecture consistent with the organization of smart city data—ranging from IoT infrastructure, fog computing, to cloud computing. The

architecture employs small labeled datasets together with large amounts of unlabeled data, utilizing semi-supervised learning to update and refine decision-making procedures. Through the combination of deep neural networks (DNNs), reinforcement learning (RL), and semi-supervised learning, the proposed model is capable of learning control policies and delivering adaptive, context-sensitive smart city services in changing environments. In addition, the paper provides some of the application scenarios of smart city, such as water saving, energy management, and smart farming. In such scenarios, the DRL agent utilizes sensor measurements and citizen complaint information to automate decision-making processes—such as leak detection, control of energy-efficient appliances, or crop disease detection. The authors did specify some of the most important challenges, that includes data privacy, data analysis, the lack of structured datasets.

(Ravi et al., 2017) This paper “A Deep Learning Approach to on-Node Sensor Data Analytics for Mobile or Wearable Devices” talks about a smart way to use deep learning for detecting human activities (like walking, running, etc.) using data from sensors on mobile phones or wearable devices. Usually, deep learning needs a lot of power and memory, which small devices don't have. This can be done, and the authors created a method that mixes two things: Deep learning, which used patterns from sound-like images of the data (called spectrograms). Shallow features, which are simpler, hand-made data patterns.

By combining both, their method works better and faster than other models. It gives more accurate results while using less power. In short, their approach is smart, fast, and ready to be used in real-world wearable technology.

(Nie, 2017) The authors observe that smart cities implement IoT towards sustainable urban dwellings, but the swift piling up of sensor data is challenging to process and

draw meaningful insights. To overcome this, the paper proposes an innovative prediction model based on LSTM networks—a form of recurrent neural network especially suited to deal with time-series data. This model helps to predict the level of important pollutants like ozone (O<sub>3</sub>) and nitrogen dioxide (NO<sub>2</sub>), which have a serious effect on public health. The data utilized for this research was obtained from the City Pulse EU FP7 Project, using pollution data from Aarhus (Denmark) and Brasov (Romania). The model consists of three main components: the prediction module based on LSTM, it is a measuring unit that determines the air quality levels based on AQI thresholds, and a decision unit to initiate health alerts. The model was extensively experimented with different hyperparameters to achieve the optimal model performance. The resultant LSTM model was compared with a Support Vector Regressor (SVR) model, demonstrating better performance in prediction accuracy as well as classification metrics like precision, recall, and F1-score. In particular, the LSTM (Long Short-Term Memory) model has attained an accuracy of 95% for predicting air quality states and was more correct than SVR for high-risk "red" air quality warnings—vital for making accurate, and quick alert.

(Rathore et al., 2016) The authors in this work have suggested an inclusive four-level IoT-based structure to gather, process, and examine enormous amounts of urban data generated by smart devices. Some of these are sensors installed in intelligent homes, vehicles, weather systems, water systems, air-pollution-measuring stations, parking lots with smart systems, and surveillance networks. The four levels of the architecture include: (1) A lower level of data generation and collection, (2) Intermediate level I of communication between devices and networks, (3) Intermediate level II of data storage and processing with the help of Hadoop and software such as Spark and Volt DB, and (4) An upper level of data interpretation and decision-making.

The article shows how historical and real-time data can be processed on Big Data platforms such as Hadoop, Spark, and MapReduce for both short-term response (e.g., traffic control, pollution notification) and long-term urban planning (e.g., infrastructure development, energy resource distribution). To test the proposed model, the authors experimented with various datasets from smart cities such as water consumption, hectic traffic patterns, low parking space, air pollution levels, and weather conditions. Furthermore, the research offers practical

applications of IoT in city environments, including early earthquake detection, managing traffic management, CCTV surveillance for crime monitoring, and utilizing resource management in residences and public infrastructure. The system not only helped the governments to make decisions but also benefits the citizens by improving the quality of life, lowering expenses, and providing good and safe environment.

**Table 1.** Major contribution of research in the field of real time application of machine learning in smart cities

| Author                          | Year | Paper Title  | Methodology   | Algorithms   | Limitation/Challenges   |
|---------------------------------|------|--|---|--|---|
| (Taloma et al. 2025)            | 2025 | Machine learning for smart water distribution system.  | Infrastructure analysis and water quality monitoring.   | Deep learning, convolution neural networks, Recurrent neural networks.   | Data scarcity, model limitation ,privacy concerns.  |
| (Alrashdi)                      | 2024 | Fog-based deep learning framework for real-time pandemic screening in smart cities from multi-site topographies. | Segmentation using CT scans from different sources. Combines fog computing (PANDFOG system) with deep learning for edge-based processing. | Multi-decoder segmentation network built on a modified U-Net with a ResNeXt-50 encoder. Includes domain-adaptive normalization, knowledge fusion (KF) modules. | Data heterogeneity: Variability across CT datasets (different sites, machines, protocols) reduces model generalizability. Scalability issues: More edge nodes increase training complexity and can reduce generalization. Latency and jitter. |
| (Ullah et al.)                  | 2024 | Smart cities: the role of Internet of Things and machine learning in realizing a data-centric smart environment. | enabled by IoT and machine learning. Evaluates data acquisition technologies, infrastructure requirements.                                | machine learning and deep learning applications in: Traffic and energy management integrating IoT, sensor networks, VANETs, D2D communication, and 4G/5G.      | Data privacy and security: Key issues in handling urban data. Infrastructural constraints: Difficulty in integrating 5G into existing urban systems. Financial barriers.  |
| (Mohammad Tabrez Quasim et al.) | 2023 | An internet of things enabled machine learning model for Energy Theft Prevention System (ETPS) in Smart Cities.  | Developed a multi-objective prediction framework for real-time energy theft detection.  | Gated Recurrent Unit (GRU) Grey Wolf Optimization (GWO) Deep Recurrent Convolutional Neural Network.   | Dependence on structured, guided data from smart meters; performance may degrade with noisy or missing data. Data management complexity Energy theft. Performance scalability.  |

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| (Senthil Kumar Jagatheesaperumal et al.) | 2023 | Artificial Intelligence for road quality assessment in smart cities: a machine learning approach to acoustic data analysis. | Developed a hardware-based system mounted on vehicle rims to collect road surface acoustic and depth data.                                      | Multi-Layer Perceptron (MLP)<br>Support Vector Machine (SVM)<br>Random Forest (RF)<br>k-Nearest Neighbors (kNN).  | Susceptibility to environmental noise affecting acoustic data quality. Hardware reliability under different weather and road conditions. Computational demands for real-time processing on embedded systems.  |
| (Bian et al.)                            | 2022 | Machine Learning in Real-Time Internet of Things (IoT) Systems: A Survey.   | (ML) and (DL) are applied to real-time IoT systems.   | ML techniques, including SVMs, CNNs, RNNs, deep reinforcement learning, and optimization algorithms like pruning and quantization.  | include making ML models predictable and fast enough for real-time use, adapting large models to run on low-resource devices, ensuring accurate timing estimates (WCET), and handling complex scheduling. Security and privacy concerns, especially for real-time data.                                       |
| (Bhattacharya et al.)                    | 2022 | A review on deep learning for future smart cities.  | A literature review of deep learning applications in smart city domains: urban modeling, mobility, health, governance, education, and security. | Deep Neural Networks (DNN)<br>Convolutional Neural Networks (CNN)<br>Recurrent Neural Networks (RNN)<br>Transfer Learning<br>Clustering<br>Random Forest (for anomaly detection). | Difficulty in selecting suitable DL technologies for diverse city functions<br>High initial investment concerns<br>Need for lightweight ML models for IoT devices<br>Limited availability of large, quality datasets<br>Real-time streaming challenges<br>Integration issues among smart devices and systems. |
| (Srihith et al.)                         | 2022 | Future of Smart Cities: The Role of Machine Learning and Artificial Intelligence.   | uses of AI, ML, and DRL in smart cities. It examines applications in smart transport, energy grids, healthcare, and cyber-security.             | Supervised/Unsupervised Learning<br>Reinforcement Learning (RL)<br>Markov Decision Process (MDP)<br>Q-Learning<br>Deep Q-Networks<br>Deep Reinforcement Learning (DRL).           | Need for large training datasets for accuracy<br>Challenges in UAV trajectory optimization<br>Lack of standard protocols for integration across smart city components.  |
| (Sharma et al.)                          | 2021 | Machine learning in wireless sensor networks for smart cities: A survey.  | machine learning (ML) techniques are applied in wireless sensor networks (WSN) to enhance smart city applications.                              | Supervised Learning: SVM, decision trees, ANN, k-NN<br>Unsupervised Learning: k-means, PCA<br>Reinforcement Learning: Q-learning, SARSA, deep Q-learning.                         | High computational complexity and energy use in ML models<br>Difficulty deploying ML on resource-limited sensor nodes<br>Need for skilled developers to implement ML algorithms.  |

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| (Luckey et al.)    | 2020 | Artificial Intelligence Techniques for Smart City Applications.                                 | application of AI, especially ML, in smart monitoring systems within smart cities. The focus is on infrastructure like bridges and buildings equipped with sensors for structural health monitoring.  | including supervised, unsupervised learning (e.g., clustering, PCA), and hybrid models.   | Engineers often mistrust "black-box" ML models due to their lack of transparency, especially in critical infrastructure.  |
| (Ameer et al.)     | 2019 | Comparative Analysis of Machine Learning Techniques for Predicting Air Quality in Smart Cities. | Data Gathering (sensors for pollutants) Communication (transmission through technologies like Wi-Fi, LTE, ZigBee).  | Decision Tree Regression (DTR)<br>Random Forest Regression (RFR)<br>Gradient Boosting Regression (GBR)<br>Multi-Layer Perceptron Regression (MLPR).   | Gradient Boosting had high error rates and longer processing times. Decision Trees had fast processing but higher error rates. MLP showed good performance but higher computational costs.  |
| (Mohammadi et al.) | 2018 | Semi supervised Deep Reinforcement Learning in Support of IoT and Smart City Services           | The paper introduces a semi-supervised deep reinforcement learning (DRL) model using variational autoencoders (VAE) to handle both labeled and unlabeled IoT data.  | The algorithm is based on the Deep Q-Network (DQN), enhanced with VAE for semi-supervised learning, resulting in 23% higher accuracy and 67% more rewards compared to traditional supervised DRL. | A major challenge is the limited availability of labeled data in IoT environments, which can impact model performance. The complexity of real-world conditions like signal fluctuation, noise, and the variability of BLE signals also affects localization accuracy. |
| (Nie)              | 2017 | International Conference on Big Data: proceedings.  | This study proposes a deep learning model to predict air quality in smart cities using IoT data. The researchers use real-world pollution data (ozone and nitrogen dioxide levels) and apply a specially designed Long Short-Term Memory (LSTM) neural network. | used is LSTM, a type of deep learning model that is good at learning from time-series data. It predicts future pollution levels based on past measurements.                                       | While the LSTM model performs well, the study highlights the general challenges of working with IoT data: large volumes, variety, and the need for efficient, real-time analysis.   |

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| (Ravi et al.,)          | 2017 | A Deep Learning Approach to on-Node Sensor Data Analytics for Mobile or Wearable Devices.          | The method combines deep learning features extracted from spectrograms of inertial sensor data with shallow features (like statistical measures). | A hybrid deep learning architecture using: Spectrograms as input to capture frequency-domain features. 1D convolutional neural networks (CNNs) for efficient feature.   | Computational constraints on mobile and wearable devices limit model complexity. Deep learning models alone may not generalize well due to data diversity (sensor orientation, variability).   |
| (Rathore et al.)        | 2016 | Urban planning and building smart cities based on the Internet of Things using Big Data analytics. | The paper presents a four-tier architecture for smart city development using Internet of Things (IoT) devices and Big Data analytics.             | Machine learning, pattern recognition, and decision models for insights.  | Handling large volumes of heterogeneous real-time data<br>Ensuring data quality, privacy, and security<br>Managing sensor metadata and redundancy<br>Real-time processing.   |
| (Matsunaga and Fortes.) | 2010 | On the use of machine learning to predict the time and resources consumed by applications.         | Experiments were conducted using BLAST and RAXML to predict execution time, memory usage, and disk space.   | k-nearest neighbor (k-NN) – with various configurations.<br>Linear Regression (LR)<br>Decision Table/Tree (DT)<br>Radial Basis Function Network (RBFN)<br>Support Vector Machine (SVM) – linear and polynomial kernels. | Data sparsity:<br>Algorithms like K-NN and RBFN perform poorly in areas with low training data density.<br>Complexity of tuning:<br>Algorithms such as k-NN and RBFN require tuning of parameters like number of neighbors or neurons. |

#### 4. Exploring advantages and disadvantages

##### Advantages

Machine learning in intelligent cities can simplify and improve life. It makes the city consume things such as electricity and water more intelligently and minimizes wastage. It can also make cities safer by detecting problems beforehand and enabling the police or rescue teams to respond more quickly. On roads, ML can enable traffic congestion to be minimized by managing traffic lights and indicating improved routes. It can also monitor air and water quality and alert people if something is off. People are able to receive services better suited to their needs, and the city is able to make quicker and more intelligent decisions using live data. Overall, it makes the city smoother and enhances daily life for all.

##### Disadvantages

Although it is very helpful, there are some disadvantages as well. Constructing these intelligent systems is very expensive and requires individuals who can operate them. There are privacy issues as well because a lot of personal information is gathered on a continuous basis. If the information is not good or unbiased, the output may be incorrect. They also require good internet and regular updates, which can be difficult in some areas. Occasionally, ML can be biased or flawed and what is appropriate in one section of a city may not be appropriate elsewhere. Additionally, there are individuals who don't know how it works and may not be able to trust it or use it as comfortably

#### 5. Limitations and Challenges

Despite recent advances in machine learning, realizing its full potential in smart cities

presents a range of challenges.

Most pressing is the issue of data privacy and security. Smart cities are fundamentally dependent on collecting a vast amount of individual data which may include, among many other types of data, location and movement, even health care data. Building trust with the public for these systems is on some levels already hard and it is also becoming more challenging as ML systems become more elaborate and opaquer.

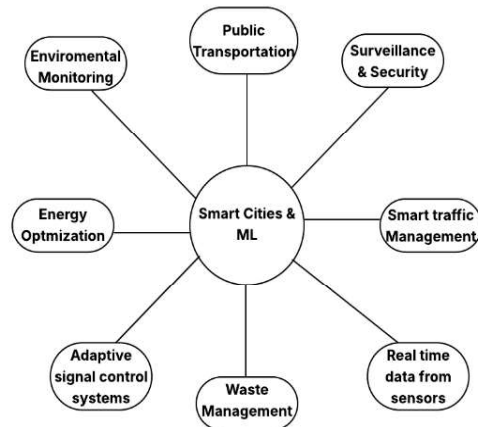
Bias in data sets and algorithms is a second notable issue. If the training data for machine learning models is biased in terms of representation or plurality, the output will also be biased and potentially harmful to the community, especially regarding policing or even health care. For example, if an algorithm is trained on data from predominantly white people, the algorithm may work well, while simultaneously produce harmful discrimination against BIPOC residents it engages with.

There are also technical and infrastructure related issues. Our future cities will likely require real time.

## 6. Future Scope

Real time Machine learning is going to be a great thing in future and by fixing some problems in present we can make this futuristic technology possible in present world. It helps us to solve one of the major problems that occurs in smart city i.e. traffic. With Real time traffic control-system we could help people to face less traffic which is eventually going to solve our problem in pollution, greenery and also, it's going to save people's time which is more valuable than anything else. In today's world with changing technology where we see a new tech every day. We haven't been able to switch our fuel reserve system and we're still highly depended on fossil fuel. So, it's very important that we try to save and utilities it more efficiently. With machine learning we could control that energy supply chain. By

Real time data we can increase and decrease the amount of coal we are using to generate electricity and be more reliable on renewable source of energy.



**Figure 2.** Future scope of machine learning in smart cities

With great power comes great responsibility. And along with these future techs we should never compromise our people safety.

With new technology coming in our society, we need new ways to protect our people. And with machine learning in our local security camera and toll plaza we can feed the system the data of criminal which is going to detect criminals roaming around in our streets and alert the local police authority to arrest them and protect us. Along with a safe place we also need a healthy place to survive. With Machine learning and smart sensors, we can control the wastage in our area by managing waste by sorting and cleaning in correct Time that's cause bad environment for us and our families.

## 7. Conclusion

Using machine learning in smart cities has the potential to enhance the way that we live immensely. It can facilitate the running of the city more efficiently as a whole with improvements to traffic management, energy conservation and response for emergency

services. All this is possible thanks to smart technology and machine learning.

There are still some issues to unpack. Firstly, we must ensure that the technology is indeed functioning as intended. Secondly, AI must be utilized globally in a safe and equitable manner with clearly defined protocols to safeguard citizens. Thirdly, cities need to create resilient and agile technologies in compliment with inclusive engagement with their communities.

If these three factors can be addressed successfully, we are at the beginning of constructing not only smart but equitable, sustainable cities ready for the future economic, environmental and societal challenges.

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## References:

- Alrashdi, I. (2024). Fog-based deep learning framework for real-time pandemic screening in smart cities from multi-site tomographies. *BMC Medical Imaging*, 24(1). <https://doi.org/10.1186/s12880-024-01302-8>
- Ameer, S., Shah, M. A., Khan, A., Song, H., Maple, C., Islam, S. U., & Asghar, M. N. (2019). Comparative Analysis of Machine Learning Techniques for Predicting Air Quality in Smart Cities. *IEEE Access*, 7, 128325–128338. <https://doi.org/10.1109/ACCESS.2019.2925082>
- Bhattacharya, S., Somayaji, S. R. K., Gadekallu, T. R., Alazab, M., & Maddikunta, P. K. R. (2022). A review on deep learning for future smart cities. *Internet Technology Letters*, 5(1). <https://doi.org/10.1002/itl2.187>
- Bian, J., Al Arafat, A., Xiong, H., Li, J., Li, L., Chen, H., Wang, J., Dou, D., & Guo, Z. (n.d.). *Machine Learning in Real-Time Internet of Things (IoT) Systems: A Survey*.
- Ghazal, T. M., Hasan, M. K., Alshurideh, M. T., Alzoubi, H. M., Ahmad, M., Akbar, S. S., Al Kurdi, B., & Akour, I. A. (2021). IoT for smart cities: Machine learning approaches in smart healthcare—A review. In *Future Internet* (Vol. 13, Issue 8). MDPI AG. <https://doi.org/10.3390/fi13080218>
- Haque, S., Eberhart, Z., Bansal, A., & McMillan, C. (2022). Semantic Similarity Metrics for Evaluating Source Code Summarization. *IEEE International Conference on Program Comprehension, 2022-March*, 36–47. <https://doi.org/10.1145/nnnnnnn.nnnnnnn>
- Huotari, M., Malhi, A., & Främling, K. (2024). Machine Learning Applications for Smart Building Energy Utilization: A Survey. *Archives of Computational Methods in Engineering*, 31(5), 2537–2556. <https://doi.org/10.1007/s11831-023-10054-7>
- Lucky, D., Fritz, H., Legatiuk, D., & Dragos, K. (n.d.). *Artificial intelligence techniques for smart city applications*. <https://www.researchgate.net/publication/339042595>

- Mohammadi, M., Student Member, G., Al-Fuqaha, A., & Member, S. (n.d.). *Enabling Cognitive Smart Cities Using Big Data and Machine Learning: Approaches and Challenges*. Retrieved from <http://www.havenondemand.com>
- Nie, J.-Yun. (2017). *2017 IEEE International Conference on Big Data proceedings: Dec 11-14, 2017, Boston, MA, USA*. IEEE.
- Panesar, A. (2019). Machine Learning and AI for Healthcare: Big Data for Improved Health Outcomes. In *Machine Learning and AI for Healthcare: Big Data for Improved Health Outcomes*. Apress Media LLC. <https://doi.org/10.1007/978-1-4842-3799-1>
- Prawiyogi, A. G., Purnama, S., Meria, L., Giri, A., Universitas Buana, P., Karawang, P., & Karawang, I. (2022). Smart Cities Using Machine Learning and Intelligent Applications. *International Transactions on Artificial Intelligence (ITALIC)*, 1(1), 102–116. <https://doi.org/10.34306>
- Quasim, M. T., Nisa, K. ul, Khan, M. Z., Husain, M. S., Alam, S., Shuaib, M., Meraj, M., & Abdullah, M. (2023). An internet of things enabled machine learning model for Energy Theft Prevention System (ETPS) in Smart Cities. *Journal of Cloud Computing*, 12(1). <https://doi.org/10.1186/s13677-023-00525-4>
- Rathore, M. M., Ahmad, A., Paul, A., & Rho, S. (2016). Urban planning and building smart cities based on the Internet of Things using Big Data analytics. *Computer Networks*, 101, 63–80. <https://doi.org/10.1016/j.comnet.2015.12.023>
- Ravi, D., Wong, C., Lo, B., & Yang, G. Z. (2017). A Deep Learning Approach to on-Node Sensor Data Analytics for Mobile or Wearable Devices. *IEEE Journal of Biomedical and Health Informatics*, 21(1), 56–64. <https://doi.org/10.1109/JBHI.2016.2633287>
- Sharma, A., Podoplelova, E., Shapovalov, G., Tselykh, A., & Tselykh, A. (2021). Sustainable smart cities: Convergence of artificial intelligence and blockchain. *Sustainability (Switzerland)*, 13(23). <https://doi.org/10.3390/su132313076>
- Sharma, H., Haque, A., & Blaabjerg, F. (2021). Machine learning in wireless sensor networks for smart cities: A survey. In *Electronics (Switzerland)* (Vol. 10, Issue 9). MDPI AG. <https://doi.org/10.3390/electronics10091012>
- Srihith, I. V. D., Kumar, I. V. S., Varaprasad, R., Mohan, Y. R., Srinivas, T. A. S., & Sravanthi, Y. (2022). Future of Smart Cities: The Role of Machine Learning and Artificial Intelligence. *South Asian Research Journal of Engineering and Technology*, 4(5), 110–119. <https://doi.org/10.36346/sarjet.2022.v04i05.005>
- Taloma, R. J. L., Cuomo, F., Communiello, D., & Pisani, P. (2025). Machine learning for smart water distribution systems: exploring applications, challenges and future perspectives. *Artificial Intelligence Review*, 58(4). <https://doi.org/10.1007/s10462-024-11093-7>
- Ullah, A., Anwar, S. M., Li, J., Nadeem, L., Mahmood, T., Rehman, A., & Saba, T. (2024). Smart cities: the role of Internet of Things and machine learning in realizing a data-centric smart environment. *Complex and Intelligent Systems*, 10(1), 1607–1637. <https://doi.org/10.1007/s40747-023-01175-4>
- Ullah, Z., Al-Turjman, F., Mostarda, L., & Gagliardi, R. (2020). Applications of Artificial Intelligence and Machine learning in smart cities. In *Computer Communications* (Vol. 154, pp. 313–323). Elsevier B.V. <https://doi.org/10.1016/j.comcom.2020.02.069>

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