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Review Article

Future of Smart Cities: The Role of Machine Learning and Artificial Intelligence

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Abstract: The goals of "smart cities" include relieving the burden of growing urbanisation, cutting down on energy use, protecting the environment, boosting the local economy and people's standard of living, and facilitating wider access to and use of cutting-edge Information and Communication Technologies (ICT). In smart cities, ICT is essential for policymaking, decision making, plan execution, and the delivery of useful services. The primary goal of this analysis is to investigate the part that AI and machine learning play. Examples of ed tech include Deep Reinforcement Learning (DRL) and Machine Learning (ML). In a complicated smart city setting, the aforementioned methods can be used to develop the best possible rules. Smart transportation, cyber-security, energy-efficient usage of smart grids (SG), efficient use of Unmanned Aerial Vehicles (UAVs) to guarantee the best 5G and beyond 5G (B5G) communications, and a smart health monitoring are all discussed in length in this paper. Finally, we discuss the research challenges that have yet to be met and potential future research directions that could bring the concept of a "smart city" closer to fruition.

Keywords: Internet of Things (IoT), Smart Cities, Machine Learning (ML), Artificial Intelligence (AI), 5G.

I. INTRODUCTION

According to projections [1, 2], cities will house 66 to 70 percent of the global population by 2050. Current urbanisation trends will impact the ecology, administration, and security of cities [3]. "Smart cities" are a solution for many nations to better manage resources and energy and keep pace with urbanisation. Smart city projects can design and implement technologies with reduced carbon emissions. Several nations (the United States, the European Union, and Japan) are creating and implementing smart city plans to address problems. Information and communication technologies (ICTs) [4, 5] must be utilised effectively in order to successfully manage data processing, data transmission, and the execution of complex strategies in order to guarantee a smooth and risk-free operation.

The great majority of applications for data-intensive smart cities [6] rely heavily on the Internet of Things. When dealing with large and intricate information, it can be difficult to determine which course of action will be the most precise and fruitful. Utilize AI, ML, and DRL for the most accurate analysis of enormous data sets [2, 7]. These techniques have the ability to provide near-optimal control decisions [8] by taking a long-term objective into account. Increasing the overall amount of data utilised for training can aid in improving the accuracy and precision of the just-described approaches [9]. The authors of [10] give evidence that better data analysis for big data and smart city development occurred simultaneously. As technologies like smart cities, As the IoT [11], blockchain technology, unmanned aerial vehicles (UAVs), as well as AI, ML, and DRL-based approaches continue to improve (see Figures 1–3), new opportunities will become available.

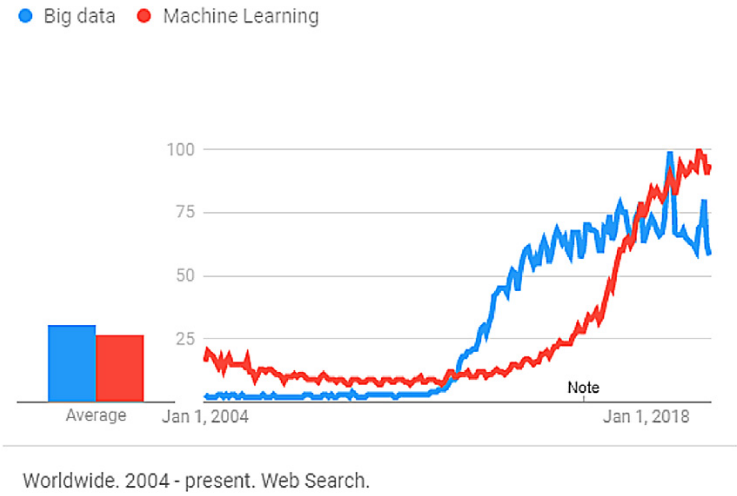

Fig 1: This Google Trends graph shows Big Data and ML from 2004 to 2020

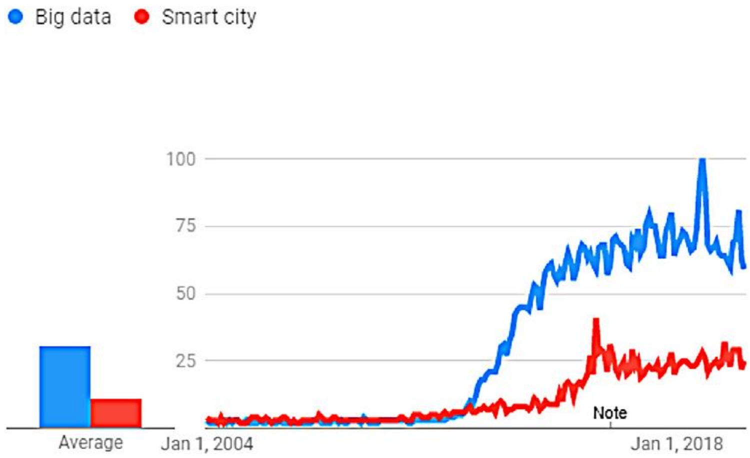

Fig 2: The prominence of smart cities and big data over time, Since 2012

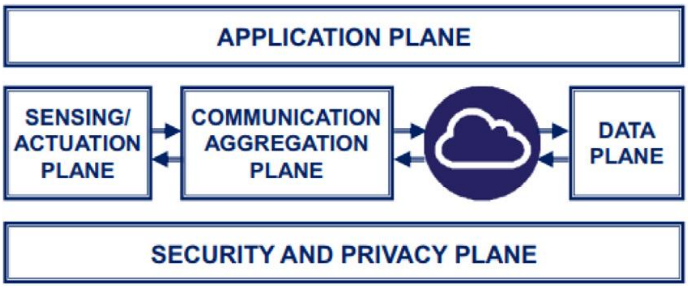

Fig 3: A smart city architecture including environment, protocols, data transmission, and security, privacy

We've investigated ITS approaches based on DRL. Cybersecurity is essential to the construction of a smart city. A full, dynamic, and proactive cyber-security plan must be drafted for each section of the proposed design. Cybersecurity techniques based on AI, ML, and DRL have influenced smart city firms. The authors of [12] cover ML and DRL in smart city applications with IoT sensors [13]. Energy production, administration, and utilisation have an impact on SG ICT operations.

AI's daily impact grows. AI changes daily activities, human thought, and environmental relationships. How can new legislation protect current and future generations from AI's downsides while maximising its upsides? AI-assisted policymaking and law making [14]. [15] proposes a DRL-and neural-network-based criminal behaviour recognition and evaluation system for a smart city. [16] suggests an ML-based design that can discover faults and fix them. Section 3 addresses ITS, Section 4 examines cyber-security upgrades, and Section 5 discusses smart city energy management.

Section 6 delves into the 5G and B5G ML and DRL UAV applications. Section 7 discusses smart health care. Sections 8 and 9 outline future research concerns, trends, and solutions.

II. ML: a simple summary

In machine learning, there are three types of learning: supervised, RL, and unsupervised. RL utilises each and every one of the branches shown in Fig. 4. It examines the differences between supervised learning and uncontrolled learning. Research will be done on RL as well as its primary algorithms. In supervised learning, an artificial intelligence network is trained to map input to output with the help of a dataset containing both the input and target values. Regression and classification are both aspects of supervised learning. Linear regression, support vector machines, and random forests are all examples of supervised learning. When training an AI network to recognise patterns, responses, and distributions, unsupervised learning makes use of data that has not been labelled or categorised in any way. The problems of clustering and association are examples of unsupervised learning. Examples include the k-means and auto-encoder algorithms.

Markov Decision Process (MDP): Most RL problems require MDP. MDPs are concerned with finding the best solutions to sequential decision issues (SDPs). An MDP is unable to provide absolute answers to stochastic stochastic dynamic programming problems (SDPs), but it can provide the best answer. States, actions, a transition model, and a reward function are the components that make up an MDP model. A state, an action, and the state that comes after it all play a part in determining reward and transition.

Reinforcement Learning (RL): The RL agent maximises its long-term benefit through environmental interactions. RL agents communicate and learn. The agent's best work did this. The ideal course of action is one that maximises the reward in the long run. An agent is expected to both profit from ongoing activities and investigate potential new ones. The question of whether or not to maximise the benefit from known manoeuvres or explore new frontiers is a significant problem in real life (RL). This balance between exploitation and exploration is a fundamental challenge. RL can function both with and without the use of models. The use of function approximators is essential to sample-efficient model-based RL. Model-based approaches are inadequate for probabilistic, complex, and high-dimensional models. Value functions, policy search, return functions, and transition models are some of the tools that can be used to tackle model-based RL challenges. Model-free RL includes MC and TD. TD techniques Q-Learning and SARSA.

Dynamic programming (DP): Richard Bellman's mid-20th-century optimization approach DP simplifies difficult jobs recursively. Model-based DP requires environmental understanding. In RL issues, DP is used to identify an ideal policy by iterating values or policies.

Monte Carlo (MC) Technique: Randomness is utilised in Monte Carlo. MC techniques for the very first and very second time. The Initial-Visit MC measures the frequency with which subsequent episodes return to a given state after the initial visit. The Every-Visit MC is calculated by taking the average of a state's total number of episode returns. MC algorithms are simple to put into action. (III) Direct involvement educates MC.

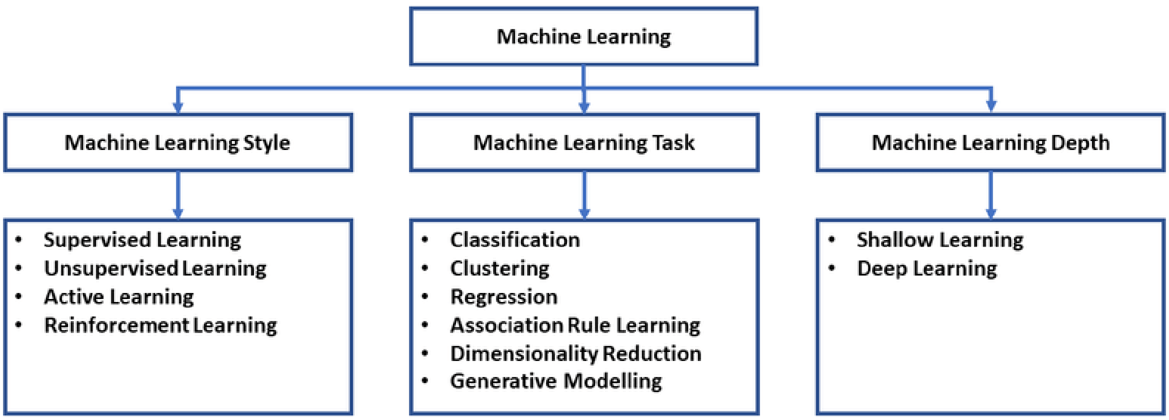

Fig 4: ML categorization

Temporal difference techniques (TD): TD techniques are model-free RL algorithms that learn by bootstrapping. In RL, TD predicts long-term future rewards based on a signal's future values. popular approach for evaluating policies. TD-based algorithms include Q-learning and SARSA.

SARSA: State-Action-Reward-State-Action (SARSA), related to Q-learning, is an active RL-TD control case approach. SARSA replaces Q-learning with policy. The update is labelled "State-Action-Reward-State-Action" to show that it learns the best Q-value from policy-compliant actions, not greedy ones.

Q-Learning: Probabilistic DRL with Q-learning Q-learning is a model-free, off-policy TD controller [17]. The Q-learning algorithm learns by observing. In Q-learning, the next action a' is chosen to maximise the Q-value of the future state. Q-learning and SARSA converge faster with eligible traces. Protocol efficiency decreases with more actions and states. Q-learning approximates functions.

Actor–critic Method: RL-based actor–critic algorithms. The value function and policy are combined. A critic determines an algorithm's value function, whereas an actor alters policy. It combines policy and value estimates. Small and large state-action spaces can use it. Previously, actors-only and critics-only were combined. The critic simulates and approximates value functions. The actor's policy values are modified via the value function [18].

Bayesian: Dynamic reinforcement learning (DRL) guarantees that an agent's rewards will rise over time. The agent will relocate to states with high payments and avoid low-paying states. Environmental uncertainty is important while maximising reward. Bayesian models give a framework for analysing model uncertainty [19]. Computational cost Bayesian approaches may solve the exploitation–exploration conundrum because they minimise over-fitting and accommodate uncertainty in learning parameters [20]. Myopic and Thompson sampling are Bayesian approximation approaches. Thompson sampling solves the exploration–exploitation conundrum.

Deep Q Network: TD, especially Q-learning, is frequently used in RL, but its effectiveness in large state spaces is restricted. Before, value functions were stored in a table or matrix. Q-learning uses a two-dimensional array for the Q table. Estimating value functions in huge state spaces with many actions is difficult. RL that is based on the approximation of neural networks is generalizable. Deep Q-Network (DQN) [21] is a network that measures value functions in state space. Q-learning trains networks.

III. Smart Transportation

The term " Smart Transportation" refers to transportation infrastructure that makes use of cutting-edge sensors, control systems, and information and communication technologies [22]. Sustainable ITS [23] requires continuous monitoring and forecasting of urban traffic flow data. AI, ML, and DRL algorithms are all useful tools for this kind of predicting and monitoring. The following is a synopsis of recent developments in ITS that will promote the growth of "smart" urban areas. As part of their research on ITS applications in smart cities, [24] looked into the potential of ML and DRL for analysing fleet management, traffic flow, channel estimation, passenger hunt in MEC, accident estimation, and other services. Researchers in [25] developed a study using DRL methods and edge analytics for ITS. Challenges like trajectory planning, fleet management, and cyber-physical security are the subject of this study. The writers of [26] suggest a DRL-based technique as a means to enhance driving behaviour decision-making in a wide range of traffic conditions. With this method, a data compressor creates a hyper-grid matrix from the raw data, a two-stream DNN extracts latent properties, and a DRL methodology determines the optimal next step. Simulations of linked-car traffic confirmed the feasibility and efficacy of the suggested scenario. This essay delves into some of the safety worries associated with mobile edge computing (MEC). It is shown how vulnerabilities in cyber defence can be handled using unsupervised learning in tandem with DRL. comparison of the suggested model to other ML-based methods There is a 6% improvement in accuracy when using the proposed method. In [27], researchers projected future highway traffic using DRL. They used LSTM-RNN to foresee traffic on the Gyeongbu Expressway (South Korea). The results of the tests provided reliable forecasts of the short-term movement of highway traffic. The authors of [27] investigated strategies to locate riders by analysing taxis' GPS tracks. With the help of DNN, TRec was created. In TRec, you take control of a cab and try to predict traffic and your revenue for the day. The usefulness and efficacy of TRec can be demonstrated with a solid dataset. The authors of the research [28] created a network-based prediction technique using the LSTM (long short-term memory) algorithm to optimise system performance and deliver accurate forecasts regarding wireless communication channel parameters. Due to the LSTM network's capacity to store relevant information in a matrix, spatial-temporal correlation analysis is simplified. The simulation's findings were utilised to demonstrate the model's efficacy. They developed an effective offloading strategy for computation at the edge of the network using DRL [29]. Using a constrained Markov chain to characterise computation and communication phases, the authors created a mixed optimization problem to improve QoE. The numerical results show that the NP-hard problem can be split into two smaller problems. DRL-based V2V resource allocation was developed by [30] for both unicast and broadcast scenarios. Independently, a vehicle or v2v link can figure out the optimal power level and sub-band for data transmission. Results from simulations demonstrate that users and agents learn to minimise V2V interference and V2V latency. DRL-based methods [31] model vehicular traffic. The layered auto-encoder model uncovers traffic flow layers. The proposed traffic prediction system is superior than existing alternatives. Quickly manoeuvrable, easily deployed, increasing payload capacities, great durability, and low production cost are just some of the reasons why UAVS are so important to smart city ITs. In ITS, unmanned aerial vehicles (UAVs) are utilised to transfer blood and distribute goods. The flight path, power consumption, and ITS of UAVs are optimised using machine learning and deep reinforcement learning. The [32] report details an approach to UAV deployment that takes traffic into account. The MEC nodes are activated for traffic. Using simulations, the proposed method was proven effective. In [33], the authors presented a distributed architecture of flying UAVs based on DRL to protect roaming users inside a certain area. The goals of this model are to maximise area coverage, minimise energy consumption, maintain connectivity, and restrict the number of flying UAVs in the study area. The simulations demonstrate the superiority of the model. UAVs for high-throughput downlink communication were the subject of research in [38]. Model-driven research examines UAV and vehicle changeover stages. The energy consumption of UAVs was evaluated using three different DRL-based DDPG algorithms. The results of the simulations show that the model is correct.

IV. Cyber-security

In order to provide digital services, the sensors, actuators, and relays that make up a smart city's network need to be trustworthy, safe, and secure. [34] Cybersecurity flaws can be introduced via interconnected hardware and software. The majority of the data that is collected by smart cities comes from Internet of Things devices that are hosted in the cloud [35]. The requirements for a smart city are outlined in [36]. Implement AI, ML and DL techniques while also protecting networks from any dangers. Hadi *et al*., conducted research on the architecture of smart cities from the viewpoints of communication, privacy, and security [37]. Integration took place for the infrastructure as well as the sensors, actuators, and communication protocols. [12] conducted research on ML and DRL algorithms for IoT security as well as new security problems. The authors performed an analysis of the ML and DRL protocols with regard to the security of the IoT [38]. They supplied responses after conducting research on ML and DRL in contemporary medical practise. The paper [39] suggests using a DRL-based architecture to thwart hacker attacks on smart cities. The method that has been proposed can detect hackers based on how they interact with data, thereby providing proactive protection for the network. Using this method can assist in the building of secure applications for smart cities. Offloading solution for fog, cloud, and IoT [40] based on machine learning to reduce power consumption and latency. Particle Swarm Optimization is responsible for selecting the fog nodes with the highest efficiency for compute offloading (PSO), and Neuro-Fuzzy models are responsible for ensuring that data is kept secure at the gateway. It reduces the amount of lag. The ECC network design and the difficulties were suggested in [41]. The architecture of the ECC makes it possible to migrate dynamic services. The earlier version of the ECC architecture takes into account the cognitive characteristics of mobile users. Studies indicate that the ECC architecture offers a higher level of efficiency when compared to conventional computer systems. A DRL-based Online Offloading technique is proposed in [42] for the purpose of offloading binary decision making. Tasks can be executed at the node or MEC device level when binary offloading is used. The paradigm that has been developed simplifies the computing burden of extremely large networks. The time needed to process data is cut down using the strategy that was proposed. The separation of trusted service requests from malicious ones is accomplished through the process of intrusion detection by analysing, compressing, and classifying the traffic data. The performance of the system was validated through simulations. [43] examines the difficulties associated with securing airborne UAVs and suggests an ANN-based solution to these problems. The suggested paradigm allows UAVs to consume resources frequently while retaining legitimate safety during ITs, freight delivery, and data streaming. The preceding strategy was shown accurate by simulations. [44] concentrated on GPS spoofing, a technique that can deceive ground controllers as well as unmanned aerial vehicles. They were able to detect GPS spoofing by using ML-ANN. Signal-to-noise ratio (SNR), Doppler shift, and pseudo-range are three characteristics that distinguish GPS transmissions. The technique that was described recognises GPS spoofing while generating very few false alarms. The findings of the simulation imply that the technique will improve the mission-specific service provided by UAVs.

V. Smart grids

The utilisation of smart city operations and energy is being revolutionised by big data [45]. ICT, IoT [46], and a significant amount of data are utilised by the SGs [47]. Data from a wide variety of sources are analysed by SGs so that managerial and operational choices can be made. The application of big data analytics enhances the efficiency, effectiveness, and safety of the power grids that serve smart cities. Big data analysis is utilised by the PMU for the purposes of dynamic model calibration, and state estimation, transmission grid visualisation [53]. Big data facilitates SG applications [48]. The topic of investigation in [49] is 5G in SGs. The current and upcoming communication architectures for 5G were analysed by SGs. The paper [50] provides an detailed investigation and examination of ML and DRL in the context of SGs applications and cyber-security. In this research, the authors investigate DRL transient stability, load control, fault analysis and power grid management applications in [51]. A model is proposed in [52] that takes into account the methods that are based on ML and shared energy as an SGs' system to help with complicated logical decisions based on accessible data. Even when the conditions are challenging, the machine learning-based model keeps the network efficiency stable and ensures that key loads continue to receive power. The paper [53] presents a DLSTM method to predict energy prices and need for the upcoming days by making use of actual market data. NRMSE and MAE conducted an analysis on the performance of the model. DLSTM outperforms traditional pricing strategies and load forecasting methods. In order to investigate DR policies in the context of time-dependent power prices, [54] developed a building simulation prototype that was accurate to its measurements. As a result of the efforts of two DR procedures, a heat pump and thermal storage system were successfully maintained and managed. Two different protocols were established and tested with the help of metre data in an effort to optimise energy consumption as well as costs, the environment, utilities, calculation models, and prediction models. An independent machine learning platform that assists in the construction of ML-based decision factors is proposed in [55]. The prior platform maximised the effectiveness of high-level learning by optimising complicated designs and expert interruptions. The platform provides ML-based database management applications that intelligent cities can employ. For the purposes of intrusion detection and location identification in SGs, ML and PLC modems come highly recommended. PLC modems look for deviations in CSI that could have been generated by an intruder. Utilization of energy is tracked by the Protocol. The passage [56] talks about cybersecurity and ML-based security guards. Deep-Q-network detection, often known as DQND, is a method that was suggested to preserve the data integrity of AC power systems. During the training phase, the suggested protocol is implemented on both the central and targeted networks. Experiments have shown that the technique described above is more accurate and efficient. The document [57] endorses the utilisation of DRL-based UAVs for the purpose of inspecting electrical connections. Faults in power lines, such as pole fractures and degradation, can be identified using the proposed method. Experiments have demonstrated that intelligently monitoring power lines can enhance SG efficiency. The authors of the paper [58] monitored SGs as well as electrical wires with a camera that tilts, pans, and zooms. [59] used DRL-equipped unmanned aerial vehicles (UAVs) to monitor wind turbines. They devised a system that can evaluate the harm done to UAVs. The precision of the model is comparable to that of people.

VI. 5G and B5G DRL UAV applications

The data throughput, reliability, and latency of 5G and B5G wireless communications are expected to be significantly improved. It is common knowledge that AI, ML, and DRL-based algorithms are the most efficient means of resolving complex communication issues that include vast amounts of network data [60]. Our primary focus will be on 5G and B5G connectivity for unmanned aerial vehicles (UAVs), which will be essential for the development of smart cities and the maintenance of their environmental friendliness. [61] has created a system that can detect cyberattacks on 5G and B5G networks. DRL performs an assessment of traffic based on an analysis of network flows. A method for the detection of cyberattacks on 5G and Internet of Things networks is presented in Reference 86. A dense neural network protocol is utilised in the technique that is presented in order to identify cyber-intrusions. Despite its utility, UAVs continue to face challenges. There are several areas where LTE service is unavailable, particularly in the air. For user equipment that is grounded, the antennae of the LTE base station are oriented downward. Even with 5G and B5G, achieving ubiquitous sky coverage is challenging because to the challenges posed by architecture, interference, and line-of-sight (LoS) limitations. The majority of today's communication systems are plagued with non-convex optimization difficulties. A DRL built on ML is capable of handling challenging scenarios. Landing Unmanned Aerial Vehicles (UAVs) on Mobile Platforms; The following is a brief list of projects that are linked to UAVs. Reinforcement learning was utilised by [62] in order to optimise the trajectories of UAVs. This method lessens the interference caused by GBS and improves the efficiency of data transmission. Each UAV figures out its own trajectory, determines the level of transmission power it uses, and creates an association vector. ESN-based DRL allows for the optimization of UAV trajectories as well as the utilisation of available resources. This is the first time that ESN-based DRL has been attempted to improve the energy efficiency, latency, and general interference of UAVs, as stated by the author. UAVs would be responsible for transporting the BS in this network design, and Q-learning would be used to increase the airborne sum rate. In order to lessen the impact of ground-based signal interference.

VII. Machine learning and smart city healthcare

For example, AI, ML, and DRL have found significant application in the field of health intelligence, which has benefited from increased data speeds, better sensors, elevated Smart appliances, and cloud services [63]. These techniques are essential for the diagnosis of diseases, the forecasting of cures, the analysis of social media, and medical imaging [64]. We investigate several smart city healthcare projects as well as contemporary developments in research. The authors of [65] investigated 5G communication in the medical field, focusing specifically on its techniques, hardware, architectural goals, and overall goals. Their contributions are centred on a health care architecture and technology that is based on 5G, a classification of the many communication technologies and protocols as well as questions concerning the different tiers of the network (routing, scheduling, congestion control, etc.). The authors of [66] used AI, ML, and DRL in their research on massive data sets in the context of health care systems. The processing of complex data, categorization, diagnosis, illness risk, the most effective treatment, and patient survival projections are all topics that are covered here. The utilisation of the aforementioned methodologies results in complications, such as the requirement for precise model training, the requirement to deal with real clinical situations, and the requirement for physicians to have an understanding of data analysis tools as well as the data that is being analysed [67] explores how AI will influence research and development in the pharmaceutical industry. HealthGuard was proposed by [68] methods of machine learning are utilised in order to detect potentially fraudulent activities in smart healthcare systems (SHS).

VIII. Future Research Challenges

In the literature pertaining to smart cities, applications that are powered by AI, ML, and DRL show potential. Academic institutions and private companies can collaborate on the following open research topics to improve the performance of smart cities by utilising AI, ML, and DRL.

- In order to make decisions that are more accurate and precise, it is necessary to collect a significant number of training data (for example, the speed of the vehicle, its position, the distance between vehicles, the behaviour of the driver, the height of the UAVs, the relay BS, and so on).
- Improving ITS efficiency during the connection between a vehicle and an unmanned aerial vehicle (UAV) can be accomplished by optimising the onboard capabilities of the UAV (cache, computation, process, sensor, and networking resources), as well as the trajectory.
- A measurement campaign that replicates vehicle-to-UAV, vehicle-to-vehicle, UAV-to-UAV, UAV-to-GBS channel, and so on, using a variety of UAVs and vehicle speeds travelling in a range of directions, in addition to regular and uneven infrastructure.

This campaign also includes regular and uneven infrastructure. Why Create a standard for the development of big data in SGs, as well as interoperability communication protocols and AI, ML, and DRL methodologies that can boost SG performance to levels that are nearly ideal. Power-down optimization is a top priority for both SGs and electric utilities. It is essential for the effectiveness of a network to conduct research into the times required for communication. Algorithms that are based on machine learning and dynamic programming can be used to assist in the development of approaches that can move between 5G technologies while maintaining a constant power supply. Apps are used to keep a smart city safe and secure. Infiltrations of smart metre security can lead to manipulation of energy supplies and inefficiencies in SG operations. In order to ensure the cybersecurity of smart cities, novel technologies based on the analysis of enormous data sets are required.

IX. CONCLUSION

We examined recent developments and accomplishments in smart city research conducted in academic institutions and private companies. The theories of AI, ML, and DRL are summed up in a nutshell inside this paper. By utilising the protocols described earlier, we were able to design near-optimal techniques for use in smart city applications. In the context of smart cities, we discussed the applications of AI, ML, and domain-specific language (DRL) in the establishment of smart governance; AI-assisted and AI-compatible new regulations; energy-efficient ITS, SGs, and cybersecurity; and UAV-assisted 5G and B5G communications. We gave a quick overview of the growing significance of the above-mentioned smart health care procedures, including accurate diagnostics, health recovery, Internet of Things device security, and medical discovery. In conclusion, we demonstrated how the aforementioned methods may be utilised to investigate current research subjects and emerging tendencies in the field of smart cities.

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