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Article

THE FUNCTION OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN THE FUTURE OF SMART CITIES

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Abstract: "Smart cities" aim to alleviate the strain of increasing urbanization, reduce energy consumption, safeguard the environment, improve the local economy and people's quality of life. The idea of smart cities is examined in this study, along with how machine learning (ML) and the Internet of Things (IoT) contribute to the creation of a data-centric smart environment. Smart cities use data and technology to raise the standard of living for residents and increase the effectiveness of city services. Machine learning and the Internet of Things have become essential technologies for allowing solutions for smart cities that depend on extensive data gathering, analysis, and judgment. An overview of the many uses for smart cities is given in this paper, along with a discussion of the difficulties in integrating IoT and machine learning in urban settings. The study also contrasts various case studies of effective IoT and machine learning-based smart city deployments. According to the research, these technologies have the power to change urban settings and make it possible to build more efficient, sustainable, and liveable cities. Information and Communication Technologies (ICT) plays a crucial role in smart city policymaking, decision-making, plan execution, and service delivery. This article goes into great detail about smart health monitoring, cyber-security, energy-efficient smart grid (SG) use, smart transportation, and the effective use of unmanned aerial vehicles (UAVs) to ensure the greatest 5G and beyond 5G (B5G) communications. Lastly, we go over the research obstacles that still need to be overcome and possible avenues for future study that can further the idea of a "smart city."

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

1. Introduction

By 2050, 66 to 70 percent of the world's population is expected to live in cities, according to forecasts [1, 2]. The environment, governance, and security of cities will be impacted by the current trends in urbanization [3]. For many countries, "smart cities" offer a way to better manage energy and resources while keeping up with urbanization. Figure 1 represents the overview of smart city architecture. Technologies with lower carbon emissions can be designed and implemented in smart city initiatives. To solve issues, a number of countriesincluding the US, the EU, and Japanare developing and putting into practice smart city plans. To provide a seamless and risk-free operation, Information and Communication Technologies (ICTs) [4, 5] must be used effectively to handle data processing, data transmission, and the execution of complicated strategies. The vast majority of data-intensive smart city applications [6] mostly rely on the Internet of Things (IOTs). It might be challenging to decide which course of action will be the most accurate and successful when working with huge and complex data. For the most accurate analysis of massive data sets, use Artificial Intelligence (AI), Deep Reinforcement Learning (DRL) and Machine Learning (ML) [2, 7]. When a long-term goal is taken into consideration, these methods can produce judgments for control that are almost optimal [8]. The accuracy and precision of the previously mentioned methods can be enhanced by increasing the total amount of data used for training [9]. The authors of [10] provide proof that smart city development and improved data analysis for big data happened at the same time. As innovations such as blockchain technology, smart cities, and the Internet of Things [11] continue to advance, new opportunities will arise.

We have studied Integrated Systems (ITS) based on DRL. The development of a smart city requires cybersecurity. For every component of the suggested design, a comprehensive, proactive, and dynamic cyber-security plan needs to be created. AI, ML, and DRL-based cybersecurity strategies have impacted smart city businesses. ML and DRL in smart city applications with IoT sensors are covered by the authors of [12] [13]. ICT operations are impacted by the production, management, and use of energy. The influence of AI expands every day. AI alters human thought, daily activities, and interactions with the environment. How can new laws maximize AI's benefits while shielding present and future generations from its drawbacks? AI-supported legislation and policymaking [14]. The paper [15] suggests a criminal behavior recognition and assessment system for a smart city that is based on DRL and neural networks. The article [16] proposes an ML-based approach that can identify and correct errors. Section 2 deals with the overview of Machine Learning. ITS is covered in Section 3, cyber-security enhancements are examined in Section 4, and smart city energy management is covered in Section 5. The 5G and B5G ML and DRL UAV applications are covered in detail in Section 6. Smart health care is discussed in Section 7. Future research issues, trends, and solutions are described in Sections 8 and 9.

2. Machine Learning: A Brief Overview

There are three categories of learning in machine learning: supervised, Reinforcement Learning (RL), and unsupervised. For example, RL uses all of the branches depicted in Figure 2. It looks at how supervised and uncontrolled learning differ from one another. Research on RL and its main algorithms will be conducted.

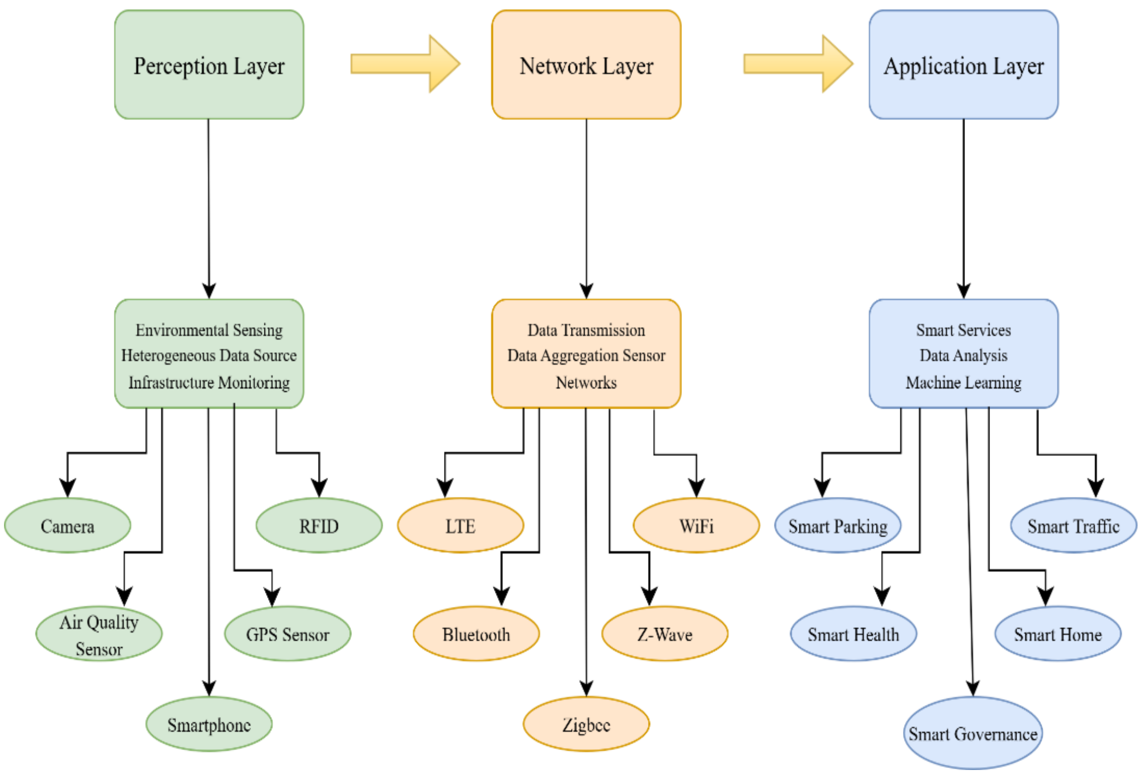

Figure 1. Smart City Architecture

In supervised learning, a dataset that includes both the input and target values is used to train an artificial intelligence network to map input to output. Two components of supervised learning are classification and regression. Examples of supervised learning include random forests, support vector machines, and linear regression. In order to train an AI network to identify patterns, responses, and distributions, unsupervised learning uses data that hasn't been labelled or otherwise categorized. Examples of unsupervised learning include the association and clustering problems. The k-means and auto-encoder algorithms are two examples.

A. Reinforcement Learning (RL)

By interacting with its surroundings, the RL agent maximizes its long-term gain. RL agents converse and acquire knowledge. This was accomplished by the agent's finest job. The optimal strategy is the one that maximizes the long-term benefit. It is required of an agent to look into possible new operations as well as make money from current ones. A major dilemma in real life (RL) is whether to maximize the advantages of tried-and-true strategies or to venture into uncharted territory. One of the main challenges is striking a balance between exploration and exploitation. RL is capable of operating both with and without models. Function approximators are a crucial component of sample-efficient model-based reinforcement learning. For high-dimensional, complicated, and probabilistic models, model-based methods are insufficient. Model-based RL problems can be addressed with a variety of methods, including value functions, policy search, return functions, and transition models.

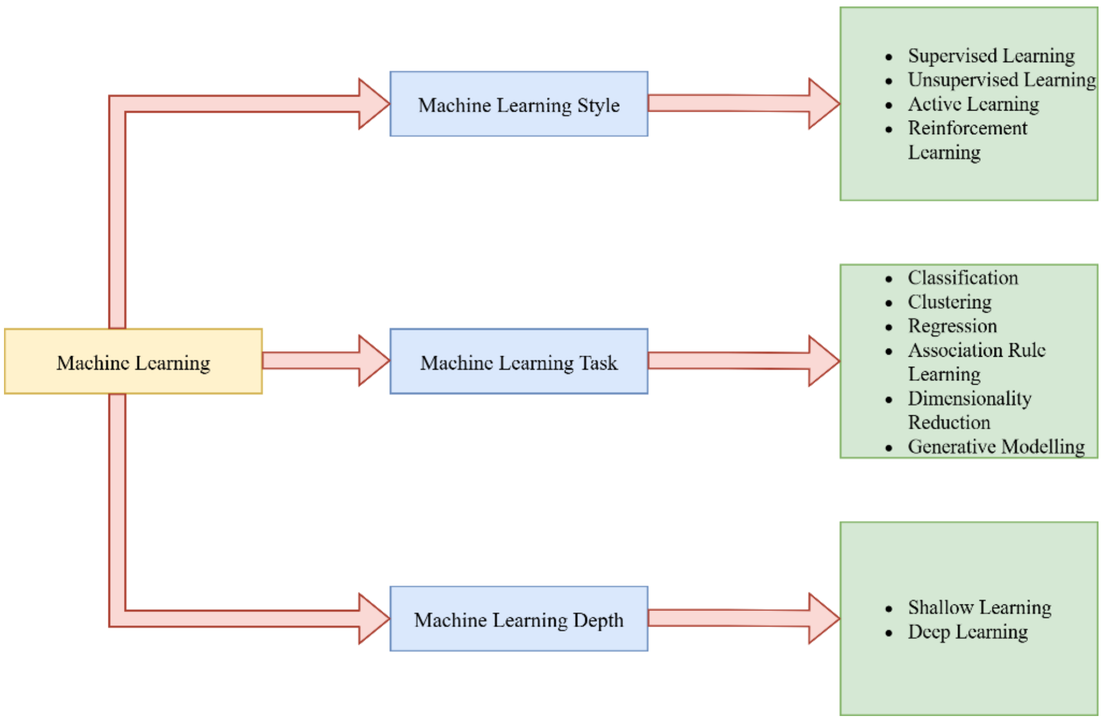

Figure 2. Machine Learning Categorization

a. Markov Decision Process (MDP)

MDP is necessary for the majority of RL tasks. Finding the best answers to Sequential Decision Problems (SDPs) is the focus of MDPs. While an MDP can offer the optimum solution, it cannot offer definitive solutions to Stochastic Dynamic Programming issues (SDPs). The elements that comprise an MDP model are states, actions, a transition model, and a reward function. Reward and transition are influenced by a state, an action, and the state that follows.

b. Dynamic Programming (DP)

It is an optimization technique developed by Richard Bellman in the middle of the 20th century that uses recursive simplification to make complex tasks easier. Understanding the environment is necessary for model-based DP. By iterating values or policies, DP is utilized to find the optimal policy in RL problems.

c. Monte Carlo (MC) Technique

Monte Carlo makes use of randomness. This is the first- and second-time using MC methods. The frequency with which future episodes return to a particular state following the original visit is measured by the original-Visit MC. A state's overall number of episode returns is averaged to determine the Every-Visit MC. It is easy to implement MC algorithms.

d. Temporal Difference Techniques (TD)

TD approaches are bootstrapping, model-free reinforcement learning algorithms. Based on the future values of a signal, TD forecasts long-term future rewards in reinforcement learning. common method for assessing policy. SARSA and Q-learning are two examples of TD-based algorithms. State-Action-Reward-State-Action (SARSA) is an active RL-TD control case technique that is associated with Q-learning. SARSA uses policy in place of Q-learning. The update is named "State-Action-Reward-State-Action" to demonstrate that it learns the optimal Q-value from acts that comply with policy rather than those that are motivated by greed.

e. Q-Learning

Probabilistic DRL with Q-learning Q-learning is an off-policy TD controller that does not require a model [17]. The Q-learning algorithm picks up knowledge through observation. The next action, is selected in Q-learning in order to maximize the future state's Q-value. SARSA and Q-learning converge more quickly with eligible traces. The more activities and states in a protocol, the less efficient it becomes. Functions are approximated by Q-learning.

f. Actor-critic Method

It is an algorithm based on reinforcement learning. The policy is paired with the value function. While an actor modifies policy, a critic establishes the value function of an algorithm. It blends value and policy estimations. It can be applied to both small and big state-action spaces. Actors-only and critics-only were previously merged. Value functions are approximated and simulated by the critic. The value function is used to change the actor's policy values [18].

g. Bayesian

Deep reinforcement learning (DRL) ensures that an agent will receive more rewards as time goes on. The agent will avoid low-paying states and move to states with higher salaries. Uncertainty in the environment is crucial for optimizing reward. A framework for analyzing model uncertainty is provided by Bayesian models [19]. Because computational cost Bayesian techniques minimize over-fitting and account for uncertainty in learning parameters, they may be able to resolve the exploitation-exploration dilemma [20]. Bayesian approximation techniques include myopic and Thompson sampling. The exploration-exploitation dilemma is resolved by Thompson sampling.

h. Deep Q Network

Although TD, and in particular Q-learning, is widely employed in reinforcement learning, its efficacy in vast state spaces is limited. Value functions were previously kept in a matrix or table. A two-dimensional array is used for the Q table in Q-learning. It is challenging to estimate value functions in large state spaces with plenty of activities. RL that relies on neural network approximation is more broadly applicable. One network that measures value functions in state space is the Deep Q-Network (DQN) [21]. Networks are trained by Q-learning.

3. Smart Transportation

Transportation infrastructure utilizing state-of-the-art sensors, control systems, and information and communication technology is referred to as "smart transportation" [22]. Data on urban traffic flow must be continuously monitored and forecasted in order for ITS to be sustainable [23]. DRL algorithms, ML, and AI are all helpful tools for this type of monitoring and prediction. An overview of current ITS advancements that will support the expansion of "smart" metropolitan areas is provided below.

The potential of ML and DRL for analysing fleet management, traffic flow, channel estimation, passenger hunt in Mobile Edge Computing (MEC), accident estimation, and other services was examined by [24] as part of their study on ITS applications in smart cities. Researchers in [25] created research for ITS utilizing edge analytics and DRL techniques. This study focuses on issues such as fleet management, trajectory planning, and cyber-physical security. In order to improve driving behaviour and decision-making in a variety of traffic situations, the authors of [26] propose a DRL-based method. With this approach, a two-stream DNN extracts latent features, a data compressor generates a hyper-grid matrix from the raw data, and a DRL methodology decides the best course of action. Linked-car traffic simulations validated the viability and effectiveness of the proposed scenario. This paper explores some of the security concerns related to MEC. It is demonstrated how unsupervised learning combined with DRL can be used to address cyber defence flaws. When comparing the proposed model to existing machine learning-based techniques, the accuracy of the former is improved by 6%. Researchers used DRL to forecast future highway traffic in [27]. They forecasted traffic on the Gyeongbu Expressway (South Korea) using LSTM-RNN. The test findings yielded accurate predictions for the short-term flow of traffic on the route. By examining taxis' GPS traces, the authors of [27] looked at ways to find passengers. TRec was developed with DNN's assistance. You take charge of a taxi in TRec and attempt to forecast traffic and your daily earnings. A strong dataset can be used to illustrate TRec's value and effectiveness. Using the LSTM (Long Short-Term Memory) algorithm, the research's authors [28] developed a network-based prediction method to maximize system performance and provide precise predictions about wireless communication channel parameters. Spatial-temporal correlation analysis is made easier by the LSTM network's ability to store pertinent data in a matrix. The results of the simulation were used to illustrate the effectiveness of the model. Using DRL, they created a successful offloading approach for computation at the network's edge [29]. The authors developed a mixed optimization problem to enhance QoE by characterizing the computation and communication phases using a constrained Markov chain. The NP-hard problem can be divided into two smaller issues, according to the numerical results. [30] developed DRL-based V2V resource allocation for broadcast and unicast scenarios. A vehicle or V2V link can determine the best sub-band and power level for data transfer on its own.

Simulations show that agents and users gain the ability to reduce V2V latency and interference. Automobile traffic is modelled using DRL-based techniques [31]. Traffic flow layers are revealed by the layered auto-encoder model. The suggested traffic prediction method outperforms the current options. Unmanned Aerial Vehicles (UAVs) are crucial to smart city ITs for a number of reasons, including their remarkable durability, ease of deployment, quick manoeuvrability, rising payload capacities, and low production costs. UAVs are used in ITS for distribution of products and blood transfers. Machine learning and deep reinforcement learning are used to optimize the flight path, power consumption, and ITS of unmanned aerial vehicles. A strategy to UAV deployment that considers traffic is described in the [32] report. Traffic is allowed on the MEC nodes. Simulations were used to demonstrate the effectiveness of the suggested approach. To secure roaming users inside a specific area, the authors of [33] proposed a distributed architecture of flying UAVs based on DRL. This model aims to limit the number of flying UAVs in the research area, maximize area coverage, minimize energy consumption, and preserve connectivity. The models' supremacy is demonstrated by the simulations. Research on UAVs for high-throughput downlink communication was conducted in [38]. Model-driven study looks at the stages of vehicle and UAV transition. Three distinct DDPG algorithms based on DRL were used to assess the energy consumption of UAVs. The simulations' outcomes demonstrate that the model is accurate.

4. Cyber-security

The sensors, actuators, and relays that comprise a smart city's network must be reliable, secure, and safe in order to deliver digital services. [34] Connected hardware and software can pose cybersecurity vulnerabilities. Cloud-hosted Internet of Things devices provide the vast majority of the data that smart cities gather [35]. In [36], the prerequisites for a smart city are listed. Put AI, ML, and DL strategies into practice while safeguarding networks from threats. Research on smart city architecture from the perspectives of security, privacy, and communication was done by Hadi et al. [37]. In addition to the sensors, actuators, and communication protocols, the infrastructure was integrated. [12] investigated novel security issues as well as ML and DRL methods for IoT security. The authors conducted a study on the security of the Internet of Things by analysing the ML and DRL protocols [38]. Following their studies on ML and DRL in modern medical practice, they provided answers. A DRL-based architecture is proposed in the paper [39] as a means of preventing hacker assaults on smart cities. Proactive network protection is possible with the suggested strategy, which can identify hackers based on their data interactions. This approach can help with the development of safe smart city applications. Machine learning-based offloading solutions for fog, cloud, and IoT [40] that lower latency and power consumption. Neuro-Fuzzy models are in charge of making sure that data is protected at the gateway, while Particle Swarm Optimization is in charge of choosing the fog nodes with the best efficiency for compute offloading. It lessens the amount of latency. In [41], the design of the ECC network and its challenges were proposed. The ECC's architecture allows for the migration of dynamic services. The cognitive traits of mobile users are taken into consideration in the previous iteration of the ECC architecture. Research shows that when compared to traditional computer systems, the ECC architecture provides a higher degree of efficiency. In order to offload binary decision making, a DRL-based online offloading technique is suggested in [42]. When binary offloading is implemented, tasks can be carried out at the node or MEC device level. With the established paradigm, the computational cost of very large networks is simplified. The suggested approach reduces the amount of time required to process data. The method of intrusion detection involves analysing, compressing, and categorizing the traffic data in order to distinguish between malicious and trusted service requests. Simulations were used to verify the system's performance. investigates the challenges of protecting UAVs in the air and proposes an ANN-based solution. The proposed paradigm permits frequent resource consumption by UAVs while maintaining legitimate safety during data streaming, freight delivery, and ITs. Simulations demonstrated the accuracy of the previous approach. [44] focused on GPS spoofing, a method that can fool both unmanned aerial aircraft and ground operators. By employing ML-ANN, they were able to identify GPS spoofing. Three features that set GPS broadcasts apart include signal-to-noise ratio (SNR), Doppler shift, and pseudo-range. The method described is capable of identifying GPS spoofing with minimal false alarm production. The simulation's results suggest that the method will enhance the mission-specific service that UAVs offer.

5. Smart Grids (SGs)

Big data is revolutionizing the use of smart city operations and energy [45]. SGs make use of ICT, IoT [46], and a substantial amount of data [47]. SGs analyse data from a wide range of sources in order to make operational and managerial decisions. Application of big data analytics improves the power grids that support smart cities in terms of efficacy, safety, and efficiency. The PMU makes use of big data analysis for transmission grid visualization, state prediction, and dynamic model calibration [53]. SG applications are made easier by big data [48]. 5G in SGs is the subject of research in [49]. SGs conducted an analysis of 5G communication architectures, both present and future. In the context of SG applications and cyber-security, the publication [50] offers a thorough analysis and assessment of ML and DRL. The authors of this study look into fault analysis, load control, DRL transient stability, and power grid management applications in [51]. In order to assist with complex logical decisions based on available data, a model is put out in [52] that considers techniques based on machine learning and shared energy as an SGs system. Despite difficult circumstances, the machine learning-based model maintains a steady level of network efficiency and guarantees that important loads will always be powered. Using real market data, the publication [53] proposes a DLSTM approach to forecast energy prices and demand for the following days. The model's performance was analysed using NRMSE and MAE. DLSTM performs better than load forecasting techniques and conventional pricing schemes. A building simulation prototype that was faithful to its measurements was created by [54] in order to study DR strategies in the setting of time-dependent power costs. A heat pump and thermal storage system were effectively maintained and managed as a result of the work of two DR processes. To optimize energy usage, costs, the environment, utilities, calculation models, and prediction models, two distinct protocols were developed and evaluated using meter data. In [55], a stand-alone machine learning platform is suggested to help in the creation of ML-based decision factors. The previous platform optimized complex designs and expert interruptions to maximize the effectiveness of high-level learning. Intelligent cities can use the platform's ML-based database management applications. It is highly advised to use ML and PLC modems for intrusion detection and location identification in SGs. PLC modems search for CSI aberrations that might have been caused by an intruder. The Protocol monitors energy consumption. Cybersecurity and machine learning-based security measures are discussed in the paragraph [56]. One technique that was proposed to maintain the data integrity of AC power systems is deep-Q-network detection, or DQND. The proposed protocol is put into practice on both the central and targeted networks during the training phase. The method mentioned above is more accurate and effective, according to experiments. The application of DRL-based UAVs for electrical connection inspection is supported by the publication [57]. The suggested technique can be used to detect power line faults such pole fractures and deterioration. Experiments have shown that SG efficiency can be increased with sophisticated power line monitoring. SGs and electrical cables were observed by the authors of the research [58] using a tilting, panning, and zooming camera. [59] monitored wind turbines using unmanned aerial vehicles (UAVs) fitted with DRL. They came up with a technique that can assess the damage done to UAVs. The model's accuracy is on par with human accuracy.

6. Applications for 5G and B5G DRL UAVs

The It is anticipated that 5G and B5G wireless communications will greatly increase data speed, dependability, and latency. It is well known that the most effective way to address complicated communication problems involving enormous volumes of network data is to use algorithms based on AI, ML, and DRL [60]. The development of smart cities and the preservation of their environmental friendliness will depend on 5G and B5G connectivity for UAVs, which will be our key focus. has developed a method for identifying cyberattacks on 5G and B5G networks [61]. Based on an examination of network flows, DRL evaluates traffic. Reference 86 presents a technique for identifying cyberattacks on 5G and Internet of Things networks. To detect cyber-intrusions, the method that is provided makes use of a sophisticated neural network protocol. UAVs still confront difficulties in spite of their usefulness. LTE coverage is not available in a number of locations, especially in the air. The LTE base station's antennae are pointed downward for customer equipment that is grounded. It is difficult to achieve ubiquitous sky coverage, even with 5G and B5G, because to issues with architecture, interference, and line-of-sight limits. The bulk of communication systems in use today suffer from non-convex optimization issues. A DRL based on machine learning can manage difficult situations. In order to optimize the UAVs' trajectories, [62] employed reinforcement learning. This technique increases data transmission efficiency while reducing GBS interference. Every UAV decides its own course, establishes an association vector, and chooses the amount of transmission power it consumes. Utilizing available resources and optimizing UAV trajectories are made possible by ESN-based DRL. According to the author, this is the first attempt to use ESN-based DRL to enhance the general interference, latency, and energy efficiency of UAVs. In this network design, the BS would be transported by UAVs, and the airborne sum rate would be increased by the application of Q-learning. in an effort to mitigate the effects of interference from ground-based signals.

7. Healthcare in Smart Cities and Machine Learning

For instance, AI, ML, and DRL have been widely used in the field of health intelligence, which has profited from improved sensors, faster data rates, smarter appliances, and cloud services [63]. The diagnosis of illnesses, the prediction of treatments, social media analysis, and medical imaging all depend on these methods [64]. We look into current scientific advancements as well as a number of smart city healthcare initiatives. The authors of [65] looked into 5G communication in the medical domain, paying particular attention to its methods, hardware, architectural objectives, and overarching aims. Their contributions focus on a 5G-based health care architecture and technology, a classification of the various communication technologies and protocols, and issues pertaining to the various network tiers (routing, scheduling, congestion control, etc.). In their study of large data sets in the context of health care systems, the authors of [66] employed AI, ML, and DRL. This section covers a number of subjects, including the processing of complex data, classification, diagnosis, sickness risk, the best course of therapy, and patient survival estimates. The use of the previously mentioned approaches leads to issues like the need for accurate model training, the need to handle actual clinical scenarios, and the need for doctors to comprehend both the data being analyzed and the data analysis tools [67]. Machine learning techniques are used in HealthGuard, which was proposed by [68], to identify possibly fraudulent activity in Smart Healthcare Systems (SHS).

8. Future Research Challenges

AI, ML, and DRL-powered applications have shown promise in the literature associated with smart cities. The following open research topics can be worked on by academic institutions and private businesses to use AI, ML, and DRL to enhance the performance of smart cities. To produce more accurate and precise decisions, a large amount of training data must be gathered (e.g., vehicle speed, position, distance between vehicles, driver behaviour, height of UAVs, relay BS, and so on). By optimizing the UAV's onboard capabilities (cache, computing, process, sensor, and networking resources) and trajectory, it is possible to increase ITS efficiency during the connection between a vehicle and a UAV. A measuring campaign that uses a range of UAVs and vehicle speeds traveling in different directions, along with regular and uneven infrastructure, to imitate vehicle-to-UAV, vehicle-to-vehicle, UAV-to-UAV, UAV-to-GBS channel, and so on. Both regular and uneven infrastructure are part of this strategy. The rationale behind developing a standard for big data development in SGs, as well as interoperability communication protocols and AI, ML, and DRL approaches that can raise SG performance to almost optimal levels. Electric utilities and SGs both place a high premium on power-down optimization. A network's ability to function effectively depends on its ability to study the times needed for communication. Techniques that can transition between 5G technologies while keeping a steady power supply can be developed with the use of algorithms based on dynamic programming and machine learning. A smart city is kept safe and secure through the usage of apps. Energy supply manipulation and inefficiencies in SG operations may result from breaches in smart meter security. Innovative solutions based on the analysis of massive data sets are needed to guarantee the cybersecurity of smart cities.

9. Conclusion

We looked at the latest advancements and successes in smart city research carried out by private businesses and university institutions. This paper provides a concise overview of the ideas of AI, ML, and DRL. We were able to create nearly ideal methods for usage in smart city applications by utilizing the previously mentioned protocols. We covered the use of AI, ML, and domain-specific language (DRL) in smart city contexts, including the development of smart governance, AI-assisted and AI-compatible new regulations, energy-efficient ITS, SGs, and cybersecurity, and UAV-assisted 5G and B5G communications. We briefly discussed how the aforementioned smart health care practicesaccurate diagnoses, health recovery, Internet of Things device security, and medical discoveryare becoming increasingly important. Finally, we showed how the previously described techniques may be applied to explore current research topics and new trends in the smart city space.

Abbreviations

Artificial Intelligence (AI)

Deep Reinforcement Learning (DRL)

Machine Learning (ML)

Integrated Systems (ITS)

Internet of Things (IOTs)

Information and Communication Technologies (ICTs)

Reinforcement Learning (RL)

Stochastic Dynamic Programming (SDPs)

State-Action-Reward-State-Action (SARSA)

Long Short-Term Memory (LSTM)

Mobile Edge Computing (MEC)

Unmanned Aerial Vehicles (UAVs)

Signal-to-Noise Ratio (SNR)

Smart Healthcare Systems (SHS)

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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