Machine Learning Applications in Internet-of-Drones: Systematic Review, Recent Deployments, and Open Issues

ARASH HEIDARI, Department of Computer Engineering, Tabriz Branch, Islamic Azad University, Tabriz, Iran
NIMA JAFARI NAVIMIPOUR, Department of Computer Engineering, Faculty of Engineering and Natural Sciences, Kadir Has University, Istanbul, Turkey
MEHMET UNAL, Department of Computer Engineering, Nisantasi University, Istanbul, Turkey
GUODAO ZHANG, Department of Digital Media Technology, Hangzhou Dianzi University, Hangzhou, China

Deep Learning (DL) and **Machine Learning (ML)** are effectively utilized in various complicated challenges in healthcare, industry, and academia. The **Internet of Drones (IoD)** has lately cropped up due to high adjustability to a broad range of unpredictable circumstances. In addition, **Unmanned Aerial Vehicles (UAVs)** could be utilized efficiently in a multitude of scenarios, including rescue missions and search, farming, mission-critical services, surveillance systems, and so on, owing to technical and realistic benefits such as low movement, the capacity to lengthen wireless coverage zones, and the ability to attain places unreachable to human beings. In many studies, IoD and UAV are utilized interchangeably. Besides, drones enhance the efficiency aspects of various network topologies, including delay, throughput, interconnectivity, and dependability. Nonetheless, the deployment of drone systems raises various challenges relating to the inherent unpredictability of the wireless medium, the high mobility degrees, and the battery life that could result in rapid topological changes. In this paper, the IoD is originally explained in terms of potential applications and comparative operational scenarios. Then, we classify ML in the IoD-UAV world according to its applications, including resource management, surveillance and monitoring, object detection, power control, energy management, mobility management, and security management. This research aims to supply the readers with a better understanding of (1) the fundamentals of IoD/UAV, (2) the most recent developments and breakthroughs in this field, (3) the benefits and drawbacks of existing methods, and (4) areas that need further investigation and consideration. The results suggest that the **Convolutional Neural Networks (CNN)** method is the most often employed ML method in publications. According to research, most papers are on resource and mobility management. Most articles have focused on enhancing only one parameter, with the accuracy parameter receiving the most attention. Also, Python is the most commonly used language in papers, accounting for 90% of the time. Also, in 2021, it has the most papers published.

Authors' addresses: A. Heidari, Department of Computer Engineering, Tabriz Branch, Islamic Azad University, Tabriz, Iran; email: Arash_heidari@ieee.org; N. Jafari Navimipour (corresponding author), Department of Computer Engineering, Faculty of Engineering and Natural Sciences, Kadir Has University, Istanbul 34083, Turkey and Future Technology Research Center, National Yunlin University of Science and Technology, Douliou, Yunlin 64002, Taiwan; email: JNNima@yuntech.edu.tw; M. Unal, Department of Computer Engineering, Nisantasi University, Istanbul, Turkey; G. Zhang (corresponding author), Department of Digital Media Technology, Hangzhou Dianzi University, Hangzhou 310018, China; email: guodaozhang@hdu.edu.cn.

0360-0300/2023/03-ART247 $15.00
https://doi.org/10.1145/3571728

CCS Concepts: • **Computing methodologies** → *Machine learning*; *Machine learning approaches* • **Information systems** → *Information systems applications*; *Computing platforms* • **General and reference** → *Document types*; *Surveys and overviews*;

Additional Key Words and Phrases: Internet of Drones, IoD, review, UAV, Machine Learning, Deep Learning

ACM Reference format:
Arash Heidari, Nima Jafari Navimipour, Mehmet Unal, and Guodao Zhang. 2023. Machine Learning Applications in Internet-of-Drones: Systematic Review, Recent Deployments, and Open Issues. *ACM Comput. Surv.* 55, 12, Article 247 (March 2023), 45 pages.
https://doi.org/10.1145/3571728

1 INTRODUCTION

People's quest for new things is evolving in tandem with the advancement of social science and information technology [1, 2]. Drones are a type of technology that can fly without the assistance of a pilot, and they can also be ground-based; they are becoming more prevalent in people's lives [3]. As drones' commercial use continues to expand, scientific researchers' attention has been drawn to their core technology. So, the **Internet of Drones (IoD)** is described as a system architecture designed to allow interactions between independent flying vehicles and various networked devices installed on the ground [4]. Also, **Unmanned Aerial Vehicles (UAVs)** are envisioned as interconnected devices that can be organized in groups and functionally specified to fulfill strategic goals in the IoD framework [5–7]. Besides, many studies use IoD and UAV interchangeably, and the concepts are incredibly similar and close [8]. On the other hand, drones are envisioned in the IoD as intelligent devices capable of flying all over a given territory, performing a range of tasks such as surveillance and environmental sensing, and acquiring data of interest in real-time for any future use [9]. In addition, drones that can interact and exchange data are useful for flight coordination, even if they are not set to create swarms [10]. Drones simultaneously communicate with a reference ground structure, accumulating and expanding data to enable services or deliver current information to remote users linked to specialized application servers [11]. As a consequence of its decreasing production costs, precise in-flight trajectory control, increased payload capacities, effective energy harvesting technologies, and simplicity of use, the IoD is a promising technology [12].

However, throughout the previous couple of decades, **Artificial Intelligence (AI)** has been lauded as a hopeful solution to assist in many problems in the **Internet of Things (IoT)** and IoD. **Machine Learning (ML)**, one of the frequently used AI approaches, is the term used to describe the intelligence demonstrated by computers [13]. Additionally, **Deep Learning (DL)** is an enhanced and scalable ML extension that strengthens and facilitates the usage of learning algorithms [14]. As an ML subclass, DL has been extensively utilized to create complicated models using enormous amounts of data in a more basic scenario [15]. These DL-based methods appear promising, but they rely primarily on the availability of enormous volumes of data to predict outcomes [16]. Therefore, it is crucial to understand the significance of datasets in getting results from methods. One of the most popular methods for image classification, DL has been widely used in computer vision studies in conjunction with **Convolutional Neural Networks (CNNs)** [17]. The key benefit of DL is its ability to help with large volumes of data throughout learning [18, 19]. A wide margin might be used to increase accuracy. Information fusion makes it possible to merge many datasets and use them in DL models to improve prediction accuracy [20]. Experts may easily comprehend the outcomes by evaluating and assessing a DL model's predictions because they provide crucial insights into the input data and learned characteristics [23]. Furthermore, edge and fog systems are extremely useful in any pandemic situation. These pieces of equipment aid in the complexity and scalability of infrastructures, making it simpler to cope with challenges [21, 22]. To train models with constrained datasets while overcoming financial and logistical constraints, **transfer learning (TL)** is utilized. Identifying comparable important spatial qualities at the beginning of training from enormous datasets in many fields enables systems to be trained quickly and precisely [23]. Therefore, TL might be a way to combine the required computer power and promote more potent deep learning techniques, which could address several issues [24]. Because of the flexibility and adaptability of IoD systems in a variety of settings and their ability to improve the performance of other communication networks, the IoD has sparked a lot of attention in published studies [25]. IoDs are now increasingly used in various areas owing to technological, tactical, and/or practical advantages, including load transfer (based on the particular cargo application needs), simple deployment and employment, high mobility, real-time monitoring, and coordination [26]. Drones could be utilized in regions or for operations that are either difficult for people to reach or unsafe for humans to execute, improving network connectivity, security, and performance, particularly when paired with several other wireless communication systems [27, 28]. A variety of IoD implementations could be allowed thanks to the vast range of capabilities [29]. Surveillance systems, sport and training, telecommunications, search and rescue, mission-critical services, smart agriculture, stock management, art and creativity, and so on are only a few examples [30].

This paper is a comprehensive and detailed assessment of the use of ML approaches in the IoD realm that considers all of the categories, such as resource management, surveillance and monitoring, object detection, and so on. To provide a comprehensive overview of modern systems that use these technologies, the research emphasized the achievements and variety of applications of IoD utilizing DL-ML approaches. This focus is to improve security and routing, reduce energy consumption, lower delay, and increase accuracy in terms of object detection, monitoring, and so on. Given prior assessments of the numerous ML applications created for the IoD space, this evaluation significantly contributes by focusing on the fascinating study topic. This study employs an SLR to find, analyze, and integrate outcomes from relevant studies. Resource management, surveillance and monitoring, object detection, power control, energy management, mobility management, and security management are the six primary kinds of ML strategies used in the IoD-ML realm. For each category that applied DL-ML methods in this area, we evaluated numerous features such as advantages, obstacles, usages, simulation environments, and security. This article discusses the use of ML approaches in the IoD-UAV area and addresses numerous concerns. We have also gone over future work in detail, highlighting all problems to rectify. Besides, in our paper, we choose to use IoD in general over UAV. In a nutshell, the following are the contributions of this article:

- Providing a thorough examination of the current problems in the ML-IoD area;
- Introducing a systematic overview of the existing strategies for the ML-IoD domain;
- Presenting an explanation of the important issues in the ML-IoD realm;
- Investigating each subcategory that referred to ML-IoD with various properties such as benefits, challenges, used environments, simulations, applications, security, etc.;
- Presenting a thorough examination of state-of-the-art methods;
- Highlighting the critical zones able to develop the mentioned techniques in the future.

The organization of this work is determined by the categories listed below. The next section that follows discusses the fundamental concepts and terminology of IoD. Section 3 looks at the related review papers. Section 4 outlines the research methodology and article selection tools. Section 5 describes the chosen article classes. Section 6 offers the findings and comparisons. Sections 7

Table 1. Abbreviation Table

Abbreviation	Definition	Abbreviation	Definition
ANN	Artificial Neural Networks	**MAC**	Medium Access Control
AI	Artificial Intelligence	**MA-DRL**	Deep Reinforcement Learning with Multi-head Attention Mechanism
D2D	Drone-to-Drone	**MEC**	Mobile Edge Computing
D2X	Drone to Everything	**MDP**	Markov Decision Process
DBM	Deep Boltzmann Machine	**ML**	Machine Learning
CNN	Convolutional Neural Networks	**NN**	Neural Network
DL	Deep Learning	**ObDRL**	Design of an Onboard Deep Q-Network
DQN	Deep Q-Network	**PCSF**	Power Control in Secure FL
FL	Federated Learning	**PPO**	Proximal Policy Optimization
GAP	Generalized Assignment Problem	**PQC**	Post-Quantum Cryptography
HOG	Histogram of Oriented Gradients	**QoE**	Quality of Experience
FANET	Flying Ad-hoc Network	**RNN**	Recurrent Neural Networks
ICN	Information-Centric Networking	**SGD**	Stochastic Gradient Descent
ICT	Information and Communication Technologies	**SORT**	Simple Online and Real-time Tracking
IoD	Internet of Drones	**TPR**	True Positive Rate
IRS	Intelligent Reflective Surface	**UAS**	Unmanned Aircraft Systems
IoDT	Internet of Drone Things	**UAV**	Unmanned Aerial Vehicles
ITS	Intelligent Transportation System	**VCDC**	Velocity Control and Data Capture
LoS	Line-of-sight	**VLC**	Visible Light Communication
LSTM	Long Short-Term Memory	**YOLOv3**	You Only Look Once v3
M2M	Machine to Machine	**ZKP**	Zero-Knowledge Proof

and 8 provide the open problems and conclusion. Table 1 also contains a list of the abbreviations used in the article. In addition, Figure 1 depicts the study's outline.

2 BASIC CONCEPTS AND CORRESPONDING TERMINOLOGIES

This section covers the terms and concepts used in the IoD field.

2.1 Unmanned Aircraft/Aerial Systems (UAS)/Drones

Unmanned Aircraft Systems (UAS) and UAV are interchanged terms [31]. The growth of UAS for numerous applications such as agriculture, military, and industrial surveillance has resulted in major technological breakthroughs to integrate UAS into new sectors and industries, particularly in city areas [32]. UAS, often known as "Drones," is being used in several real-time activities, including wildlife management and monitoring, pollution research, emergency response, earth observation, photography, military surveillance, and linear infrastructure monitoring, including railroads and pipelines [33]. UAS installations are expected to be used for civic, commercial, and scientific purposes shortly. UAS consists of three major parts: (1) an independent or human-operated control system that is highly situated on the ground or embedded in the drone's controller chip to maintain it airborne; (2) a drone; and (3) a command, communication, and control system that connects all types of communications [34].

2.2 Smart Drones

The drone would have its personality. It is indeed versatile, fixable, and deployed; it can analyze a wide range of numbers from any place at any time [35]. It is just a low-cost method of capturing

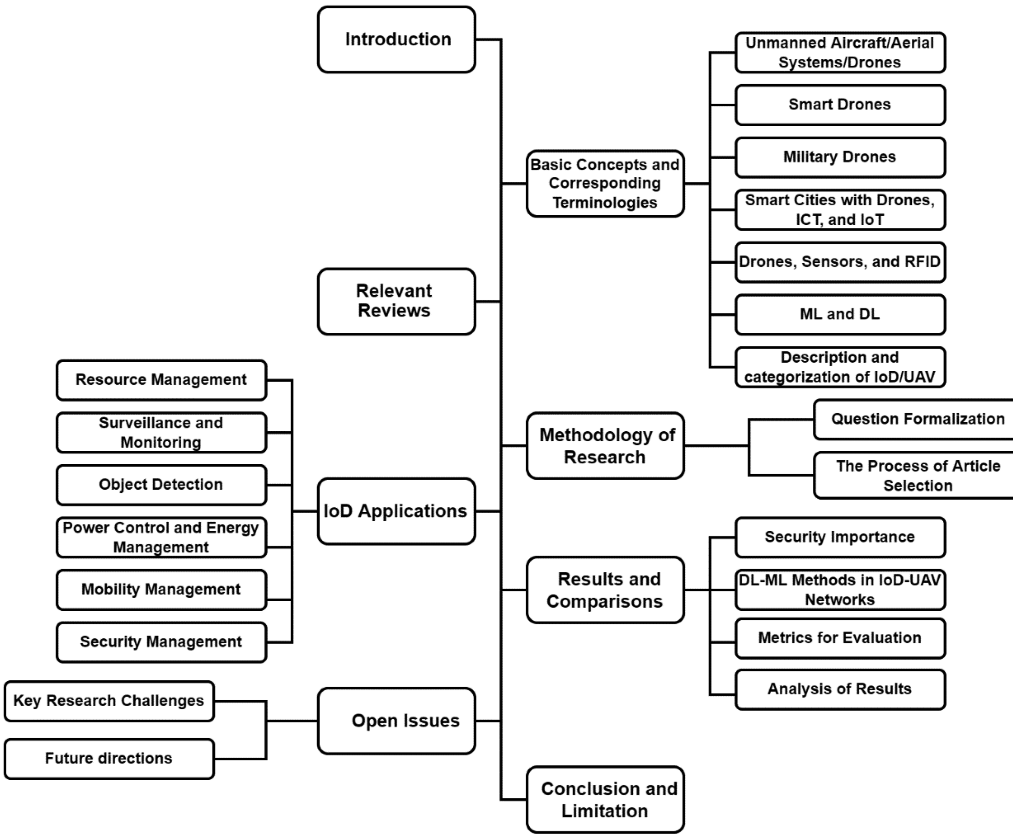

Fig. 1. Overall flow of the study.

and transferring data to smart systems capable of doing critical data analysis, like the real-time image or video analysis [36]. Agriculture, package delivery, insurance inspection, military, rapid aid, law enforcement, disaster recovery, environmental monitoring, and other industries would profit immensely from drone utilization [37]. Thus, drones play an important part in enhancing our lives, social connections, and the quality of life in smart cities [38]. In the following years, the number of drones in the air is projected to increase dramatically. Because of their capacity to accomplish complicated tasks successfully and efficiently in real-time, drones have great potential to enable several apps in the military, civilian, governmental, and commercial sectors [39]. Besides, the drone phenomenon and its possible use for smart cities have been discussed in numerous publications. One of them looked into the connection difficulties surrounding drones in smart cities and how drones may improve smart city applications, including path planning, monitoring, observation, object recognition, distributed processing, navigating, data collecting, and collision avoidance [40]. Moreover, numerous studies have shown how to increase the practicality and effectiveness of drone route planning by increasing the convergence rate and resilience, resulting in a more appropriate flying path [17]. A cluster of drones is represented by a collection of drones that utilizes the **Flying Ad-hoc NETwork (FANET)** innovation to communicate and share data collected with other IoT devices on the ground [41, 42]. Drones could effectively improve the QoS of 5G wireless networks by utilizing their natural abilities, portability, and agility. Drones have also been used to boost wireless coverage and capacity for temporary events like sports, disaster recovery, and criminal detection [43].

2.3 Military Drones

The government has been using drones for a long time; it is considered a world authority in the sector. Even so, its application scenarios are quite distinct [44]. Most of its methodological solutions are beyond the organization's boundaries because they require resources and authority not available in the public/commercial setting, including military frequency bands, or are impractical (high-cost drone components and designs). Alternatively, investigators look for economical solutions for commercial and public subscribers; they do not require access to resources that are not normally accessible [45].

2.4 Smart Cities with Drones, ICT, and IoT

Communication technologies, sensors, software, robots, people, and real-time processing have become part of the **Information and Communication Technologies (ICT)** ecosystem. Some cities, for example, use ICT to preserve a sustainable lifestyle, whereas London uses ICT to manage garbage and guarantee appropriate resource usage [46]. Furthermore, while ICT is critical to the advancement of smart cities, security issues must be addressed due to ICT's intrinsic nature. Drone technology is the IoT's future and is expected to revolutionize IoT development and applications, particularly in smart cities. According to several academics, drones are critical IoT devices [47]. In addition, IoT objects have been employed to improve the potential duties of swarm drones for autonomous collaboration. IoT has a lot of potential to help economic and environmental sustainability, thanks to technological advancements [48]. RFID, sensors, 5G cellular networks, millimeter-wave high-integration on-chip bandpass filters, **Machine to Machine (M2M)** communications, and other hot and green technologies make cities smarter and greener [49–52].

2.5 Drones, Sensors, and RFID

RFID is one of the fascinating wireless communication technologies allowing for the IoT. It also does not require **Line-of-Sight (LoS)** and could quickly convert the real environment into a visual map [45]. There are two kinds of RFID devices: passive and active. RFID is significant in making the world a cleaner place by lowering car emissions, conserving energy, and improving trash disposal, among other things [53]. Green RFID necessitates shrinking RFID tags and developing energy-efficient methods for tag estimation optimization. Several studies looked at how drone and RFID technology could be used to improve drone battery life and defect detection accuracy [54, 55]. Integrating drones and RFID can provide extra data that may be used in supply chain management systems. Also, several works have presented a feasibility analysis of how a multifunctional RFID tag may be recharged utilizing a drone in an environmental monitoring operation [56]. Furthermore, many solutions have been proposed to monitor operations in hostile settings utilizing RFID and a drone. Besides, researchers developed a set of RFID tags that could be fitted with different sensors and dispersed across the surveillance area using a drone-mounted reader. The primary goal of utilizing a drone is to gather data from RFID sensors strewn around the environment by approaching them directly, hovering above them, and downloading measured data [57]. Previous studies suggest that the system is well-coordinated, and tags could be effective monitoring tools, particularly when monitoring a broad region or in a hostile climate [56].

In addition, a sensor node, as previously stated, comprises many tiny sensing devices, processing equipment, power sources, and communication unit(s) [58]. From around the world, sensor nodes are already being installed to monitor global and local environmental circumstances. They have limited power, processing, and storage space, but the **Base Station (BS)** node is quite powerful [59]. Temperature, pressure, sound, humidity, acceleration, and other environmental factors are read by each sensor node. Sensors interact with one another and use ad-hoc technology to

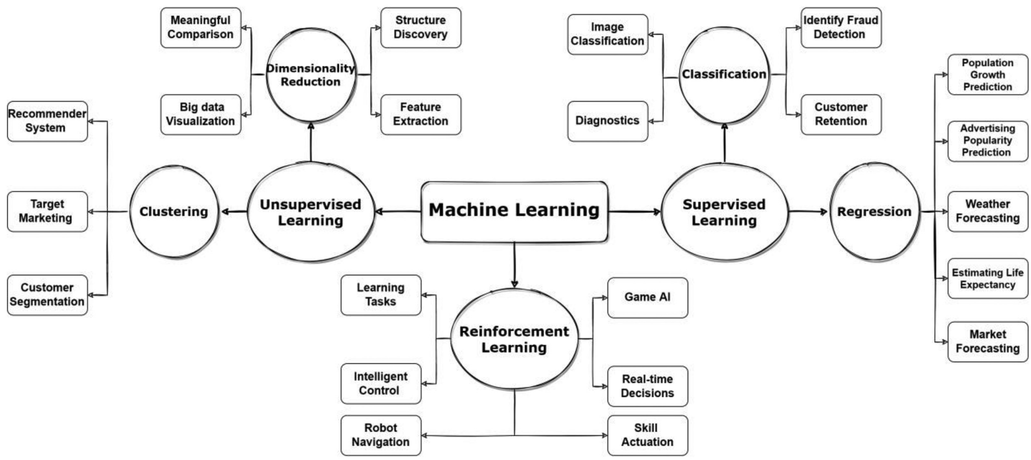

Fig. 2. Various ML techniques and implementations.

send the required sensory data to the BS [60]. Also, WSNs have been utilized in several smart city applications, including fire detection, target tracking, environmental sensing, routing, load balancing, changing military restrictions, machine health control, and industrial process monitoring [61]. The concept of green IoT was born out of the need to save energy by putting sensor nodes in sleep mode for most of their lives [62]. When data transfer happens at ultra-low power, WSNs may be easily implemented. Sensors may gather energy from the sun, vibrations, kinetic energy, temperature differentials, and other natural sources. As a result, green WSN is a developing idea that aims to optimize lifetime and throughput while lowering CO2 emissions. Various studies showed the advancement of the combination of a WSN with a solar-powered drone to increase the drone's flexibility for various uses. Using the integrated system, the CO2 concentration was measured in real-time throughout data gathering. In addition, the integrated system's data was analyzed using the **Particle Swarm Optimization approach (PSO)**. A special integrated system was also used to gather data with minimal power and a broad coverage area [63].

2.6 ML and DL

The development of DL, also known as hierarchical learning, is one of the key achievements of modern AI [64]. Until around the 1990s, traditional ML techniques were used to make inferences and predictions on results [65]. However, it had some flaws, including relying on handcrafted features, limited human-level accuracy, and so on [66]. Handcrafted feature engineering is not necessary in the case of DL; instead, features are extracted during the training phase [67]. Furthermore, with the aid of advanced techniques, modern machine processing resources, and the availability of big datasets, DL allows for more precise classifications and forecasts [68]. The study of object identification and monitoring is one ML-based IoD application where DL techniques are constantly being effectively expanded. Modern scientific research has seen a huge increase in the usage of **Neural Networks (NN)** and DL, both of which can learn from context. Due to their adaptability to many data sources in various domains, these two algorithms have been widely used in multiple applications, including forecast and classification problems, smart homes, image recognition, self-driving vehicles, and the like [69]. Figure 2 depicts many strategies used in ML. DL mimics the human brain's information filtering for correct decision-making [70]. However, DL enables a system to process inputs in a manner resembling the human brain by layering information to enable data prediction and categorization. Similar to the multilayer filters utilized by NNs in the brain, these layers act as input to the following layer [71]. The feedback loop is maintained until the output is identical to the initial output. Each layer is given a set of weights to help it produce an exact output, and these weights are changed as training progresses to ensure accuracy [72].

Supervised, semi-supervised, and unsupervised are the three categories of DL approaches. The supervisory signal, the intended value, uses each known value as an input vector. The process uses existing tags to forecast the labels of the planned output [73]. Traffic signals, spam detection in a file, audio-to-text conversion, face recognition, and other situations can all benefit from the application of classification algorithms that use supervised learning [74]. A strategy that bridges the unsupervised and supervised ML spectrum is semi-supervised learning. Unlabeled values, as well as labeled values, are used as training data in semi-supervised learning. Semi-supervised learning falls somewhere in the middle of supervised and unsupervised learning. Unlabeled data improves learning accuracy dramatically if matched with a slight amount of labeled data [75, 76]. Various conceptual notions concerning DL approaches emerge. The first is that nearby data has the same name. The cluster presumption, which specifies that every data in a cluster has the same name, is the second possibility. The third element is that the data is restricted to a particular dimension rather than being used in its entirety [77]. Unsupervised learning identifies and categorizes the interrelationships between components. These approaches are used in clustering, anomaly detection, and NN. Unsupervised learning is widely used in the security area to discover abnormalities [77]. Most DL approaches use **Artificial Neural Networks (ANN)** for feature extraction and processing. In DL approaches, the term “deep” represents the number of layers required to change the data [78].

2.7 Description and categorization of IoD/UAV

UAVs are flying base stations that are employed in wireless networks to improve capacity and coverage, balance traffic congestion, minimize power consumption and delay, and so on [79, 80]. Using UAVs as a relay to offer communication in real-time circumstances is a cost-effective approach [81]. Before employing UAVs, it is important to understand their various kinds, classifications, and regulatory requirements. UAVs for remote sensing could well be divided into two categories: fixed-wing UAVs and rotary-wing UAVs. **High-Altitude Platform (HAP), Medium-Altitude Platform (MAP)**, and **Low-Altitude Platform (LAP)** are some of the classifications that may be made based on altitude. HAPs could be employed in the stratosphere above an altitude of 18 km. Although LAPs could well be utilized at a length of around 100 m to 2 km, MAPs can indeed be employed at an altitude window of 3 to 9 km. UAVs may be divided into three different classes—small, medium, and large—based on their maximum altitude and range. While big UAVs provide NLoS communications, small and medium UAVs can offer **Line-of-Sight (LoS)** communication [82]. The kind and size of UAVs determine the legal restrictions that apply to them. Use of small UAVs weighing under 250 g is permitted; **No Permission, No Take-Off is not required (NPNT)**. But NPNT compliance is required for medium and large UAVs. UAVs offer ground users the most capacity and coverage when used as relays. UAVs have superior connectivity quality since they are more likely to establish LoS contact linkages across short distances. Owing to its advantages, UAV-assisted systems have become a very interactive method of giving ground users versatile and affordable communication. UAVs may be used in any battle situation where human involvement is extremely dangerous. UAVs are widely used in both commercial and military applications. However, a portion of these modern smart UAVs is employed for services like emergency management, urban areas, disease control, smart cities, industry 4.0, warehousing, and public safety that are delivered from the air [83]. Figure 3 depicts the classification of UAVs according to their size, altitude, range, endurance, and legal status.

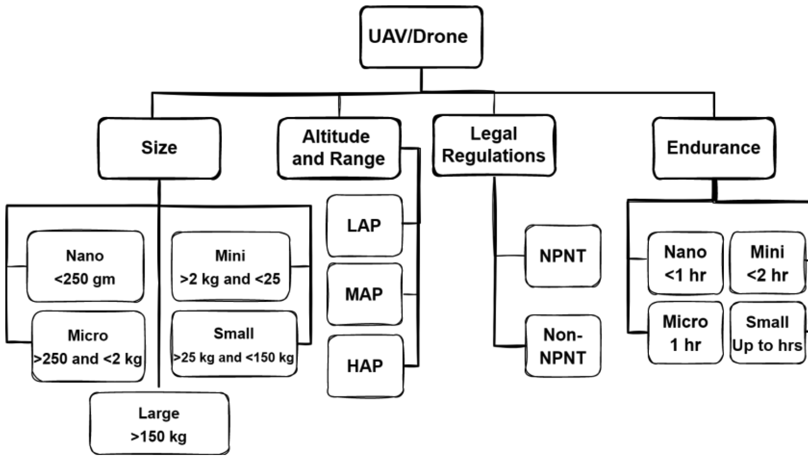

Fig. 3. UAV classification based on size, altitude, endurance, and road regulations.

3 RELEVANT REVIEWS

This section's primary objective is to review some existing survey studies on ML-IoD and related topics. Its goal is to properly emphasize the current work's major results in comparison to what is currently accessible in the research. The drone sector and the number of drones are fast expanding, thanks to advances in science and technology. Drone-related issues, on the other hand, have piqued academics' interest. In addition, the IoD is a hierarchical network control framework designed to govern drone accessibility to controlled airspace and provide navigation services among nodes. So, Boccadoro et al. [84] offered a comprehensive summary of the IoD networking architecture study. For this purpose, the existing scientific literature is thoroughly examined and classified to identify current research trends. At the first level of analysis, their recommended classification scheme maintains the Internet protocol stack from the physical layer to the application layer without ignoring cross-layer techniques. The papers have been further categorized and characterized at a finer description level for each stack tier using the developed model. While detailing the threats to IoD dissemination, their paper also discussed existing unresolved topics to suggest future research areas.

Also, Nayyar et al. [85] addressed the common jargon related to the IoDT, real-time applications, innovations enabling IoDT, comparisons to unmanned aerial vehicles (UAVs), and substantial security risks, all of which are essential study aspects for investigators aiming to secure IoDT for application in the future. The study report includes two important real-world case studies involving IoDT executions in smart agriculture and smart cities. Also, Kumar discussed new research on attacks, satellites, quantum drones, architectures, methods, and elements of quantum and **Post-Quantum Cryptography (PQC)**. They checked out recent research directions, difficulties, limits, and future implications in various fields. Their study was beneficial in exploring the many paths in the quantum sector, as quantum computing and related elements were predicted to have enormous promise shortly. Therefore, their study covered quantum drones, methods, satellites, architectures, IoDs, a constellation of satellites, long-distance communication, attacks on communication and quantum networks, and PQC features. Although quantum computing was not a new field, many concepts, including quantum drones, networks, satellites, and communication, were still in the early stages of development.

In addition, Abdelmaboud [86] outlined the requirements of privacy, security, and communications and the classification of IoD depending on the most important aspects. They also covered the most prevalent business case studies, recent breakthroughs, and strategies for IoD contexts. Finally, they talked about the IoD's issues and research prospects in the future. The paper offered a taxonomy of the IoD based on the most critical points of view. They included the most prevalent business cases and the most up-to-date IoD approaches. Finally, they addressed issues IoD deals with and guide future research. In addition, Yahuza et al. [87] discussed recent privacy and security trends affecting the IoD network. They looked into the various drone classes' privacy and security issues levels. They discussed the necessity for a secure IoD architecture and provided a recommendation. They also provided a thorough taxonomy of IoD network attacks. They also checked out some of the most recent IoD attack mitigation solutions. They detailed the methods for evaluating performance and the metrics used by the procedures. Lastly, they suggested some studies for the future to assist researchers in identifying the most recent opportunities in IoD research. In addition, Alsamhi et al. [88] gave an overview of the concept of various ML approaches in robotics communication. They looked at how machine learning techniques have been used to improve robot communication based on connectivity, quality of service, mobility, and effective data collection factors to improve the robot execution of complex jobs in a collaborative assembly. They also discovered that ML plays a critical role in boosting robots' abilities to make robots smarter to do jobs successfully and efficiently and collaborate with people. They provided brief research problems, directions, outstanding concerns, and analyses to improve the communication criteria of robots.

Alqurashi et al. [89] presented theoretical foundations for ML models and algorithms for IoUAV applications, recent related works, and future directions. They thoroughly analyzed IoUAV and UAVs interacting with and working with the environment. Additional impairment difficulties that are also highlighted are faced by applications connected to smart UAV and IoUAV systems. They discussed ML methods that allow unmanned devices to behave intelligently. Also, they offered a broad discussion about methods and future challenges. Also, to improve various designs and functional aspects such as channel modeling, resource management, location, and security, and the like [85] evaluated all relevant research works thoroughly. These studies applied ML approaches to UAV-based communications. Their article explores various UAV-enhanced wireless communication concerns, including wireless security and public safety applications, physical layer and resource management issues, trajectory design, and caching. They addressed unresolved problems in networking and security, which encouraged more investigation into the use of AI/ML in UAV-based networks.

Wang et al. [90] discussed supervised learning, unsupervised learning, reinforcement learning, and ML while reviewing the thirty-year history of the field. They also looked into their use in appealing wireless network applications, such as heterogeneous networks, cognitive radios, the IoT, **Machine to Machine (M2M)**, and others. They sought to help the readers understand the rationale and technique behind the various ML algorithms so they might use them for as-yet undiscovered applications as well as hypothetical future wireless network situations. Additionally, it was discovered during the evaluation of these papers that none of them used the SLR strategy and that none of the ML-IoD articles included all classifications necessary for analyzing DL-ML techniques. Also, according to the findings, most of the abovementioned reviews either focused on a certain component of the ML-IoD realm or described a specific type of data collection. Furthermore, the majority of these surveys included no comparative analysis and only examined fewer than 20 papers, including a significant amount of non-peer-reviewed research. This paper focuses on peer-reviewed publications that propose ML applications for the IoD area, including resource management, surveillance and monitoring, object detection, power control, energy management, mobility management, and security management. As a result, we take a slightly different approach than the majority of articles. Table 2 also includes a summary of related works. Also, the research methodology will be described in the following section.

Table 2. Compilation of Relevant Works

Authors	Main idea	Advantage	Disadvantage
Boccadoro et al. [84]	Defining the numerous elements of IoD and providing an IoD environment classification technique.	• An in-depth description of future work. • Challenges and potential guidance are discussed.	• The article selection process is not clear. • There is no comparison between the articles.
Nayyar et al. [85]	Giving a conceptual presentation of new terms, such as IoDT, and associated technologies.	• Discussion is completely dissected.	• The article selection process is not clear. • Future work is not being discussed.
Kumar et al. [91]	Giving an overview of quantum drones and networks' existing state of knowledge.	• A comparative analysis of works is offered.	• The article selection process is not clear. • There is no discussion of future work in detail. • Some DL applications in ML-UAV are overlooked.
Abdelmaboud [86]	Investigating the IoD's most important requirements.	• Examine the most common IoD commercial case studies. • Address the IoD's open challenges and future research.	• There is no comparison between the articles. • The article selection process is not clear.
Yahuza et al. [87]	Investigating the current privacy and security problems affecting IoD networks in-depth.	• Address the security and privacy IoD's open challenges and future research areas.	• The article selection process is not clear. • There is no comparison between the articles.
Alsamhi et al. [88]	Evaluating the confluence of ML and communication for collaborative assembly of robots working in space, on land, and underwater.	• The techniques have been categorized.	• The article selection process is not clear. • There is no comparison between the articles.
Alqurashi et al. [89]	Demonstrating the theoretical background of ML models and IoUAV methods.	• A thorough examination of the methods.	• There is no comparison between the articles.
Bithas et al. [92]	Highlighting AI/ML approaches from all conceivable categories and their use in UAV networks.	• Future work is being discussed. • Considering several aspects of the techniques.	• The article selection process is not clear.
Wang et al. [90]	Discussing supervised learning, unsupervised learning, and reinforcement learning in the context of ML's thirty-year history.	• Future work is being discussed. • A thorough examination of the methods.	• The article selection process is not clear. • Some DL applications in ML-UAV are overlooked.
Our work	Providing a complete and in-depth evaluation of the usage of ML-DL methods in the IoD-UAV domain.	• The article selection process is clear. • Future work is being discussed. • A thorough examination of the methods.	• Privacy and ethical concerns are not addressed.

4 METHODOLOGY OF RESEARCH

We reviewed relevant reviews that, in some manner, examined ML-IoD techniques in the previous section. This section applies the SLR [93, 94] approach to further comprehend the IoD domain. The SLR is a thorough analysis of all studies conducted on a particular topic [95, 96]. This section finishes a thorough analysis of the application of DL techniques in the IoD field. The validity of the study selection techniques is next looked into. The subsections also provide more information on the search strategy, including the selection criteria and research questions.

4.1 Question Formalization

The basic goals of the study are to identify, discriminate, analyze, and assess all key articles in the IoD arena of ML applications. An SLR could be used to study the elements and characteristics of methods for achieving the previously mentioned goals. SLR also aims to get a deeper knowledge of this business's critical difficulties and issues. The following are some of the **Research Questions (RQs)** that have been defined:

✓ **RQ 1**: How can DL and ML approaches in the IoD and UAV domains be categorized? What are some of their specific examples?
Section 5 *contains the answer to this question.*

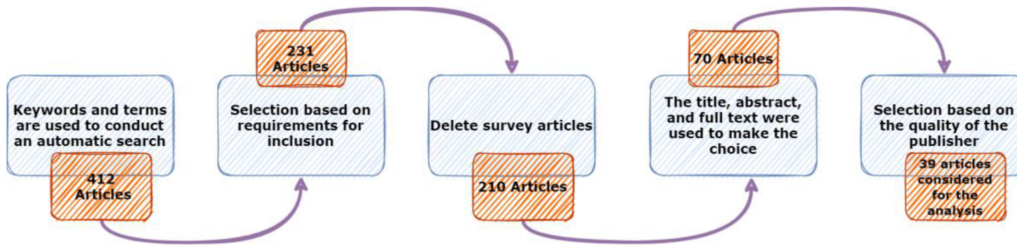

Fig. 4. The phases of the article searching and selection process.

Table 3. Search Terms and Keywords

S#	Search Terms and Keywords
S1	"Deep learning" and "IoD"
S2	"Machine learning" and "Internet of Drones"
S3	"Deep learning" and "UAV"
S4	"Neural network" and "Unmanned Aerial Viechels"
S5	"AI methods IoD" or "Artificial intelligence UAV"
S6	"Deep learning" and "Drones"
S7	"IoDT" and "UAV"
S8	"UAV networks"

✓ **RQ 2**: What methods do the researchers use to conduct their research?
Sections 5.1 *through 5.7 provide answers to this question.*

✓ **RQ 3**: What implications can be drawn from the statistics concerning the papers that have been reviewed? What factors drew the most attention in the articles? What are the most common ML-IoD applications?
Section 6 *contains the answer to this question.*

✓ **RQ 4**: What are the untapped future directions in this domain?
Section 7 provides answers to this query.

4.2 The Process of Article Selection

This study's article search and selection method is divided into four stages. Figure 4 illustrates these categories. In the first phase, the phrases and keywords utilized to search the papers are shown in Table 3. An electronic database search led to the discovery of the papers in this collection. Journals, conference papers, books, chapters, notes, technical studies, and special issues were also discovered. The first stage resulted in 412 articles being delivered.

The ultimate number of papers to study is determined in Stage 2 through two processes. The articles are initially evaluated (stage 2.1) using our criteria. There are currently 231 papers left. Besides, stage 2.2 excludes review papers; at the previous stage, 21 (or 10 percent) of the remaining 231 articles were review articles. IEEE publishes the majority of research publications (25.2 percent). Springer and Elsevier publish the majority of review papers (5.54 percent). There are currently 210 articles available. In Stage 3, the titles and abstracts of the papers were reviewed. The papers' methodology, assessment, discussion, and conclusion have been double-checked to ensure that they are relevant to the study. At this time, 70 papers have been selected for further review. Finally, 39 papers were picked to review and examine the other publications since they matched the tight criteria. The majority of the selected papers are published by IEEE (51.3 percent, 20 articles). Hindawi and Tech Science Press have the lowest number (2.6 percent, one article).

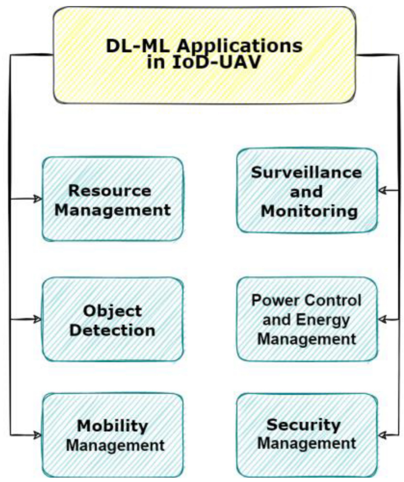

Fig. 5. The proposed taxonomy of ML-IoD applications, which separated six distinct methods.

Also, the number of publications published in 2021 is more than in 2020, with 21 papers. The IEEE Internet of Things Journal publishes the most papers (12.82 percent, five articles). Also, in the following part, the ML-IoD mechanism is explored in-depth, and its properties are discussed.

5 IOD APPLICATIONS

In Section 4, we explored how we choose articles and the factors that are significant to us, and then we listed the articles selected and appraised based on their merits. This section addresses the ML applications that can be used to solve a wide range of issues and problems in the IoD-UAV realms. This section will discuss thirty-nine papers that meet our selection criteria. First, we categorize the techniques into six groups based on their intended application: The proposed taxonomy of ML-IoD techniques is shown in Figure 5, including resource management, surveillance and monitoring, object detection, power control, energy management, mobility management, and security management.

5.1 Resource Management

The structure of the IoD network and the dispersion of resource access demands fluctuate rapidly over time due to the numerous uses and high mobility of drones, leading to time-varying resource requirements from drones in the service domain. Assigning suitable quantities of the spectrum, processing, and caching resources to each resource access demand to fulfill the QoS needs of offloaded workloads and multi-dimensional resource management are some of the resource management tasks. So, Koubâa et al. [97] proposed a compute offloading design methodology for Internet-connected drones. Furthermore, they undertook a detailed practical investigation to compare the performance of the compute offloading strategy with the edge computing method of DL applications in the environment of UAVs in terms of energy, bandwidth, and latency. Their method was a cloud-based IoD framework that enables users with a continuous Internet connection to drones and enabled drones to offload DL computing to the cloud for real-time analysis of acquired visual data. They specifically explored the tradeoff between computation and communication costs of alternative techniques. The outcomes illustrated that the computation offloading technique enabled us to deliver significantly better throughput than the edge computing method, notwithstanding the longer connection latency.

Yang et al. [98] created a multi-UAV-assisted MEC system where many UAVs act as MEC nodes to provide computational offloading services for terrestrial IoT gadgets with limited local computational capacity. A differential evolution-based multi-UAV deployment technique was provided to balance the burden on UAVs. The accessibility issue was described as a **Generalized Assignment Problem (GAP)**, which was then solved using a near-optimal approach. They might load balance these drones while keeping coverage constraints and meeting the **Quality of Service (QoS)** of IoT nodes. Besides, for work scheduling in a given UAV, a **Deep Reinforcement Learning (DRL)** algorithm was devised, which improved task implementation effectiveness in each UAV. Eventually, the outcomes revealed that their proposed load balance-focused UAV deployment approach and the task scheduling algorithm were possible and superior.

Besides, Su et al. [99] presented a regression model that used the **Recurrent Neural Networks (RNN)** and the attention mechanism. Their approach could properly compute the likelihood of buffer starvation and the particular distribution of starvation events in every condition throughout the video streaming transmission process, i.e., buffer starvation behavior could be assessed and studied at the packet level. They presented a reinforcement learning approach that included an intrinsic incentive system to intelligently plan the transmission of video streams after acquiring the hunger probability distribution. Their technique was capable of maximizing long-term cumulative **Quality of Experience (QoE)** by dynamically changing the start-up time and data packet prefetching technique in the face of random noise. It was also extremely adaptable to a variety of network conditions. In the 5G-powered UAV video streaming transmission scenario, the efficacy of the technique described in this research was verified. Their approach was demonstrated to be able to consistently enhance the quality of video transmission service in a complicated wireless network environment, which opened up new avenues for 5G low-latency research.

Moreover, Wei et al. [100] proposed a DRL-based approach combining interactive exploration with **Prioritized Experience Replay (PER)**. Their distributed exploring approach allowed drones to learn cost-effective offloading policies jointly, resulting in a flexible learning strategy in the event of a UAV failure. Additionally, PER enabled drones to investigate transitions with a large TD error, potentially improving dynamic UAV mobility patterns performance. By evaluating the suggested approach to current compute offloading techniques, the findings showed that the proposed technique surpassed the comparable techniques in terms of convergence rate, energy-task efficiency, and average processing time.

Also, Al-Hilo et al. [101] offered a UAV caching-based approach in which the UAV assisted vehicle users in downloading requested content while fetching stuff for its cache from identical vehicles. The suggested approach also took into account the UAV's limited energy supply and sought to strike a balance between traffic offloading and energy usage. The issue of UAV trajectory, radio resources, and caching replacement was then mathematically formulated as an optimization problem to identify a suitable trajectory that maximized the UAV's energy efficiency. They demonstrated UAV-assisted content delivery in VANETs without the need for an internet connection. The mathematically described system model was easily solved utilizing the **Proximal Policy Optimization (PPO)**-DRL technique with two proposed algorithms. The solution approach was compared to other baseline methods to determine its adequacy. The findings showed that even UAVs without internet access could help serve content to automobiles by taking the opportunity to collect content from approaching vehicles.

Yang et al. [102] provided DL-enabled visual target tracking for UAVs. Owing to the restricted computing resources budget of tiny UAVs, a unique implementation of a trained CNN model for target recognition was used, in which the lower layers of the CNN were distributed on the UAV. At the same time, the higher levels were installed at the MEC server. This system satisfied the demand for quick video image analysis while considering practical social restrictions. When the picture quality was good, the lower layers of the CNN could give enough features to allow for satisfactory tracking efficiency; only local calculations on the UAV were required. Also, the poor picture quality would necessitate further processing at the MEC server using the CNN's upper layers. In this regard, their study proposed an offloading methodology to solve the tradeoff between delay and energy usage, bearing in mind numerous real-world restrictions, including changing picture quality, UAV-MEC server communications bandwidth, and resource sharing among multiple UAVs. The statistical results helped them gain valuable insights into MEC-assisted UAV tracking in a realistic setting.

Plus, Li et al. [103] looked at a UAV-assisted IoT network's integrated flight cruise control and data collecting schedule. The flight resource assignment was developed as a **Markov Decision Process (MDP)** to avoid data loss because of buffer overflows at IoT nodes and fading airborne channels. Given the enormous state and action spaces, it was suggested that the onboard **Deep Q-Network (DQN)** be used to identify the IoT item for data collection, establish the instantaneous waypoints for aircraft cruise control, and transmit the power of the chosen IoT object. To speed up the training of the onboard DQN, the UAV's probable following waypoints in the action space were decreased even further by the limited heading direction and maximum cruising speed. Additionally, the suggested technique was built utilizing the Keras DL package and Google TensorFlow. The results showed that the UAV's trajectories might be adequately trained to minimize the loss function by increasing the learning iterations.

Finally, in an "air-to-ground" intelligent software collecting system, Zhang et al. [104] developed a solution for the UAV-based data collection approach. The novel aspect of this study was that, after employing IoT nodes to finish the data collecting process using the suggested bandwidth-weighted traffic-pushing optimization method, the model inferred future changes based on the existing network state via a DQN. The entire network could then "forward look" the uploaded information to possibly idle nodes in the potential by creating the suggested air-to-ground intelligent information pushing optimization method, resulting in optimal system performance. They demonstrated the optimality of their suggested routing algorithm and forwarding strategy through the final mathematical simulations that were more relevant in the dynamic "air-to-ground" dispersed data collecting system than other benchmark solutions.

Table 4 discusses the resource management applications used in IoD and their properties.

5.2 Surveillance and Monitoring

Drones are viewed as a smart city element that offers citizens smart mobility and surveillance. IoDs are equipped with various sensors that, when combined, could support a wide range of applications. A drone, for example, has orientation, time-of-flight, ranging and radio detection, light-pulse distance, magnetic-field change, and chemical and thermal sensors. It can be controlled remotely and can move independently without the requirement for human interaction in some cases. Drones are utilized in multiple civilian surveillance applications such as firefighting, remote sensing, air traffic control, package delivery, monitoring, and infrastructure inspection. Small-scale drones will also operate in low-altitude skies, providing a range of services.

Al-Sa'd et al. [105] provided a first step toward creating a database of RF signals from numerous drones in various flying modes. They captured, analyzed, and recorded raw RF data from various drones across multiple flight modes such as off, on, connected, flying, hovering, and video capturing. Three DNNs were implemented to determine a drone's existence, location, kind, presence, type, and flying mode. So every DNN's system was assessed using only a 10-fold cross-validation method and several metrics. The classification results revealed a general drop in performance whenever the number of classes increased. The average accuracy dropped from 99.7 percent for the first DNN (two classes) to 84.5 percent for the second DNN (four classes),

Table 4. The Methods, Properties, and Features of ML-Resource Management Mechanisms

Authors	Main idea	Advantages	Research challenges	Simulation environment	Method	Application	Environ-ment
Koubâa et al. [97]	Presenting an architecture that allows drones to transfer DL computation to the cloud.	-Low energy consumption	-High delay -Low security	Python OpenCV library	CNN	Providing wireless coverage	IoD-cloud
Yang et al. [98]	Intending to build a multi-UAV-assisted MEC system to achieve global load balancing.	-Load balancing -Low complexity -Low delay	-High energy consumption	Python	Q-learning	Data management	IoD-UAV
Su et al. [99]	Presenting a DNN that returns the probability distribution of buffer starvation.	-High robustness -Appropriate for complex situations	-High energy consumption -High delay	Python	RNN+Q-learning	Video streaming scheduling	UAV-5G
Wei et al. [100]	Proposing a multi-UAV-MEC network to enhance energy-task efficiency and minimize average processing time.	-Fast convergence -Average processing time	During the computation offloading, privacy and robustness are not taken into account.	Pytorch	Q-learning	Providing wireless coverage	Multi-UAV-MEC network
Al-Hilo et al. [101]	Delivering content on VANETs with the use of UAVs.	-Moderate convergency	-Low mobility	PyTorch	Q-learning	Providing wireless coverage	UAV-IoT
Yang et al. [102]	Suggesting edge offloading for DL-enabled target tracking.	-Low delay	-Task failure is not considered	TensorFlow	CNN	Providing wireless coverage	IoT-UAV
Li et al. [103]	Using the DQN to improve the online flight cruise control and data collection schedule.	-Low pocket loss rate	-Poor scalability -Security and privacy are not taken into consideration.	Keras DL library with Google TensorFlow	DQN	Data collection	IoT-UAV
Zhang et al. [104]	Using the intelligent DQL system in a UAV patrolling environment.	-Low energy consumption -High reliability	-High delay	Not mentioned	Q-learning	Providing wireless coverage	IoT-UAV

and finally to 46.8 percent for the third DNN (10-classes). Nonetheless, the suggested techniques' findings demonstrated the viability of the created drone RF database for identification and detection.

Also, Meng et al. [106] demonstrated an underwater drone with fisheye lenses and took panoramic photographs using an image-generating algorithm and a 360-degree panoramic camera. The underwater drone and 360-degree panoramic image production were created using open-source software; the compute components were enhanced using a Raspberry Pi compute module. They built an underwater drone that operated automatically and tested it in a lake. The 360-degree panorama photos were appropriately created. With AlexNet and GoogLeNet, practically all fish species were recognized with more than an 85% recognition rate (AlexNet achieved 87 percent). The time it took to recognize 115 photos was 6 seconds. As a result, AlexNet could be employed in a real-time application with great precision.

Hernández et al. [107] proposed a DL-based pipeline for identifying flood-related drone-based photos. They developed a DL-based auto-encoder to emphasize the essential elements of the drone photographs. The characteristics were then decreased and clustered to aid natural disaster first responders in dealing with big datasets. They tested the DL-based pipeline in multiple low-power GPU-based edge computing platforms to see if it would be a viable alternative to the primary goal of producing a DL-based autonomous drone for emergency circumstances. However, they determined that intelligent autonomous drone technology would be a game-changer in the fight against climate change.

Besides, Dasgupta et al. [108] demonstrated a WSN and DL methodology for crop forecast and weed monitoring. The model Naïve Bayes method was employed in their study for crop recommendation based on many parameters identified by WSN sensor nodes, resulting in an accuracy of 89.29 percent. It was better than several other algorithms described in the article, such as regression or DQN. The use of a neural network in DL identified weeds in a specific area of crop development, providing farmers with an extra preventive measure. The complete application created for farmers minimized physical labor and time spent on various agricultural operations, enhanced total land production, lowered the risk of losses due to crop failure in a specific soil, and reduced the risk of weed damage to crops.

Ghazal et al. [110] suggested an edge-fog-cloud architecture with mobile IoT edge nodes carried by autonomous robots for thermal anomaly detection in aluminum plants. They employed companion drones as fog nodes to provide first-responder services and a cloud backend to analyze thermal abnormalities. A self-driving DL framework and a thermal anomalies detection and visualization method were also proposed. They also offered a self-driving DL architecture and a method to detect and visualize temperature abnormalities. Compared to human surveyors or stationary IoT nodes monitoring the same industrial region, the results revealed that their robot surveyors were less expensive, had faster reaction time, and correctly identified anomalies. Their self-driving architecture had a root mean square error of 0.19, equivalent to VGG-19, but with considerably less complexity and 60 frames per second frame rate, which was three times that of VGG-19. While adjusting to varied resolutions and camera frame rates, its thermal to visual registration technique maximized mutual information in the image-gradient domain.

In addition, Madasamy et al. [111] presented a unique **Deep You Only Look Once (deep YOLO V3)** method to identify the multi-object. It utilized a regression-based approach to find items using a probabilistic model. They built 106 convolution layers containing two completely linked layers and 812*812*3 input size to identify drones of tiny size. They pre-trained the convolution layers at half the resolution for classification and then doubled it for detection. Each layer's number of filters would be set to 16. The last scale layer had more than 16 filters to increase the identification of tiny objects. This design incorporated up-sampling techniques to enhance unwanted spectral pictures into the current signal, rescaling certain characteristics. This YOLO design was chosen since it took into account fewer memory resources and computed costs instead of a larger number of filters. The suggested system was developed and taught to execute a single type of class termed drone, with the embedded system-based deep YOLO used for object recognition and tracking. The suggested YOLO method forecast multiple bounding boxes per grid cell more accurately. The model was tested on a large number of tiny drones in multiple environments, including open fields and a maritime setting with a complicated environment.

Finally, Barnawi et al. [109] suggested employing onboard heat sensors to capture raw data via an IoT-UAV-based system. Depending on the temperature measured, the thermal picture produced by the thermal camera was utilized to determine the possible persons in the image of a huge crowd in a metropolis with COVID-19. An effective hybrid technique for face detection and recognition system was presented to recognize persons in infrared pictures recorded in a real-time situation with high body temperature. A face mask detection system was also included, identifying whether or not a person is wearing a mask on their face. Furthermore, their strategy used the face characteristics acquired by the UAV to track the patients. A real-time alert was provided to the personal mobile app location where the user had registered when a suspicious patient was identified. With this warning, appropriate steps might be taken to follow and isolate the patient and recommend seeing a doctor. The scheme's performance was assessed using various ML and DL classifiers. The suggested system had an average accuracy of 99.5 percent using different performance assessment measures, showing its practical application in real-time settings. Also, Table 5 discusses the surveillance and monitoring applications used in IoD and their properties.

Table 5. The Methods, Properties, and Features of ML Surveillance and Monitoring Mechanisms

Authors	Main idea	Advantages	Research challenges	Simulation environment	Method	Application	Environment
Al-Sa'd et al. [105]	Creating a database for DNN-based drone detection and identification system.	-Moderate accuracy -High scalability	-High complexity -Security is not considered	Python using Keras	DNN	Real-time monitoring	IoD
Meng et al. [106]	Developing a DL-based technique for fish recognition.	-Attained an accuracy of 87 %	-High energy consumption -Low reliability	OpenSCAD	CNN	Real-time monitoring	IoD
Hernández et al. [107]	Proposing a DL-based pipeline for analyzing drone-captured natural disaster photos.	-Low energy consumption -High scalability -Low delay	-Low robustness -Low reliability	Scikit-learn Python	Stochastic Neighbor Embedding+Au to-encoder	Monitoring and surveillance	IoT-IoD
Dasgupta et al. [108]	Presenting a model for crop prediction and weed monitoring.	-High accuracy	-Low reliability -High complexity -High energy consumption	NLTK Python Library	The Naïve Bayes algorithm	Precision agriculture	IoD-WSN
Ghazal et al. [110]	Proposing a hybrid architecture for autonomous thermal anomaly monitoring.	-Low complexity -Moderate response time	-Poor scalability	Python	CNN	Civil infrastructure inspection	IoT-IoD
Madasamy et al. [111]	Proposing a YOLO V3 to detect small objects.	-High accuracy	-The model is unable to identify things of greater size.	Python	Deep YoLo CNN	Surveillance and monitoring	UAV-IoD
Barnawi et al. [109]	Using the DL method for thermal and conventional cameras placed on the UAV.	-99.5 % accuracy was achieved on average.	-Security concerns are ignored.	DLIB	CNN	Real-time monitoring	UAV-IoT

5.3 Object Detection

In computer vision, object detection is one of the main principles of picture processing. The IoD-UAV captured a unique object detection situation in this image. Typically, these photos hold several little target data. Using an NN to recognize objects is an effective way to evaluate visual data. Thus, IoDs have many applications in geophysical research, disaster monitoring, and urban management. The superior small object detection technique broadens the scope of IoD applications. So, Wang et al. [112] proposed a joint-learning segmentation scheme that combines the **Conditional Random Field (CRF)** model with an improved U-net model to improve the accuracy of IoD object segmentation. It uses the enhanced U-net model as the joint-learning framework's front-end model for feature fusion and the CRF model as the joint-learning framework's backend model for transforming to gradient-optimization-based RNNs. The findings demonstrate that the efficacy of ground object segmentation has increased to 86.1 percent, which would be a remarkable development. The technique works well in the segmentation task for IoD-based remote sensing, which could also aid in the IoD's achievement of wide-area intelligent monitoring in an innovative city system.

Genc et al. [113] investigated a cognitive drone system, also known as a UAV domain, to measure the power and performance of cognitive apps on these new mobile devices. They looked at the Follow the Leader application, which intelligently identifies, detects, and follows a moving human target. The application's most computationally intensive kernel was object identification, an ML activity. They chose two CNN multiclass object detectors—Faster R-CNN and YOLO—that were trained end-to-end from raw image pixels and two single-class object detectors—Haar cascade classifiers and **Histogram of Oriented Gradients (HOG)** detectors. They utilized the Python implementation together with the pre-trained model for Faster R-CNN. They stated that completing fundamental computer vision tasks such as object recognition was necessary for developing new and intelligent applications like sports photography and package delivery. Finally, they showed how typical software-level optimizations like picture downsampling and lossy compression might exchange minor accuracy losses for large performance and energy efficiency gains.

Also, Li et al. [116] proposed an object identification model with global context cross YOLO-GCC to recognize small-sized traffic components in UAV picture sequences. The notion of asymmetric convolution was introduced to improve the object detection model's resilience. In addition, a global context attention module was introduced to extract more efficient features for real-time performance, boosting tiny object identification accuracy. The suggested model's efficacy was demonstrated by assessing and comparing different UAV datasets. The suggested YOLO-GCC model improved the standard GCNet and YOLOv3 architecture for object detection. The YOLOv3 and GCNet networks were integrated into the YOLO-GCC architecture using GC DarkNet as the backbone. To improve detection outcomes, the multi-layer feature maps and anchors were removed. The experimental outcomes showed that the suggested method might effectively relieve traffic congestion more than previous techniques.

Tian et al. [114] presented a dual NN technique to detect tiny targets that rapidly screen the missed targets in one-stage by categorizing the secondary characteristics of the suspected target areas. To begin, the one-stage detector detected UAV pictures, resulting in confidence greater than or equal to the threshold being recognized as the target. Areas with a result less than the threshold were suspected of harboring missed targets. Second, the VGG backbone extracted the feature map of the UAV picture. For secondary identification, the feature map and the location information of the suspicious regions were merged. The dual network's features were then late fusion, and the re-identified results were used to guide the first confidence addition. Areas with a confidence level greater than the threshold were designated targets after the addition. They combined first and secondary identification targets to acquire the final detection results. Their approach reached breakthrough performance according to experimental results on the VisDrone, UAVDT, and MS-COCO datasets.

Finally, Pawełczyk and Wojtyra [115] provided an object detection dataset specifically created to train computer vision-based object detection ML methods for the task of binary object detection. It could allow automated, industrial automation camera-based detection of multiple drone objects by means of a camera feed. The collection added a diverse array of drone photos to current multiclass image classification and object detection datasets like ImageNet, MS-COCO, PASCAL VOC, and anti-UAV. Furthermore, semi-automated labeling was developed, tested, and found very beneficial for object detection applications. They considered various object detection methods to see if a large-scale drone detection system based on ML methods was feasible in the long run. Compared to the DNN model, HaarCascade could be utilized as a minimum viable product model with mediocre performance, but it failed to scale up adequately for a larger dataset. Also, Table 6 discusses the object detection applications used in IoD and their properties.

5.4 Power Control and Energy Management

Drones are used as IoT devices to collect data such as air pollution levels and traffic conditions over numerous points of interest and have been tested in multiple applications, including object tracking and traffic surveillance. Due to the restricted battery capacity of drones, energy-efficient solutions in IoD systems are essential. Meanwhile, fluctuating wireless channel conditions may impact user QoS when a drone soars through the air. One solution to these problems is power control, which adapts to changing channel conditions while controlling energy usage.

Also, ML could be utilized to supply numerous services in fog-aided IoD, where vast training data was gathered by drones and evaluated in the fog node. For this purpose, to combat eavesdroppers, Yao and Ansari [117] developed secure **Federated Learning (FL)** on fog-aided IoD networks. The convergence of the FL was studied and established. They looked into the wireless transmission power regulation issue to maximize the system security while keeping the FL training duration and drone battery capacities in mind. To maximize the wireless transmission power of each drone, a

Table 6. The Methods, Properties, and Features of ML-Object Detection Mechanisms

Authors	Main idea	Advantages	Research challenges	Simulation environment	Method	Application	Environment
Wang et al. [112]	Creating a joint-learning segmentation scheme that integrates the CRF model and an improved U-net model.	-The ground object segmentation accuracy increased to 86.1 percent.	-High delay	Tensorflow	RNN	Remote sensing	IoD
Genc et al. [113]	Using micro UAVs to investigate ultra-low-power computing.	-Low energy usage	-Low security -Low robustness	Caffe	CNN	Remote sensing	IoT-IoD
Li et al. [116]	Using the DQN technique for detecting tiny traffic components in UAV pictures.	-High convergence speed -High stability	-Security and privacy are not taken into consideration.	(Simulation of Urban Mobility (SUMO)	CNN+DQN	Small object detection	UAV
Tian et al. [114]	Detecting small objects on UAV photos using a NN.	-High accuracy -Loe delay	-High energy consumotion	Python	CNN	Object detection	UAV
Pawełczyk and Wojtyra [115]	Introducing and sharing a new drone detection dataset comprised.	-High accuracy	-High complexity of the evaluated method	Tensorflow	CNN	Object detection dataset	UAV-IoT

non-linear programming task was posed. They developed a **Power Control in Secure FL (PCSF)** algorithm to address the issue. The findings demonstrated that PCSF outperformed two other approaches, producing a high system security rate and a quick FL training time.

Yao and Ansari [117] looked at optimizing power management and energy harvesting control in time-varying IoD networks. They devised a joint optimization model to evaluate each drone's wireless transmission power and the transmitted energy from the charging station to each epoch to lower the long-term average system energy cost, keeping the drones' battery capacities and QoS requirements in mind. In order to show how the network state varies with different power and energy harvesting control strategies, an MDP was created to characterize their difficulty in time-varying IoD networks. They came up with a modified actor-critic DRL method to solve their problem. They demonstrated through thorough simulations and the implications of different settings on the performance of their proposed technique that it beats existing algorithms.

Faraci et al. [118] supplied an improved RL technique used in the system controller to manage fleet utilization effectively, considering the unpredictability of bandwidth demand and green power supply. The efficacy of the suggested tool was demonstrated by the results collected in various test cases and situations. The findings showed that the RL had beneficial benefits, which were particularly noticeable in the case of wind turbines. In the context of green power generation, the benefit gained from the RL was larger when the generator power output was proportionate to the number of pads rather than the enormous generation. To make the work of the system controller easier, a single-inverter-multi-pad power converter was also used to ensure a constant charging duration. The inductance and capacitance of the filter in a pad were adjusted to ensure that the same current was sent to the drone battery through a wireless power transfer link regardless of misalignment.

Finally, Xu et al. [119] looked at a backhaul framework for self-organizing UAV networks that combined topology construction and power adjustment. They developed a DRL-based strategy to create the backhaul framework. Each UAV made decisions to improve the backhaul rate with little information exchange and minimized malicious power competition. They divided the backhaul architecture into three sections: multi-channel power allocation, total power control, and transmission target selection. Afterward, heterogeneous DRL algorithms with customized rewards were used to solve the three submodules to regulate UAV behavior. DQL was used to address TS by constructing topologies with fewer relays and ensuring the backhaul rate. Compared to DQL and the max-min technique, the suggested framework effectively delivered system-level and overall

Table 7. The Methods, Properties, and Features of ML-Power Control and Energy Management Mechanisms

Authors	Main idea	Advantages	Research challenges	Simulation environment	Method	Application	Environ-ment
Yao and Ansari [117]	Investigating power control for FL in a fog-aided IoD network.	-High security -Low delay	-High complexity	Not mentioned	FL	Power management	IoD-fog
Yao and Ansari [120]	Exploring the joint optimization of power and energy management.	-Low energy consumption	-High complexity -High delay -Poor scalability	Python by TensorFlow	Actor-critic Q-learning	Power management	IoD
Faraci et al. [118]	Using RL to determine the number of drones, a system controller can provide optimal power management.	-Boost the amount of energy saved	-Low dependability	MATLAB	Q-learning	Power control and energy scheduling	IIoT-UAV
Xu et al. [119]	Exploring a backhauling architecture in self-organizing UAV networks.	-Higher backhaul rate -Fewer hops	-Security and privacy are not taken into account.	Not mentioned	DRL	Power control	IoD

performance gains, i.e., higher backhaul rate, lower transmission power, and fewer hops. Also, Table 7 discusses the power control and energy management applications used in IoD and their properties.

5.5 Mobility Management

Incorporating different kinds of small-coverage base stations and drone-based base stations is a difficult subject. With high mobility speed circumstances, the vulnerability gets severe. As a result, mobility difficulties and their determinants should always be handled effectively. A few studies have started focusing on mobility management in the IoD concerns, such as mobility prediction, security, and battery consumption models. By utilizing and aggregating the social structure of the Grid, neighboring towns, and transportation mediums such as buses and other vehicles, Mukherjee et al. [121] suggested an **Internet of Drone Things (IoDT)** based delay-tolerant network supported grid network ecosystem. A social grid structure might be imagined in this idea by taking into account connectivity between grids, users, households, and charging stations using the information store and forward mechanism. Their research found that the opportunistic network was extremely dependable when the sites were geographically interconnected across a large distance. In this scenario, the UAV units were seen as part of the IoT platform and were utilized to form the Internet of IoDT. Also, the presented model was a load forecasting system that combined mathematically sound gradient boosting algorithms with the **Long Short Term Memory (LSTM)** method. A hybrid architecture was created for better prediction in the face of noise and incorrect data transmission from the physical layer. Furthermore, the suggested model could generalize to diverse data collection and deliver prediction results with a 0.167 MSE score, 7.231 MAE score, and 4.9 percent resource consumption.

Li et al. [122] discussed the concept of online **Velocity Control and Data Capture (VCDC)** decision-making in UAV-enabled IoT networks. A design of an **Onboard Deep Q-Network (ObDRL)** architecture was created to reduce total IoT unit data packet losses caused by overflowing buffers and transmission failures. The UAV's immediate patrol velocity and IoT node data transfer timing were optimized without current knowledge of the network conditions. It was discovered that experience replay combined with deep reinforcement learning might be used to train the ObDRL by storing network states and actions in each learning episode. The ObDRL was generally built with Google TensorFlow and the Keras deep learning framework. Furthermore, the IoT network's scalability and the lengths of data queues at nodes could significantly influence the UAV's VCDC.

Also, Hong et al. [123] introduced a tracking-by-detection method to track UAV targets. Their method allowed for high-precision tracking on a real-time basis. This approach used **You Only**

Look Once v3 (YOLOv3) as the detector and deep **Simple Online and Real-time Tracking (SORT)** as the tracking mode to obtain a detection speed of 54 frames per second and a MOTA of 94.4 percent, which matched the needs of real-time tracking of numerous objectives for drones. They also altered the YOLOv3 network on this premise, adjusting the model's loss function to match the features of the SPP module, the drone target, and the drone data to create the first anchor. The findings supported the suggested approach's effectiveness and showed that YOLOv3-SPP + Deep SORT was well-suited for multitarget real-time tracking of UAVs.

Tanveer et al. [124] presented an ML-based technique to achieve robust drone connectivity with lower changeover costs, with the caveat that the drone would not always connect to the largest cell in the trajectory. They proposed utilizing a Q-learning framework to create robust and adaptable handover decisions. So, their suggested Q-learning-based method was tested in three scenarios. The handover decision was gradually adjusted using Q-learning to offer effective mobility assistance with a high data rate in time-sensitive applications, tactile internet, and haptics communication. They may see a trade-off between the number of handovers and the received signal intensity, attaching the drone to the greatest cell with their technique, which decreased the overall number of handovers. The reward function's weights could be changed to alter this tradeoff.

Plus, Qi et al. [125] created a multilayered 6G IoT network using UAVs in the sky and an **Intelligent Reflective Surface (IRS).** They developed LSTM and A-LSTM, a hybrid of LSTM and attention mechanisms. However, the network parameters of the A-LSTM model might be constantly updated by the loss function throughout the training phase to achieve time series prediction. To send data in a freeride way, the system used backscattering communication. IRS improved the distance and performance of backscattering transmission by increasing the energy of the reflectable signal by beamforming. The results showed that their technique significantly improved the overall system performance and had a clear advantage over previous alternatives.

He et al. [126] proposed a unique explainable DNN-based route planner for quadrotors to fly independently in an unfamiliar area. The navigation issue was treated as an MDP in a simulation setting, and the path planner was trained using the DRL approach. A novel model explanation approach based on feature attribution was suggested to understand the trained model better. End-users could comprehend what caused a certain action thanks to some simple written and visual explanations. Researchers could also use certain global analyses to assess and enhance the trained network. Finally, real-world flight tests were carried out to demonstrate that the path planner developed in the simulation was robust enough to be used directly in the real world.

Moreover, Abedin et al. [127] developed a navigation policy for numerous UAVs that included deploying mobile **Base Stations (BSs)** to increase data freshness and connection to IoT systems. Firstly, they designed an energy-efficient trajectory optimization problem, intending to optimize the UAV-BS trajectory policy to optimize energy efficiency. To maintain data freshness at the ground BS, they included various contextual factors such as energy and information age limitations. Secondly, to tackle the defined problem of contextual constraints for UAV-BS navigation, they offered an agile DRL with an experience replay model. Furthermore, the technique was well-suited to addressing the problem. Using the trained model, an objective accomplishing trajectory strategy for the UAV-BSs captured the observable network states over time. Furthermore, the findings showed that the technique used 3.6 percent and 3.13 percent less energy than the greedy and baseline DQN methods.

Finally, Shokry et al. [128] presented a DRL system to control the trajectories of numerous UAVs in a dynamic environment when communication infrastructure was unavailable to cover vehicles efficiently. Specifically, the method increased vehicular coverage using the fewest number of UAVs and the least energy. They proposed a way to learn the optimal trajectories for deployed UAVs to expand vehicular coverage efficiently. The Actor-Critic algorithm was used to learn the vehicular

Table 8. The Methods, Properties, and Features of ML-Mobility Management Mechanisms

Authors	Main idea	Advantages	Research challenges	Simulation environment	Method	Application	Environ-ment
Mukherjee et al. [121]	Proposing a hybrid ML architecture.	- MSE score of 0.167, an MAE score of 7.231	-Poor scalability -Low security	Python	XGBoost+ LSTM	Search and rescue	IoD-IoT
Li et al. [122]	Creating an ObDRL to help UAVs with online velocity control and communication decision-making.	-Strong scalability	-High energy usage	Keras + Tensorflow	CNN	Search and rescue	IoD-IoT
Hong et al. [123]	Proposing a CNN-based approach for tracking drone targets in real-time.	-High precision -Moderate complexity	-Poor scalability -Poor robustness	YOLO dataset+ PyTorch	CNN	Search and rescue	IoD
Tanveer et al. [124]	Using Q-learning to provide efficient mobility assistance in time-sensitive applications.	-High flexibility -Strong robustness	-Low reliability	Python	Q-learning	Mobility management	IoT-UAV
Qi et al. [125]	Using UAVs in conjunction with 6G, IoT, and the LSTM technique.	-Low energy consumption -Proper accuracy	-High delay -Low robustness	Python	LSTM	Search and rescue	UAV-6G-IoT
He et al. [126]	Proposing a reactive DNN-based controller for UAV route planning that is learned using the DRL approach.	-Proper for UAVs with low resources -Strong robustness	-Low dependability	SITL environment+Gazebo environment	CNN	Search and rescue	UAV
Abedin et al. [127]	Designing the UAV-BS navigation strategy to increase data freshness.	-Low energy usage	-Security and privacy are not taken into consideration	Python	Q-learning	Trajectory optimization	UAV-IoT
Shokry et al. [128]	Using the DRL method to discover the best trajectories for deployed UAVs.	-Moderate energy usage - High scalability	-High delay -Security and privacy are not taken into consideration	Not mentioned	Deep Q-learning	Search and rescue	UAV-IoT

environment and its dynamics to manage the complex continuous action space. The technique was shown to be capable of understanding the vehicle surroundings and dynamics to control the UAVs and offer appropriate car coverage. In terms of the percentage of average coverage, their solution outperformed rival strategies like fixed and random deployment options and static UAV placement. Also, Table 8 discusses the mobility management applications used in IoD and their properties.

5.6 Security Management

The IoD is a current development in both industries and academia, with applications in civilian and military contexts. Furthermore, drones, also known as UAVs, are not typically constructed with security in mind, and fundamental security and privacy problems must be examined. So, a blockchain-based security architecture for cyber-physical systems in industrial IoD contexts is being developed to address the IoD security challenges. So, for a safe IoD environment, [129] devised a deep learning-based blockchain method. Their work resulted in a paradigm for secure **Drone-to-Drone (D2D)** and **Drone-to-Everything (D2X)** connections and a blockchain method for data dissemination security. Furthermore, their innovation allowed **Zero-Knowledge Proof (ZKP)** to be used in an IoD environment. The proposed technique used a **Deep Boltzmann Machine (DBM)** to distinguish between regular and miner nodes. The DBM-based miner selection technique allowed optimal miner node selection, leading to faster block creation and transaction commit times. Their research was verified in several ways, including communications cost, computational cost, and real-time performance evaluations. The trial revealed that the blockchain method could provide data integrity and privacy in the IoD ecosystem.

In addition, Gumaei et al. [130] presented a 5G-enabled drone and flight mode detection framework that could also constantly conduct drone recognition and flight mode detection using RF signals from drones. The detection findings could be utilized to alter the flying mode of drones or to automate flight in the event of a disconnect or restricted connectivity with edge nodes and controllers. They created a DRNN model for online detection inside a secure framework that employed blockchain technologies to improve data transfer security. The DRNN model was trained offline and then injected into edge nodes for detection. A complete series of tests was carried out utilizing a real drone dataset to assess the proposed framework's DRNN model. The findings showed that the DRNN model surpassed state-of-the-art works on identifying drones and flying modes and the originality of their framework to increase the safety of drone data transfer utilizing blockchain.

Also, Sarkar et al. [131] recommended a new **energy-aware Secure IoD paradigm (ESIoD)**. Using two smaller Haar and faster R-CNN models, an onboard computer component connected drone-based image gathering and image and video processing in a cloud server. Drone images were encrypted before being delivered to the cloud server, using either the faster AES or more secure RSA methods. All of this was accomplished in a short amount of time. In addition, the cloud-based ESIoD architecture was shown to exceed onboard computing in terms of performance. The results suggest that all real-time in-flight processing and decision-making should take place in the cloud, saving drone power and extending flight time. The findings showed that, compared to typical real-time onboard processing for the application under consideration, the ESIoD could save up to 80% onboard processing time and 3X drone battery charge.

Besides, depending on the RF features of drones, Yazdinejadna et al. [29] devised a federated drone authentication concept in IoT networks. They provided a federated learning-based drone authentication model based on the radio frequency features of drones in IoT networks. In their model for drone authentication, they applied the DNN framework with local **Stochastic Gradient Descent (SGD)** optimization on the drones. Homomorphic encryption and the secure aggregation technique were used to safeguard model parameters. Investigations showed that the federated drone authentication model had a higher **True Positive Rate (TPR)** and better performance throughout drone authentication than earlier ML-based models. The model used the FL technique to train data locally, allowing it to use decentralized data generated by drones while protecting privacy. Their DNN architecture improved drone authentication and beat non-federated ML models. In addition, as additional drones joined the network, their model could be updated and optimized regularly.

Lim et al. [135] evaluated UAVs in an FL-based sensing and collaborative learning system for IoD applications. They provided a multi-dimensional contract-matching incentive framework considering the incentive incompatibilities among the UAVs and the model owners. Each subregion received the UAV with the lowest marginal node coverage cost to complete the mission. In order to enable collaborative ML [132] while protecting privacy across a federation of independent DaaS suppliers for IoD applications like traffic prediction and parking occupancy tracking, they suggested using an ML-based method. They employed the self-revealing properties of a multi-dimensional contract to guarantee accurate reporting of UAV types while accounting for various sources of heterogeneity, like computation, sensing, transmission costs, information asymmetry, and incentive incompatibilities among UAVs and model owners.

Li et al. [133] looked into a blockchain-based trust system for the smart IoT to prevent malicious data reporting. The three key strategies of their methodology are the malicious deterrence system, stringent punishment system, and DRL with **Multi-head Attention Mechanism (MA-DRL)** system. First, a malicious deterrence system prohibits harmful players from reporting phony malicious data on the blockchain by displaying the data standards detected by fully trusted drones. Second, in order to deter harmful data reporting, the severe penalty system is intended to punish individuals who have already reported malicious data to the blockchain, reducing the frequency of dangerous data reports in subsequent assignments. Third, their approach uses the MA-DRL method to

Table 9. The Methods, Properties, and Features of ML-Security Management Mechanisms

Authors	Main idea	Advantages	Research challenges	Simulation environment	Method	Application	Environment
Singh et al. [129]	Proposing a blockchain-based system security method to ensure secure data flow.	-Low computation cost -High security	-High energy consumption	Python	Deep Boltzmann machine (RNN)	Security	IoD-IoT
Gumaei et al. [130]	Building a DRNN model for drone identification and flight mode recognition in the task of flying automation.	- High accuracy -High security	-High complexity	Real public DroneRF dataset using Python	RNN	Security	IoD-edge
Sarkar et al. [131]	proposing a novel energy-aware secure IoD.	-Low delay -Low energy consumption	-High complexity -Scalability is not considered	Python 3 in a Raspbian OS environment	CNN	Security	IoD
Yazdinejadna et al. [29]	Proposing an FL-based approach that takes advantage of the drones' RF capabilities.	-High accuracy	-High delay	PySyft and PyTorch	FL	Privacy and security	IoD-IoT
Lim et al. [135]	Proposing the use of an FL-based method to enable collaborative ML.	-High security -Low complexity	-Low scalability -	Not mentioned	FL	Privacy and security	IoD
Li et al. [133]	Proposing a blockchain-based mechanism to discourage false data.	-Reducing malicious data	-High energy consumption	Python	Q-learning	Trust and security	IoT-IoD
Al-Emadi et al. [134]	Presenting a DL method to identification utilizing a drone's audio characteristics.	-Moderate accuracy	-Low robustness	TensorFlow	GAN+CNN	Security	UAV

route the sensing trajectory of drones, which uses a smaller training network combined with a multi-head attention mechanism to lower arrangement costs for drones. Lastly, investigations are carried out to assess the system's performance. In comparison to the baseline system, data reporting quality has improved, and malicious data reporting has decreased. Experiments show that the system has improved to minimize harmful data reporting in smart IoT.

Finally, Al-Emadi et al. [134] used a state-of-the-art DL technology described as the **Generative Adversarial Networks (GAN)** to introduce a hybrid drone acoustic dataset consisting of real drone audio clips and artificially produced drone audio samples to address this gap. They also look at how drone audio works with other DL techniques in drone detection and identification, such as the CNN, RNN, and **Convolutional Recurrent Neural Network (CRNN)**. They also consider the effect of their suggested hybrid dataset in terms of drone identification. The researchers' findings highlight the effectiveness of utilizing DL methods for drone detection and identification and support their prediction about the advantages of using GANs to produce realistic drone audio recordings to improve the recognition of new and unfamiliar drones. Table 9 discusses the security management applications used in IoD and their properties. Also, we thoroughly examine and analyze the results with all of their features in the next part.

6 RESULTS AND COMPARISONS

In the previous section, we looked at six different forms of IoD methods that used different DL models. We have presented a detailed review of the usage of several ML methods in the IoD-UAV area in this paper. This paper differs from previously published studies in terms of breadth and purpose. As we saw in Section 5.4, green wireless communication is key to the green IoD. Green communications and networking are sustainable, energy-aware, energy-efficient, and environmentally conscious technologies. Minimal CO2 emissions, low radiation exposure, and energy efficiency are all part of a green communication network concept. The energy consumption of 5G mobile communication networks is examined in-depth from three perspectives: theoretical models, technological advancements, and applications [136]. Also, today, 5G is projected to influence our environment and daily lives significantly, just like the IoD promised, by making them more efficient and comfortable. E-learning, e-health, human-robot interaction, transportation and logistics, e-governance, automotive and industrial systems, media, robotic communication, and other applications and services are among the 5G applications and services that will benefit our society.

6.1 Security Importance

There have been substantial attempts to enhance the IoD network over the years. Nevertheless, as the article points out, most developmental projects have indeed been focused on IoD mobility and resource management, as seen in Section 5.1. As a result, most studies only scratched the architecture's security and privacy surface. Moreover, as this paper points out, there are a variety of drones on the market. As a result, deciding which one to use for a specific purpose is challenging. Many scholars have worked on the classification of drones to address this issue. On the other hand, the extent of privacy and security issues associated with different types of drones has been largely overlooked. The size of drones has a substantial impact on privacy and security. Smaller drones are not fully secured since adding security, and privacy mechanisms is frequently more challenging than adding security and privacy mechanisms to larger drones with more computational capability. This study also discusses physical dangers that affect the safety of IoD network entities and IoD network attacks. The successful implementation of a strong IoD paradigm will depend on properly mitigating these physical hazards. This study investigates several strategies and processes proposed by various researchers for reducing cyberattacks on the IoD network. The performance evaluation approaches and the metrics used by the methodologies are also described. It was noticed that present strategies for mitigating assaults on authenticity requirements are either ineffective or ineffective due to significant computation and communication costs. As a result, a healthy balance between these two frequently opposing objectives is required. Numerous open concerns must be addressed before the IoD paradigm can be successfully implemented.

6.2 DL-ML Methods in IoD-UAV Networks

Plus, it might be hard to ascertain which RL approach should be used in a given IoD problem. RL studies attempt to discover all potential circumstances an RL agent may encounter to establish the "best" reward function that accomplishes the objective fast and effectively. The established incentive function might lead to undesirable behavior when agents face novel circumstances. Inverse RL, which recovers the reward function by learning from demonstration, is one solution to this problem. Unlike unsupervised and supervised approaches, RL and DRL procedures have no separate training periods. As long as the agent does not reach a final state, trial-and-error is used to learn. The agent's efficacy in this situation varies based on previous data, such as the encountered environment states and actions and the subsequent exploration approach. By collecting a large dataset of earlier encounters and training the agent for multiple epochs before deploying the RL or DRL model in the real-world, offline RL might help speed up this process. Furthermore, the trial-and-error method's consecutive phases might lengthen the convergence time. By examining more state–action space in less time, the advantage actor-critic and asynchronous advantage actor-critic, two versions of the actor-critic algorithm, could manage this. The main distinction is that multiple individual agents are trained in parallel using various copies of the RL environment, then the global network is updated. Many assessed works do not adequately address the challenge of enabling network mobility. Numerous mobile nodes make up an IoD network, making its structure dynamic and potentially unstable. In addition, if the RL techniques do not explicitly enable network mobility, the system may suffer from malfunction or performance deterioration. Resources restrictions, particularly energy conservation, are a major concern when building IoD systems to extend network life. As a result, the DRL and RL methods used must reduce method complexity in terms of memory space and processing time when used on IoD systems. Low-power and lightweight RL and DRL systems may be built to run on IoD and mobile devices while improving performance and decreasing binary file size. The deployment model of the RL agents is another important aspect for optimizing and reducing the necessary resources.

However, the comparison study reveals an unlikely outcome: few experimental studies with the environmental differentiation characteristic. No effort sought to make a clear distinction between two or more settings by those who did. Numerous proposals tested their supplied implementations in multiple contexts. In contrast, they cannot qualify as assessing environmental differentiation features since their methodology did not allow for distinctions in all those settings to be expressed in the method itself. There seems to be no design change to account for varied settings, and the study pool has no datasets with discrete environmental labels. The topic has a lot of promise because recognizing various surroundings may impact the solution's effectiveness and precision. It also adds a layer of openness to automated driving, which may be required for future regulatory compliance. Nevertheless, given practical test settings, such a technique might lead to a substantial loss of accuracy. Whenever simulations are performed using current video-game engines, including the Unity or Unreal engines, it must have been found that the visual quality of these kinds of simulations appears low compared to what is feasible in modern rendering engines tradeoff. It is worth noting that Gazebo, a drone-specific simulation program, has been utilized in several projects, demonstrating the value of simulation.

Besides, with the assistance of independent decision-making, three specific DL models emerge as one of the most common in the study field. "VGG-16" is a CNN image classifier developed on the "ImageNet" dataset, with over 14 million pictures matched to thousands of labels. VGG-16 could be used for broad picture categorization or as a starting point for TL, fine-tuning photos unique to a particular drone scenario. The bulk of related studies in the study pools that utilize it or the object detection model "YoloV3" as a basis for collision avoidance or object detection/distinction use it as a base. The "ResNet" concept is based on CNN-based research that discusses how residual layer "shortcuts" might simulate the activity of whole neural layers to improve the "AlexNet" architecture. Also, ResNet is developed on the ImageNet dataset, just like VGG-16. The advantage of ResNet's shortcuts design is that it reduces processing overhead significantly, producing efficient ones with fast reaction times and similar precision. It is advantageous for drone activities that need little CPU use. DroNet mainly focuses on autonomous drone navigation and uses manually annotated automobile and bicycle footage as training data for navigating in a city setting. DroNet results from a single image are specialized for drone navigating, giving a steering angle to continue the drone traveling while avoiding objects and a collision probability of allowing the UAV to identify risky situations and respond quickly. The DroNet study is widely referenced and is utilized as a basic network for numerous additional publications in the study pool as a purpose-built autonomous drone network.

6.3 Metrics for Evaluation

Performance metrics are the mathematical formulas that evaluate an ML model's quality and provide useful feedback. The IoD-UAV model's performance has been measured employing measures like specificity, recall (sensitivity), accuracy, precision, **Confusion Matrix (CM)**, specificity, and F1 Score. So, accuracy is specified as the ratio of total correctly classified observations to total predicted observations. When all values in a Confusion Matrix are added together, the ratio of True Negatives to True Positives is calculated. So, accuracy is calculated as follows:

$$\text{Accuracy} = \frac{S_{TN} + S_{TP}}{S_{TP} + S_{TN} + S_{FN} + S_{FP}} * 100 \tag{1}$$

Precision indicated by P is a metric used to determine confidence level in predictions. The proportion of True Positive predicted observations compared to all positively predicted observations. Also, S_{TP} represents the sum of all true positives, while S_{FP} represents all false positives.

$$Precision = \frac{S_{TP}}{S_{TP} + S_{FP}} * 100 \tag{2}$$

Recall which is indicated by *Recall* is a measurement that tells us how many actual positive observations we can accurately predict. Also, S_{FN} denoted all false negatives in Equation (10).

$$Recall = \frac{S_{TP}}{S_{TP} + S_{FN}} * 100 \tag{3}$$

Furthermore, the F1 is an overall performance statistic comprised of Precision and Recall. It is represented by the Harmonic mean of Precision and Recall.

$$F1_{score} = \frac{2 * Re_{Call} * \mathrm{P}}{Re_{Call} + \mathrm{P}} * 100 \tag{4}$$

The CM is a measuring performance matrix that compares actual and predicted observations using False Positives, True Positives, False Negatives, and True Negatives labels. The total correct predictions are the sum of True Negatives and True Positives, whereas the total incorrect predictions are the sum of False Positives and False Negatives.

$$\begin{vmatrix} S_{TP} & S_{FP} \\ S_{FN} & S_{TN} \end{vmatrix} \tag{5}$$

Also, True Positives are predictions for a class that are both positive and correct. Also, true negatives are incorrect predictions but are negative to a class. False Positives (Type 1 Error) are positive and inaccurate predictions for a class. False Negatives (Type-2 Error) are negative predictions of a class but are wrong. Specificity is a metric that indicates how well the target classes were identified in the test set. Suppose there are 100 positive classes in the test set, and the classifier properly identifies 80 of them while mistakenly identifying the remaining 20. In that case, the classifier correctly identifies 80 percent of the real samples in the data. As a result, specificity is computed as follows:

$$\text{Specificity} = (S_{TN}/S_{TN} + S_{FP}) * 100 \tag{6}$$

6.4 Analysis of Results

Another investigation of IoD-ML applications in this domain discovered that eight papers (20.5 percent) used applications jointly for resource management and mobility management, putting these categories in first place jointly. Given the importance of security management and how surveillance/monitoring can affect peace and security, one advantage of this strategy is that methods can detect things that humans cannot distinguish from genuine ones. Security management and surveillance/monitoring occur jointly and concurrently, with seven articles (17.9 percent). Object detection is the third most intriguing topic, with five articles (12.8 percent). In spite of receiving the least attention, it is one of the most important ML applications in this sector. Figure 6 depicts the various applications of ML in the context of the IoD realm. TL could aid in mitigating errors and increase the efficiency of applications, particularly in resource management and its subcategories, such as offloading and scheduling, which, surprisingly, received no attention. As previously stated, developing large image datasets in a short period is difficult. As a result, applying the benefits of DL to object detection and monitoring is more difficult. As a result, TL may be helpful in this situation. A DL model, like a TL model, can be trained using a large-scale

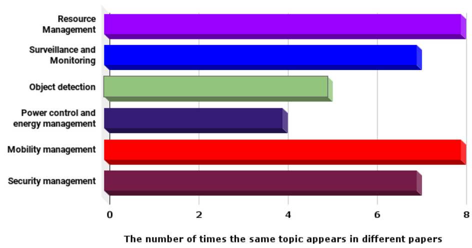

Fig. 6. In the context of the IoD realm, ML application usages.

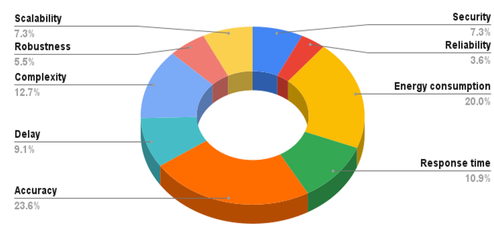

Fig. 7. Evaluated parameters in the articles.

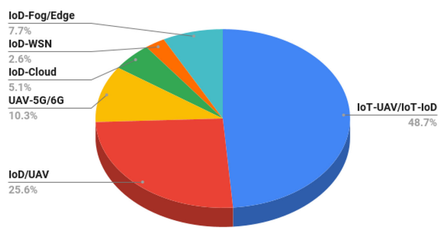

Fig. 8. The number of environments utilized in ML-IoD applications.

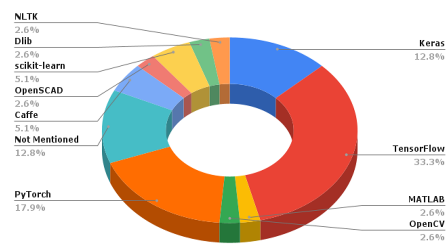

Fig. 9. The distribution of the use of different simulation environments in the ML-IoD realm.

benchmark dataset, and learned features can be used for a variety of purposes. Only two studies in our evaluation attempt to use this TL for a variety of purposes in the field of IoD. Many of these tasks could be streamlined if ML collaborates with fog or edge computing to develop models. In some cases, TL may be able to help. When the ideal algorithm is used to edge computing, a better system can be provided. Also, as indicated in Table 10 and Figure 7, the lowest parameter evaluated in the articles is reliability; nevertheless, only three of the offered papers have considered this crucial element. The accuracy parameter is the one that gets the most attention in papers, with 23.6 %, while energy consumption comes in second. The response time is ranked fourth, and the complexity is placed third. Furthermore, the problem with articles is that most have one target parameter and ignore the others almost entirely.

Furthermore, our findings revealed that the IoT-UAV/IoT-IoD environment is the most commonly used in papers (48.7 percent of 19 papers) and is used in nearly every category, particularly resource management. In addition, 26.6 percent of IoD/IoV platforms used solely without any combination with other environments take second place in the papers (10 papers). Furthermore, with a usage rate of 2.6 percent (one paper), IoD-WSN is the least used environment in these articles. Furthermore, Figure 8 depicts the frequency with which environments are used in ML-IoD applications. In the context of a simulation, theoretical, or implementation scenario regarding the suggested approaches, Python is the most predominant programming language, which is extremely attractive for investigators to employ in future work and has a broad range of uses. As seen in Figure 9, TensorFlow is the most common method, with 33.3 percent of use. PyTorch is one of the most common environments, accounting for 17.9%. With 12.8% of usage, Keras is in third place. Scikit-learn has 5.1%, Caffe has 5.1%, and not mentioned has 12.8%, with the rest of the work being done with other packages. Furthermore, our findings showed that CNN is the most frequently employed method in papers (35%) and is used in almost every category. Besides, GAN is the least used technique in these articles, with a 2.6% usage rate. In addition, Figure 10 depicts the frequency

Table 10. Considered Parameters in the Examined Papers

Type	Authors	Method	Security	Reliability	Energy consumption	Response time	Accuracy	Delay	Complexity	Robustness	Scalability
Resource Management	Koubâa, et al. [97]	CNN	•	•	✓	•	•	•	•	•	•
	Yang, et al. [98]	Q-learning	•	•	•	•	•	✓	✓	•	•
	Su, et al. [99]	RNN	•	•	•	•	•	•	✓	✓	•
	Wei, et al. [100]	Q-learning	•	•	•	✓	•	✓	•	•	•
	Al-Hilo, et al. [101]	Q-learning	•	•	•	✓	•	•	•	•	•
	Yang, et al. [102]	CNN	•	•	•	•	•	✓	•	•	•
	Li, et al. [103]	DQN	•	•	•	•	•	•	✓	•	•
	Zhang, et al. [104]	Q-learning	•	✓	✓	•	•	•	•	•	•
Surveillance and Monitoring	Al-Sa'd, et al. [105]	DNN	•	•	•	•	✓	•	•	•	✓
	Meng, et al. [106]	CNN	•	•	•	•	✓	•	•	•	•
	Hernández, et al. [107]	Auto-encoder	•	•	✓	✓	•	•	•	•	•
	Dasgupta, et al. [108]	The Naïve Bayes Algorithm	•	•	•	•	✓	•	•	•	•
	Ghazal, et al. [110]	CNN	•	•	•	✓	•	•	✓	•	•
	Madasamy, et al. [111]	CNN	•	•	•	•	✓	•	•	•	•
	Barnawi, et al. [109]	CNN	•	•	•	•	✓	•	•	•	•
Object detection	Wang, et al. [112]	RNN	•	•	•	•	✓	•	•	•	•
	Genc, et al. [113]	CNN	•	•	✓	•	•	•	•	•	•
	Li, et al. [116]	CNN+DQN	•	✓	•	✓	•	•	•	•	•
	Tian, et al. [114]	CNN	•	•	•	•	✓	•	•	•	•
	Pawełczyk and Wojtyra [115]	CNN	•	•	•	•	✓	•	•	•	•
Power control	Yao and Ansari [117]	FL	•	•	•	•	•	✓	•	•	✓
	Yao and Ansari [120]	Q-learning	•	•	✓	•	•	•	•	•	•
	Faraci, et al. [118]	Q-learning	•	•	✓	•	•	•	•	•	•
	Xu, et al. [119]	DQN	•	•	✓	•	•	•	•	•	•
Mobility management	Mukherjee, et al. [121]	XGBoost+LSTM	•	•	•	•	✓	•	•	•	•
	Li, et al. [122]	CNN	•	•	•	•	•	•	•	•	✓
	Hong, et al. [123]	CNN	•	•	•	•	✓	•	✓	•	•
	Tanveer, et al. [124]	Q-learning	•	•	•	•	•	•	•	✓	•
	Qi, et al. [125]	LSTM	•	•	✓	•	•	✓	•	•	•
	He, et al. [126]	CNN	•	•	•	•	•	•	•	✓	•
	Abedin, et al. [127]	Q-learning	•	•	✓	•	•	•	•	•	•
	Shokry, et al. [128]	Deep Q-learning	•	•	✓	•	•	•	•	•	✓

(Continued)

Table 10. Continued

Type	Authors	Method	Security	Reliability	Energy consumption	Response time	Accuracy	Delay	Complexity	Robustness	Scalability
Security management	Singh, et al. [129]	RNN	✓	•	•	•	•	•	✓	•	•
	Gumaei, et al. [130]	RN	✓	•	•	•	✓	•	•	•	•
	Sarkar, et al. [131]	CNN	•	•	✓	✓	•	•	•	•	•
	Yazdinejadna, et al. [29]	FL	•	•	•	•	✓	•	•	•	•
	Lim, et al. [135]	FL	✓	•	•	•	•	•	✓	•	•
	Li, et al. [133]	Q-learning	✓	•	•	•	•	•	•	•	•
	Al-Emadi, et al. [134]	GAN+CNN	•	•	•	•	✓	•	•	•	•

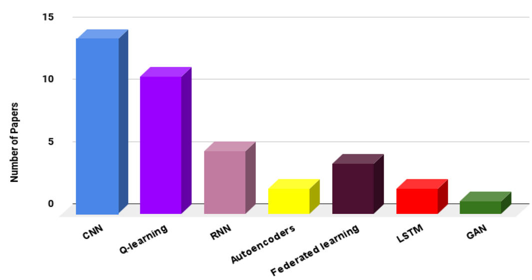

Fig. 10. Utilization of ML approaches and their frequency in selected articles in the IoD realm.

of ML approaches in the IoD realm. We hope this research will be a helpful reference for future research on IoD and ML applications.

7 OPEN ISSUES

The findings are addressed in further depth in the preceding section. The key research problems and future potential paths in the IoD area are presented in this section.

7.1 Key Research Challenges

The primary trends in drone telecommunications are connected to the expansion of the shaded area and communication protocols to ensure a target QoE. Instead of focusing on efficiency, standardizing communications and developing homogenous platforms and infrastructures that allow true integration among heterogeneous technologies might be beneficial in the context of 5G. Softwarization is a term used to describe this phenomenon. It is important to mention that a comparable phenomenon is occurring in the IoT sector, with an loT of demonstrations and specialized research focusing on integrating current IoT technologies rather than inventing new ones. The security concerns of these kinds of interactions are given special emphasis, and novel solutions based on Blockchain-based smart agreements are proposed. Further use of **Information-Centric Networking (ICN)** and **Visible Light Communications (VLCs)** technology in drones seems to be another instance. These same contributions have already been made to the VLC discussion, particularly in terms of IEEE standards analysis, modulation structure and light patterns at the physical layer, MAC layer assessment and network topology efficiency, simulation software, software of the VLC system design including its advantages and disadvantages, and relevant performance evaluation. Investigating the potential of using this innovative technology in the

IoD sector as a potential field of research would be highly intriguing. The use of VLCs and ICN technology in drones is another scenario. A few other contributions have already been made to the VLC subject, particularly in terms of IEEE standards analysis, modulation structure and light patterns at the physical layer, MAC layer analysis and network topology performance, simulation software, applications of the VLC system architecture with its advantages and disadvantages, and related performance evaluation. Investigating the potential of using this innovative technology in the IoD sector as a potential research area would be highly intriguing.

Even though previously stated, the use of ICN in the scope of the IoD is an intriguing study path that merits being explored further. What is evident from the review of the associated state-of-the-art is that the use of the ICN in the setting of **Intelligent Transportation Systems (ITSs)** does not appear to become as developed as it could have been. In addition, the authors feel that this might be a limiting problem because the ICN architecture is one of the finest options for supporting user-to-user connections due to mobile settings. As it is generally known, the rapidly developing restriction of the host-centric character of the Internet is one of the primary reasons for becoming relevant. Nevertheless, there is a constant need for seamless mobility from users of various types, pushing the Internet's abilities to their limits. Appropriate support for intrinsic mobile scenarios is required when the handover is often confirmed. The latter is a well-known communications issue since, in a mobile situation, the user remains connected to the network and does not suffer any service interruptions if, and only if, the coverage is satisfactory. Because worldwide connection cannot be provided by a single access point, including a cell in cellular networks, the challenge of handover occurs when a user moves from one access point. This happens whenever a user goes from one cell to another in a cell connection. The inherent movement of ITS systems, both from the standpoint of users and drones collecting data, poses severe restrictions on their long-term viability. It is important to note that routing issues emerge in these situations due to the requirement to know which access point the UAV is linked to in real-time for DL and UL. The UAV's information and communication exchange would be disrupted unless the paths were unknown. The ICN communication paradigm, which uses the publish-subscribe communication method, is a strong contender for meeting QoS design goals, including communication latencies, robustness, and performance. Perhaps a combination examination of some of these characteristics in ITS systems might be an intriguing research issue in the future.

There are many significant challenges in implementing protocol frameworks for **Flying Ad-Hoc Networks (FANETs)**. In contrast to wired networks and MANETs, the communications environments of FANETs are characterized by high bit-error rates, long packet latency, and frequent outages. For both civil and military activities, reliable microwave or free space optical communication systems with high data throughput and capacity are required. Following is a list of key research challenges for upcoming studies:

- ***Protocol architecture for FANET***

For FANETs, which provide the least amount of additional overhead, reliable, delay-tolerant network protocol designs are necessary. Further research is required to develop cross-layer FANET protocols that meet the demanding criteria connected with them.

- ***Modeling of mobility***

Effectively studying and developing FANETs requires the development of more accurate mobility models for small and micro drones. The mobility pattern of UAVs launched in various missions should adhere to a set of clear rules rather than random flight movements. Hence, it is crucial to precisely record the FANETs' movement data.

- ***Stability management***

The main goal of system configuration is to preserve system stability. Multi-UAV networks need reliable system control, including control strategies, tactics, and strategies, to collaborate and operate together. Future studies are necessary to accurately characterize the stability domain of FANETs working in multitasking contexts.

- ***Selecting a general gateway***

For effective gateway selection, the observed channel quality of the receiver must be efficiently quantized. Moreover, multitasking scenarios need the development of effective IoD clustering algorithms. Outstanding gateway-selection methods must satisfy the difficult mobility, energy, and capacity restrictions.

- ***Challenges in Sensor Communication***

The communication protocols for IoD sensors are developed for lightweight and extremely sensitive items that have a high risk of data loss or receiving incorrect data from other nodes. Moreover, while connecting with several drones via a network center, sensors experience routing problems. Several drone manufacturers utilize low-cost technology, which increases the risk of other network communication concerns, such as high throughput and delay between the device and the control center. Next-generation communication networks, including 5G/6G, intelligent routing, narrowband IoT systems, Sigfox, and LTE-M, will need to allow connection choices in the future to address these concerns. Finally, a uniform policy for using the authorized component for drone communication protocol should be defined.

- ***Energy harvesting***

Researchers could investigate using wireless charging approaches and energy harvesting in future studies so that DL-IoD systems may undertake sensing and model training without returning to their bases. In such a situation, the incentive system will take into account another type of participant, namely the wireless charging service provider. Furthermore, due to the cars' mobility between subregions, a deep reinforcement learning method for resource allocation may be used.

- ***Energy-efficient strategies***

Using less energy to deliver the same service in the FANETs becomes a crucial issue because of the limitations placed on the maximum weight of tiny and micro drones, which also places restrictions on the volume and weight of their power supply and memory. Energy-efficient networking strategies must be taken into account when numerous small and micro drones collaborate with other UAVs or terrestrial networks.

7.2 Future Directions

Also, drones could become useful in an increasing variety of new scenarios. Groupings of coordinated, mobile, and extremely functioning robots work together to complete complicated tasks independently to achieve a shared objective. IoD systems are quickly developing from networks of "smart" items to networks of "social" devices, operating independently with other things based on their mutual social interactions, finding and delivering services and information in a trust-oriented manner as a major element of the IoT network. All of this is in addition to the connections between the object owners. However, to completely leverage this high level of automaticity and "social intelligence," additional study is required in two areas. To prevent unnecessary untrue or negative friendships among IoDs, a reliable design of the characteristics that define social interactions is required first. Secondly, information sharing and collaboration among IoDs must be avoided to prevent threats that could jeopardize friendship ties and the capacity of a network of drones to function independently. Safety, particularly trustworthiness, is an elevated component of IoD that must be carefully examined.

Intriguing alternatives might be suggested and implemented at scale if a viable technology framework is examined. This way, implementing IoD and ICN in tandem may be a major enabler for synergistic collaboration in civil and military applications. Additional factors can include innovation, mass manufacturing, and the broad use of autonomous cars, particularly in industrial applications. It is generally understood that costs and technological advancement are inextricably linked. In such a framework, developed industrialized nations choose and implement more instantly helpful inventions and have a limited period without charge. Increasingly capital-intensive innovations become economically viable when the overall degree of capital accumulation grows. The requirement for a drone to carry out part of industrial process surveillance or supply chain support/optimization is dependent on both its cost and accessibility since industrialization is related to technological availability and significantly accelerated by fast prototyping. The analysis might be finished by delving into the legal elements of the issue. Because no single regulation governs unmanned vehicles' use, integrated employment is still a long way off. It indicates that the company or sector may face financial and regulatory obstacles to its openness to drones in a global economic environment. These features have been overlooked in all the studied works, but they will undoubtedly offer value to future studies on the IoD subject. Data owner and data ownership need to be clarified/unified in another vein. The general data protection regulation has already provided some guidance in this regard. They need to be more particular, as drones represent a relatively new area in technical progress, and new technology evolves quicker than legislation. Also, the following is a list of possible future directions:

A. ML

The application of ML for security with a focus on privacy is linked to the development of more intelligence and privacy-focused drones. ML could be used between the IoT framework and drones to keep the network safe from cyber-attacks. ML may also be used in adversarial setups to detect assaults during training and to find security weaknesses. On the other hand, current solutions do not completely eradicate all forms of weaknesses. Consequently, more research is required to develop better methods for protecting drone and IoD device collaboration networks. Another challenge is developing safe authentication solutions for varied collaboration contexts. Several flaws in smart city authentication systems were highlighted in this problem. Plus, numerous AI-based DL techniques rely on large-scale training data, such as object detection and monitoring. However, this goal has insufficient datasets because of the rapid growth of IoD devices. Also, different simulations may use AI-based ML and DL systems to analyze the effect of various social control modes on surveillance and monitoring area.

B. Security and Privacy

In IoD and IoT, there is still a need to guarantee that data acquired by drones or things can be transmitted in a secure and private way [42]. As a result of the investigation of IoD security, it was discovered that the model developed enhances IoD security and offers an experimental foundation for IoD development in the future. Nevertheless, there are some flaws in the several methodologies. Because there are fewer parameters and IoD is somewhat difficult, additional parameters in a wider range should be chosen in the follow-up study phase to make IoD more secure. Authors could use innovative DL and ML methods to improve other works in the future. The emphasis in previous IoD developments has been on data rate and safety. In IoD networks, security is defined as the combination of secrecy, integrity, authentication, and non-repudiation of transmitted data. IoD communications, eavesdropping, network jamming, poor authentication, and mobility management are important unresolved challenges. An additional major difficulty in drone communication is ensuring data confidentiality and privacy. The problem of law is inextricably linked to privacy. Even though certain issues remain unsolved, legislative interventions on the topic of privacy might be beneficial. One of the main worries is that drones flying over cities and suburbs may intrude on people's privacy. Few publications address these issues to the best of the authors' knowledge; nevertheless, numerous works address these issues from a technological standpoint, such as safeguarding transmission and reception operations. The contribution focuses on IoD privacy concerns in both civilian and military systems and a set of privacy and security standards. Researchers might also raise a red signal from the standpoints of privacy and resource accessibility that should never be allowed in any type of communication network. However, research efforts in this field might be undertaken to understand better and enhance these characteristics. Because of the disparity in communication protocols and applicability, securing IoD is a difficult undertaking. In a network, IoD nodes are vulnerable to attacks such as Sybil attacks, Wormhole attacks, Sinkhole attacks, Impersonation attacks, and Coagulation attacks. To counteract the detrimental consequences of many types of known and undiscovered cybersecurity threats, timely tactics, counter-mechanisms, and easily updatable solutions are necessary. Security and privacy should be prioritized when creating any device or application for deployment on the IoD network. Furthermore, adding security and privacy features into IoD architecture is the best practice for preventing attacks. In addition, forensic requirements should be factored into the IoD system architecture. As with other cyber-physical networks and systems, the concept of forensic-by-design should be incorporated into the IoD network design. The ability to trace and reconstruct an assault occurrence is provided by forensic methods. So, for these objectives, an intrusion detection system with ML-DL capabilities might be a highly appealing alternative. Regarding the implementation of the IoD network, smart and capable intrusion and attack detection systems are required. As technology advances, a newer version of instruction and attack tactics is implemented on the IoD network. As a result, researchers should use this unique chance to develop more smart and complex detection and prevention systems to address this critical issue. So, an ML-Intrusion Detection System, authentication procedures, and cryptographic algorithms are all part of the security system. Traditional techniques are sluggish, bulky, require more power, and may fail to offer essential network data protection. As a result, efficient countermeasure deployment and maintenance can reduce extra computational costs while preventing excessive power usage.

C. Dynamic load Balancing and task Scheduling and low Overheads

IoD overheads in memory, energy, and latency cause a slew of problems, including resource deterioration and inefficiency. In the IoT, dynamic load balancing improves operational efficiency. Real-time data capture and processing necessitate a significant amount of energy and memory. As a result, providing a variety of activities while keeping overhead minimal is an open problem. IoD's dynamic load balancing could be viewed as a viable approach and a research issue worth further investigating. So, offloading and resource allocation utilizing CNN and RL techniques can greatly reduce latency and provide load balancing in this sector. Cloud computing and edge computing will be used in the future to manage computation-intensive IoT applications. For collaboration, such intelligent external intelligent network applications require a centralized ML analysis. In terms of situation-target scheduling, applied intelligence analyses the obtained data on the required computing tasks before deciding if the tasks must be submitted to the remote cloud. The goal of migration differs from the resource requirements for real-world data or applications. Computer networking would be improved to meet worldwide standards. Such an approach could be modified at any time to accommodate future changes and enhancements. It will undoubtedly become a recurring topic.

D. Lightweight, Long-lasting Batteries or Adequate Power Sources for Civilian Drones

Because of technological development, the integrated electronic components in civilian drones are getting smaller and lighter. Power, on the other hand, is still behind. The newest consumer drone batteries have a battery life of about 30 minutes. In addition, alternative power sources like lightweight gasoline-powered generators to charge onboard batteries, fuel cells, and solar electricity must be generated. Lightweight and longer-lasting batteries are required for the successful operation of these drones.

E. Secure Data Aggregation

In the IoD network, drones collect a lot of data. These data must be safeguarded and consolidated into a single unit during transmission that can be realized by means of some methods such as precoding [137–139]. The IoD network's resources, including energy and communication expenses, will benefit from aggregating the data before transmission. Numerous ciphertexts can be combined into a single unit using encryption techniques. In addition to the aggregation capability, it is suggested that an aggregation method for the IoD network deployment offers data confidentiality and access control. Aside from data confidentiality, IoD deployment faces data sharing and access management obstacles. For example, how to safely and efficiently exchange acquired data (e.g., in the sense that only authorized entities have access to the data) remains an issue in the application where a group of drones might collaborate to collect road traffic data from various places.

F. The Low Failure Rate of IoD

IoD was created, improved, and utilized for various purposes, including environmental monitoring, agriculture, and more. IoD forms should address resource limitations, dynamic topology, scalability, adaptability, privacy, and QoS support for users to offer these services. The network's failure rate lowers IoD's overall performance. As a result, the network's failure rate must be kept to a minimum to optimize IoD's current effectiveness.

G. Survivability and Lifetime

IoD incorporates battery-operated UAVs with limited power; as a result, coordination should have been simplified at low power. Falsified signals and starving circumstances have an impact on survivability. Such issues hasten the loss of resources such as memory and energy. Increasing IoD survival and extending lifespan with limited resources necessitate a significant amount of effort from the scientific community. It should be mandatory to accommodate higher survivability, which necessitates new and creative technology and safe and effective abilities in mission planning automation and optimization in unstructured IoD settings.

H. Cooperation and end-to-end Connectivity

The effectiveness of coordination is reflected in the end-to-end connection. The source and destination connection should always be maintained in an IoD system. End-to-end connection improves interoperability between IoD and other sensors. Some applications, such as real-time monitoring, require a substantial end-to-end connection for greater coverage and collaboration.

I. Low operating Costs and High Throughput

In the planning and application of IoD, the cost is indeed a major consideration. The cost of production is related to the IoD requirements. Non-verified IoD deployment causes significant **Capital Expenditures (CAPEX)** and **Operating Expenses (OPEX)** problems, affecting cost performance. Furthermore, adopting IoD to improve services for bigger groups of isolated users is contingent on operating costs. As a result, low-cost solutions for increasing IoD's use should be created. According to current studies, the cost of operation has a significant impact on throughput. For effective communications, a trade-off between the cost of operation and average throughput attained in IoT must be established.

J. Global Resource Management-related Challenges

Resource distribution is crucial for increasing productivity and lowering costs, and it is grouped into two categories: global allocation and local allocation. Global issues focus on spending resources such as time, energy, and equipment. Furthermore, numerous **Internet of Everything (IoE)** devices, including edge workstations, cloud servers, and UAVs, could be used to achieve optimum worldwide productivity. Global efficiency in IoE digital media transmission could be boosted via networking algorithms and video coding. Each role receives power and energy depending on its commitment to performance. For example, in an intelligent buildings situation, including even a local network, an effective data gathering technique is beneficial for boosting the user's data rate [140]. Furthermore, the energy management system is critical for making the most use of limited energy for the flying terminals. That is the idea of assigning resources to different nodes. Indeed, one problem for UAV applications is maintaining efficiency despite dealing with cost issues. First, designing protocols for network service provisioning relating to information rate and computation requirements is difficult. The challenges that must be addressed are clustered systems, the utilization of cloud resources, and autonomous services. Furthermore, "resource allocation" is the most common economic activity because it involves conflicting interests of individuals, businesses, or services to get certain resources. The next problem is to find dependable and cost-effective methods of assigning client needs. An additional challenge in resource usage is knowing how to design priorities and paths to minimize activity energy expenditure appropriately. Furthermore, resource mapping seeks to provide an equal number of services to suppliers and customers. Physical limits and impediments can make resource mapping difficult, as mapping the physical components and the sensible distribution of resources fulfill the criteria. Creating methods that could quickly get a mapping process using generic approaches is crucial. The application's compatibility with the UAV platform must be verified by installing the necessary hardware. The additional problem to be tackled is developing models that could accurately quantify the performance of multi-core CPUs, PC storage media, communication channels, and data centers. Furthermore, when mapping resources, this concern may be a difficulty.

K. Reliability and Performance

IoD's performance is measured by mission completion time and resource usage efficiency. High-quality manufacturing that considers the necessary conditions while producing IoD end solutions is essential for performance and dependability. Consumption-focused indicators should be included in IoD devices to understand resource efficiency and dependability better. The performance of such resources is measured during their monitoring. Missions that make effective use of resources are more likely to succeed. As a result, resource utilization is a critical metric for IoD performance and dependability.

L. Adaptive Routing Techniques and Dynamic Topologies

IoD's on-demand and realistic settings are made possible by dynamic topologies and adaptive routing methods. In IoD networks, dynamic routing topologies enable waypoint coordination. The delays observed by traditional routing algorithms are insufficient to support IoD cooperation. As a result, adaptive routing techniques should be explored for constantly changing topologies in IoD.

M. Software for Advanced Computer Vision

Rather than using onboard surrounding analytical equipment that adds weight and energy usage, advanced computer vision software might be included in the flying drones to stream the surrounding pictures and relay them back to an object identification server for feature analysis.

N. Security and Privacy Mitigation Approaches based on Artificial Intelligence

Future studies should also include implementing federated drone authentication models using more complex ML architectures such as CNN and RNN and comparing results to state-of-the-art solutions. Using other aspects of drones, like photos or video, as part of the verification process could also be a good idea. Also, on the IoD network, numerous novel technological attacks have been deployed. As a result, it is essential to use **Artificial Intelligence (AI)** that is based on mitigation measures. Artificial neural networks, DL, and ML approaches will help improve privacy and security on the IoD network. Nonetheless, putting AI-based solutions into practice poses significant hurdles. Furthermore, selecting an effective AI algorithm for specific security requirements on the IoD network requires more research.

O. Proven Security Methods that are not too Heavy

The majority of existing solutions for preventing privacy and security breaches on IoD networks have either security weaknesses or are too heavy to employ. It is critical and crucial to maintaining a trade-off between these two aspects. As a result, developing lightweight, tried-and-true security mechanisms for IoD deployment remains a popular research topic. **Mobile Edge Computing (MEC)** devices have been incorporated into the design to ensure this. The MEC devices are movable, allowing the flying drone to move around freely. MEC equipment has higher computer power and memory capacity than drones, allowing faster and more efficient communication. To decrease transmission and computation costs, the conveyed messages are offloaded to the adjacent authenticated MEC device for processing.

P. Blockchain

Even though some works have shown promising outcomes in various domains, there is still a significant amount of room for work expansion. One such horizon is the shrinking of the blockchain at the level of individual drones. Another perspective on the issue suggests that the rate of transactions per unit of time needs to be improved further. Finally, there is still a need to investigate the performance of new consensus techniques in the field of IoDs. Also, identity sovereignty is possible with a permissioned blockchain like HF, which means the original artist retains complete control over their work. Further in-depth discussion and implementation outcomes are required to understand the complexities inherent in this proposed system. In addition, if object detection techniques increase accuracy, the system might use recognition models as a preprocessing phase before HF. As DL technology advances, we wish to see more of the interplay of cutting-edge content-unique hashing strategies, security measures, integrity techniques, and globally adopted blockchains, like the enhancement/development of DL model creation and compression for archival purposes, to ensure a globally safe artificial intelligence society.

Q. Database

In the coming, characteristics from the created drone RF database, which might be utilized for detection, could be extracted and compared to the findings of previous systems. Furthermore, the database produced could train and test various detectors and network topologies to converge on the optimum identification and recognition system. Combining the created database with other drone detection modalities, including camera pictures and videos, radar echoes, and acoustic recordings, might improve the effectiveness of the detection and identification system by using each modality's capabilities. Researchers and students could use the advanced database in a variety of ways, including (1) examining other different classifiers, (2) expanding the advanced database by augmentation, including adding channel fading or noise, (3) repeating the same tests with different drones, (4) studying the effects of RF interference and noise when detecting and identifying drones, and (5) conducting experiments with different drones.

R. Edge-enabled Delay-constrained IoDT Ecosystem

One of the key difficulties is communication between sparsely connected drone nodes with high mobility. As the number of nodes and their speeds grows, conventional routing algorithms fail to transmit messages efficiently. As a result, improving routing techniques is essential. Also, one of the most difficult scenarios is deep space or outer space grid network connection. Improved scientific study paves the way for deploying smart grid systems for space stations and solar-powered renewable energy. In this scenario, the satellites, space stations, and grid components are sparsely linked and moving exceptionally rapidly, making transmission and data transfer a significant problem. Another issue is installing an intelligent load forecasting system in both the fog and edge layers, allowing more effective data dumping and load balancing. The edge and fog devices frequently have limited resources, such as memory and CPU power. Designing a complex algorithm that conducts good load balancing and data unloading is thus one of the most difficult tasks. Furthermore, establishing, monitoring, and controlling critical load and billing information security is a vital study topic for smart grid networks' integrated, holistic security and privacy framework. Key research areas include a dew-enabled drone network and caching mechanism for managing smart grids, blockchain-based security for edge-enabled drone applications, and safe interconnection technologies for smart grid networks. Furthermore, the architecture focuses on an edge-enabled drone network with resource-constrained hardware. The hardware's performance may be harmed when processing a large data class. As a result, a sophisticated load balancing and job offloading mechanism are critical for a broad data handling class.

S. Quantum Drones

Quantum computing is also linked to IoDs, trajectory planning, and real-world applications. A quantum-inspired reinforcement learning method has been suggested in various papers. The algorithm proposes a selection policy and reinforcement techniques to enhance the outcomes. The quantum computing concept is applied in this case. Similarly, this approach may be expanded to include the use of other quantum finite automata for evaluating and optimizing the stages. Quantum satellites, quantum drones, a cluster of quantum satellites, a quantum drone internet, and relevant disciplines have recently been proposed and developed. That field has a diverse range of applications. It covers, among other things, environmental cleansing, carbon dioxide, and hydrogen control, clean technologies, modeling energy systems including heat, water, and wind, and the internet of planetary things. The majority of such ideas might require some time to develop. As a result, simulation software that aids in advancing quantum-related applications or domains might be built, implemented, or investigated. Quantum networks could include various systems, such as radars, underwater drones, satellites, magnetometers, chemical detectors, transmitters, and receivers, as previously mentioned. An examination of these networks and their characteristics might be beneficial in identifying and addressing related issues. The possibility of cyberattacks on these networks and systems must not be overlooked. As a result, topics such as quantum cybersecurity, assaults, and warfare may be investigated to gain a head start on developing solutions.

8 CONCLUSION AND LIMITATION

We have presented a detailed review of the usage of several ML methods in the IoD-UAV area in this survey. This survey differs from previously published studies in terms of breadth and purpose. The IoD is developing technology for connecting drones to evaluate continually growing data from diverse sources to create a new age of real-world applications associated with the Internet. This work offered an SLR of the ML applications for the IoD realm. Before presenting the goal of this research, we addressed the advantages and disadvantages of some systematic and peer-reviewed studies about the UAV-IoD area. Also, the advantages and disadvantages of each mechanism were explored in six categories based on their applicability. The various tools and platforms for ML-IoD were also examined. According to articles using qualitative characteristics, most publications are assessed based on accuracy, energy consumption, latency, robustness, and complexity. Meanwhile, some functions, such as robustness and reliability, go unused. Besides, various programming language libraries are utilized to analyze and implement the apparatuses, with TensorFlow accounting for 33% of the effort. According to the report, resource management and mobility management are classified by 35% of apps. However, in terms of the prospective findings, applying DL or ML to IoD takes a lot of time, effort, and tight collaboration among government, industry, and academia. On the other hand, DL has been acclaimed as a wonderful method for developing smart solutions to these challenges. The findings can assist in the development of IoD-based ML methods in real-world scenarios.

We have also met several challenges, such as the difficulty in accessing non-English papers, which has prohibited us from taking part in several development initiatives. Another limitation of our research is that several of the articles we looked at had severe flaws in terms of clear descriptions of the algorithms they utilized. Since this is a brand-new issue with little maturity in papers and methodologies, constraints such as not comparing the suggested strategy to other methods made it difficult to judge the success of the approaches. Also excluded from the review were studies that indirectly address ML in the IoD-UAV realm. Besides, other articles nearly identical to IoD-ML were also removed from consideration. Another issue we ran into was the inaccessibility of numerous articles published by specific publications.

REFERENCES

[1] R. Meneguette, R. De Grande, J. Ueyama, G. P. R. Filho, and E. Madeira. 2021. Vehicular edge computing: Architecture, resource management, security, and challenges. *ACM Computing Surveys (CSUR)* 55 (2021), 1–46.

[2] S. Vahdat. 2021. The role of IT-based technologies on the management of human resources in the COVID-19 era. *Kybernetes.* (2021).

[3] T. Lee, S. Mckeever, and J. Courtney. 2021. Flying free: A research overview of deep learning in drone navigation autonomy. *Drones* 5 (2021), 52.

[4] B. Bera, A. K. Das, and A. K. Sutrala. 2021. Private blockchain-based access control mechanism for unauthorized UAV detection and mitigation in Internet of Drones environment, *Computer Communications* 166 (2021), 91–109.

[5] C. Feng, B. Liu, Z. Guo, K. Yu, Z. Qin, and K.-K. R. Choo. 2021. Blockchain-based cross-domain authentication for intelligent 5G-enabled Internet of Drones. *IEEE Internet of Things Journal* (2021).

[6] Z. Lv, D. Chen, H. Feng, H. Zhu, and H. Lv. 2021. Digital twins in unmanned aerial vehicles for rapid medical resource delivery in epidemics. *IEEE Transactions on Intelligent Transportation Systems* (2021).

[7] B. Cao, M. Li, X. Liu, J. Zhao, W. Cao, and Z. Lv. 2021. Many-objective deployment optimization for a drone-assisted camera network. *IEEE Transactions on Network Science and Engineering* 8 (2021), 2756–2764.

[8] A. K. Das, B. Bera, M. Wazid, S. S. Jamal, and Y. Park. 2021. iGCACS-IoD: An improved certificate-enabled generic access control scheme for Internet of Drones deployment. *IEEE Access* (2021).

[9] A. Allouch, O. Cheikhrouhou, A. Koubâa, K. Toumi, M. Khalgui, and T. Nguyen Gia. 2021. UTM-chain: Blockchain-based secure unmanned traffic management for Internet of Drones. *Sensors* 21 (2021), 3049.

[10] C. Yu, J. Liu, S. Nemati, and G. Yin. 2021. Reinforcement learning in healthcare: A survey. *ACM Computing Surveys (CSUR)* 55 (2021), 1–36.

[11] N. Zhang, Q. Jiang, L. Li, X. Ma, and J. Ma. 2021. An efficient three-factor remote user authentication protocol based on BPV-FourQ for Internet of Drones. *Peer-to-Peer Networking and Applications* (2021), 1–14.

[12] S. H. Alsamhi, F. Almalki, O. Ma, M. S. Ansari, and B. Lee. 2021. Predictive estimation of optimal signal strength from drones over IoT frameworks in smart cities. *IEEE Transactions on Mobile Computing* (2021).

[13] M. Chowdhury, B. Ray, S. Chowdhury, and S. Rajasegarar. 2021. A novel insider attack and machine learning based detection for the Internet of Things. *ACM Transactions on Internet of Things* 2 (2021), 1–23.

[14] K. Liu, F. Ke, X. Huang, R. Yu, F. Lin, Y. Wu, et al. 2021. DeepBAN: A temporal convolution-based communication framework for dynamic WBANs. *IEEE Transactions on Communications* 69 (2021), 6675–6690.

[15] T. M. Ghazal, M. K. Hasan, M. T. Alshurideh, H. M. Alzoubi, M. Ahmad, S. S. Akbar, et al. 2021. IoT for smart cities: Machine learning approaches in smart healthcare—A review. *Future Internet* 13 (2021), 218.

[16] S. Yaqoob, A. Ullah, M. Awais, I. Katib, A. Albeshri, R. Mehmood, et al. 2021. Novel congestion avoidance scheme for Internet of Drones. *Computer Communications* 169 (2021), 202–210.

[17] M. Dibaei, X. Zheng, Y. Xia, X. Xu, A. Jolfaei, A. K. Bashir, et al. 2021. Investigating the prospect of leveraging blockchain and machine learning to secure vehicular networks: A survey. *IEEE Transactions on Intelligent Transportation Systems* (2021).

[18] S. Tarar and N. Bhasin. 2021. Fire hazard detection and prediction by machine learning techniques in smart buildings (SBs) using sensors and unmanned aerial vehicles (UAVs). *Digital Cities Roadmap: IoT-Based Architecture and Sustainable Buildings* (2021), 63–95.

[19] Y. Qu, H. Dai, Y. Zhuang, J. Chen, C. Dong, F. Wu, et al. 2021. Decentralized federated learning for UAV networks: Architecture, challenges, and opportunities. *IEEE Network* 35 (2021), 156–162.

[20] B. Sazdić-Jotić, I. Pokrajac, J. Bajčetić, B. Bondžulić, and D. Obradović. 2021. Single and multiple drones detection and identification using RF based deep learning algorithm. *Expert Systems with Applications* (2021), 115928.

[21] G. Vallathan, A. John, C. Thirumalai, S. Mohan, G. Srivastava, and J. C.-W. Lin. 2021. Suspicious activity detection using deep learning in secure assisted living IoT environments. *The Journal of Supercomputing* 77 (2021), 3242–3260.

[22] A. Hazra, M. Adhikari, T. Amgoth, and S. N. Srirama. 2021. A comprehensive survey on interoperability for IIoT: Taxonomy, standards, and future directions. *ACM Computing Surveys (CSUR)* 55 (2021), 1–35.

[23] A. Khamis, D. Patel, and K. Elgazzar. 2021. Deep learning for unmanned autonomous vehicles: A comprehensive review. *Deep Learning for Unmanned Systems* (2021), 1–24.

[24] D.-J. Lin, M.-Y. Chen, H.-S. Chiang, and P. K. Sharma. 2021. Intelligent traffic accident prediction model for Internet of Vehicles with deep learning approach. *IEEE Transactions on Intelligent Transportation Systems* (2021).

[25] S. Liao, J. Wu, J. Li, A. K. Bashir, and W. Yang. 2021. Securing collaborative environment monitoring in smart cities using blockchain enabled software-defined Internet of Drones. *IEEE Internet of Things Magazine* 4 (2021), 12–18.

[26] N. Thakur, P. Nagrath, R. Jain, D. Saini, N. Sharma, and D. J. Hemanth. 2021. Artificial intelligence techniques in smart cities surveillance using UAVs: A survey. *Machine Intelligence and Data Analytics for Sustainable Future Smart Cities* (2021), 329–353.

[27] E. K. Elsayed, A. M. Alsayed, O. M. Salama, A. M. Alnour, and H. A. Mohammed. 2020. Deep learning for Covid-19 facemask detection using autonomous drone based on IoT. In *International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE'20)*, 1–5.

[28] Y. Liu, K.-D. Xu, J. Li, Y.-J. Guo, A. Zhang, and Q. Chen. 2022. Millimeter-wave E-plane waveguide bandpass filters based on spoof surface plasmon polaritons. *IEEE Transactions on Microwave Theory and Techniques* 70 (2022), 4399–4409.

[29] A. Yazdinejadna, R. M. Parizi, A. Dehghantanha, and H. Karimipour. 2021. Federated learning for drone authentication. *Ad Hoc Networks* (2021), 102574.

[30] J. Kang, Z. Xiong, D. Niyato, S. Xie, and D. I. Kim. 2021. Securing data sharing from the sky: Integrating blockchains into drones in 5G and beyond. *IEEE Network* 35 (2021), 78–85.

[31] C. Guerber, M. Royer, and N. Larrieu. 2021. Machine learning and software defined network to secure communications in a swarm of drones. *Journal of Information Security and Applications* 61 (2021), 102940.

[32] D. Meng, Y. Xiao, Z. Guo, A. Jolfaei, L. Qin, X. Lu, et al. 2021. A data-driven intelligent planning model for UAVs routing networks in mobile Internet of Things. *Computer Communications* 179 (2021), 231–241.

[33] J. Angjo, I. Shayea, M. Ergen, H. Mohamad, A. Alhammadi, and Y. I. Daradkeh. 2021. Handover management of drones in future mobile networks: 6G technologies. *IEEE Access* 9 (2021), 12803–12823.

[34] K. Bhattacharjya and D. De. 2021. IoUT: Modelling and simulation of edge-drone-based software-defined smart Internet of Underwater Things. *Simulation Modelling Practice and Theory* 109 (2021), 102304.

[35] S. Singha and B. Aydin. 2021. Automated drone detection using YOLOv4. *Drones* 5 (2021), 95.

[36] R. Gupta, D. Reebadiya, and S. Tanwar. 2021. 6G-enabled edge intelligence for ultra-reliable low latency applications: Vision and mission. *Computer Standards & Interfaces* 77 (2021), 103521.

[37] U. Ahmad, H. Song, A. Bilal, S. Mahmood, M. Alazab, A. Jolfaei, et al. 2021. A novel deep learning model to secure Internet of Things in healthcare. In *Machine Intelligence and Big Data Analytics for Cybersecurity Applications* (ed.). Springer, 2021, 341–353.

[38] P. K. Dutta and S. Mitra. 2021. Application of agricultural drones and IoT to understand food supply chain during post COVID-19. *Agricultural Informatics: Automation Using the IoT and Machine Learning* (2021), 67–87.

[39] H. Shahid, M. A. Shah, A. Almogren, H. A. Khattak, I. U. Din, N. Kumar, et al. 2021. Machine learning-based mist computing enabled Internet of Battlefield Things. *ACM Transactions on Internet Technology (TOIT)* 21 (2021), 1–26.

[40] S. Srivastava, S. Narayan, and S. Mittal. 2021. A survey of deep learning techniques for vehicle detection from UAV images. *Journal of Systems Architecture* (2021), 102152.

[41] H. S. Munawar, F. Ullah, S. Qayyum, and A. Heravi. 2021. Application of deep learning on UAV-based aerial images for flood detection. *Smart Cities* 4 (2021), 1220–1243.

[42] K. Cao, H. Ding, B. Wang, L. Lv, J. Tian, Q. Wei, et al. 2022. Enhancing physical layer security for IoT with non-orthogonal multiple access assisted semi-grant-free transmission. *IEEE Internet of Things Journal* (2022).

[43] R. Shahzadi, M. Ali, H. Z. Khan, and M. Naeem. 2021. UAV assisted 5G and beyond wireless networks: A survey. *Journal of Network and Computer Applications* 189 (2021), 103114.

[44] A. Rovira-Sugranes, A. Razi, F. Afghah, and J. Chakareski. 2022. A review of AI-enabled routing protocols for UAV networks: Trends, challenges, and future outlook. *Ad Hoc Networks* 130 (2022), 102790.

[45] Y. Pan, Y. Yang, and W. Li. 2021. A deep learning trained by genetic algorithm to improve the efficiency of path planning for data collection with multi-UAV. *IEEE Access* 9 (2021), 7994–8005.

[46] A. A. Khan, M. M. Khan, K. M. Khan, J. Arshad, and F. Ahmad. 2021. A blockchain-based decentralized machine learning framework for collaborative intrusion detection within UAVs. *Computer Networks* (2021), 108217.

[47] R. P. França, A. C. B. Monteiro, R. Arthur, and Y. Iano. 2021. An overview of the machine learning applied in smart cities. *Smart Cities: A Data Analytics Perspective* (2021), 91–111.

[48] H. Sharma, A. Haque, and F. Blaabjerg. 2021. Machine learning in wireless sensor networks for smart cities: A survey. *Electronics* 10 (2021), 1012.

[49] M. Zekić-Sušac, S. Mitrović, and A. Has. 2021. Machine learning based system for managing energy efficiency of public sector as an approach towards smart cities. *International Journal of Information Management* 58 (2021), 102074.

[50] M. Rashmi Bandara, M. N. Halgamuge, and G. Marques. 2021. Machine learning and Internet of Things for smart living: A comprehensive review and analysis. *Enhanced Telemedicine and e-Health: Advanced IoT Enabled Soft Computing Framework* (2021), 155–177.

[51] K.-D. Xu, Y.-J. Guo, Y. Liu, X. Deng, Q. Chen, and Z. Ma. 2021. 60-GHz compact dual-mode on-chip bandpass filter using GaAs technology. *IEEE Electron Device Letters* 42 (2021), 1120–1123.

[52] Y. Xi, W. Jiang, K. Wei, T. Hong, T. Cheng, and S. Gong. 2021. Wideband RCS reduction of microstrip antenna array using coding metasurface with Low Q resonators and fast optimization method. *IEEE Antennas and Wireless Propagation Letters* 21 (2021), 656–660.

[53] Y. Zhang, P. Geng, C. Sivaparthipan, and B. A. Muthu. 2021. Big data and artificial intelligence based early risk warning system of fire hazard for smart cities. *Sustainable Energy Technologies and Assessments* 45 (2021), 100986.

[54] G. Ciaburro. 2021. Security systems for smart cities based on acoustic sensors and machine learning applications. In *Machine Intelligence and Data Analytics for Sustainable Future Smart Cities* (ed.). Springer, (2021), 369–393.

[55] K. Liu, Z. Yang, W. Wei, B. Gao, D. Xin, C. Sun, et al. 2022. Novel detection approach for thermal defects: Study on its feasibility and application to vehicle cables. *High Voltage* (2022).

[56] S. Khan, S. Nazir, I. García-Magariño, and A. Hussain. 2021. Deep learning-based urban big data fusion in smart cities: Towards traffic monitoring and flow-preserving fusion. *Computers & Electrical Engineering* 89 (2021), 106906.

[57] D. K. Reddy, H. S. Behera, J. Nayak, P. Vijayakumar, B. Naik, and P. K. Singh. 2021. Deep neural network based anomaly detection in Internet of Things network traffic tracking for the applications of future smart cities. *Transactions on Emerging Telecommunications Technologies* 32 (2021), e4121.

[58] S. M. Miraftabzadeh, M. Longo, and F. Foiadelli. 2021. Machine learning models in smart cities–data-driven perspective. In *Internet of Energy for Smart Cities* (ed.). CRC Press, (2021), 203–226.

[59] F. Ullah and F. Al-Turjman. 2021. A conceptual framework for blockchain smart contract adoption to manage real estate deals in smart cities. *Neural Computing and Applications* (2021), 1–22.

[60] A. Belhadi, Y. Djenouri, G. Srivastava, D. Djenouri, J. C.-W. Lin, and G. Fortino. 2021. Deep learning for pedestrian collective behavior analysis in smart cities: A model of group trajectory outlier detection. *Information Fusion* 65 (2021), 13–20.

[61] A. N. Muhammad, A. M. Aseere, H. Chiroma, H. Shah, A. Y. Gital, and I. A. T. Hashem. 2021. Deep learning application in smart cities: Recent development, taxonomy, challenges and research prospects. *Neural Computing and Applications* 33 (2021), 2973–3009.

[62] Z. Feng, L. Ji, Q. Zhang, and W. Li. 2018. Spectrum management for mmWave enabled UAV swarm networks: Challenges and opportunities. *IEEE Communications Magazine* 57 (2018), 146–153.

[63] A. Fotouhi, H. Qiang, M. Ding, M. Hassan, L. G. Giordano, A. Garcia-Rodriguez, et al. 2019. Survey on UAV cellular communications: Practical aspects, standardization advancements, regulation, and security challenges. *IEEE Communications Surveys & Tutorials* 21 (2019), 3417–3442.

[64] D. Singh, V. Kumar, and M. Kaur. 2020. Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks. *European Journal of Clinical Microbiology & Infectious Diseases* 39 (2020), 1379–1389.

[65] A. I. Khan, J. L. Shah, and M. M. Bhat. 2020. CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. *Computer Methods and Programs in Biomedicine* 196 (2020), 105581.

[66] A. Heidari, M. A. Jabraeil Jamali, N. Jafari Navimipour, and S. Akbarpour. 2020. Internet of Things offloading: Ongoing issues, opportunities, and future challenges. *International Journal of Communication Systems* 33 (2020), e4474.

[67] F. Cui, Q. Cui, and Y. Song. 2020. A survey on learning-based approaches for modeling and classification of human-machine dialog systems. *IEEE Transactions on Neural Networks and Learning Systems* (2020).

[68] M. Toğaçar, B. Ergen, and Z. Cömert. 2020. COVID-19 detection using deep learning models to exploit Social Mimic Optimization and structured chest X-ray images using fuzzy color and stacking approaches. *Computers in Biology and Medicine* 121 (2020), 103805.

[69] A. A. Ardakani, A. R. Kanafi, U. R. Acharya, N. Khadem, and A. Mohammadi. 2020. Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. *Computers in Biology and Medicine* 121 (2020), 103795.

[70] M. Injadat, A. Moubayed, A. B. Nassif, and A. Shami. 2021. Machine learning towards intelligent systems: Applications, challenges, and opportunities. *Artificial Intelligence Review* (2021), 1–50.

[71] W. Du and S. Ding. 2020. A survey on multi-agent deep reinforcement learning: From the perspective of challenges and applications. *Artificial Intelligence Review.* 1–24.

[72] M. M. Hameed, R. Ahmad, M. L. M. Kiah, and G. Murtaza. 2021. Machine learning-based offline signature verification systems: A systematic review. *Signal Processing: Image Communication* (2021), 116139.

[73] Z. Y. Khan and Z. Niu. 2020. CNN with depthwise separable convolutions and combined kernels for rating prediction. *Expert Systems with Applications* (2020), 114528.

[74] X. Yuan, J. Shi, and L. Gu. 2020. A review of deep learning methods for semantic segmentation of remote sensing imagery. *Expert Systems with Applications* (2020), 114417.

[75] B. B. Gardas, A. Heidari, N. J. Navimipour, and M. Unal. 2022. A fuzzy-based method for objects selection in blockchain-enabled edge-IoT platforms using a hybrid multi-criteria decision-making model. *Applied Sciences* 12 (2022), 8906.

[76] A. Heidari, M. A. Jabraeil Jamali, N. Jafari Navimipour, and S. Akbarpour. 2022. Deep Q-learning technique for offloading offline/online computation in blockchain-enabled green IoT-edge scenarios. *Applied Sciences* 12 (2022), 8232.

[77] T. Li, W. Bo, C. Hu, H. Kang, H. Liu, K. Wang, et al. 2021. Applications of deep learning in fundus images: A review. *Medical Image Analysis* (2021), 101971.

[78] M. A. Jabraeil Jamali, B. Bahrami, A. Heidari, P. Allahverdizadeh, and F. Norouzi. 2020. IoT Security. In *Towards the Internet of Things: Architectures, Security, and Applications* (ed.). Cham: Springer International Publishing, (2020), 33–83.

[79] Y. Hu, J. xiang Qing, Z. H. Liu, Z. J. Conrad, J. N. Cao, and X. P. Zhang. 2021. Hovering efficiency optimization of the ducted propeller with weight penalty taken into account. *Aerospace Science and Technology* 117 (2021), 106937.

[80] G. Zhou, X. Bao, S. Ye, H. Wang, and H. Yan. 2020. Selection of optimal building facade texture images from UAV-based multiple oblique image flows. *IEEE Transactions on Geoscience and Remote Sensing* 59 (2020), 1534–1552.

[81] Z. Yang, X. Yu, S. Dedman, M. Rosso, J. Zhu, J. Yang, et al. 2022. UAV remote sensing applications in marine monitoring: Knowledge visualization and review. *Science of the Total Environment* (2022), 155939.

[82] A. Gupta and S. K. Gupta. Flying through the secure fog: A complete study on UAV-Fog in heterogeneous networks. *International Journal of Communication Systems.* e5237.

[83] N. H. Motlagh, T. Taleb, and O. Arouk. 2016. Low-altitude unmanned aerial vehicles-based Internet of Things services: Comprehensive survey and future perspectives. *IEEE Internet of Things Journal* 3 (2016), 899–922.

[84] P. Boccadoro, D. Striccoli, and L. A. Grieco. 2021. An extensive survey on the Internet of Drones. *Ad Hoc Networks* 122 (2021), 102600.

[85] A. Nayyar, B.-L. Nguyen, and N. G. Nguyen. 2020. The Internet of Drone Things (IoDT): Future envision of smart drones. In *First International Conference on Sustainable Technologies for Computational Intelligence.* 563–580.

[86] A. Abdelmaboud. 2021. The Internet of Drones: Requirements, taxonomy, recent advances, and challenges of research trends. *Sensors* 21 (2021), 5718.

[87] M. Yahuza, M. Y. I. Idris, I. B. Ahmedy, A. W. A. Wahab, T. Nandy, N. M. Noor, et al. 2021. Internet of Drones security and privacy issues: Taxonomy and open challenges. *IEEE Access* 9 (2021), 57243–57270.

[88] S. H. Alsamhi, O. Ma, and M. Ansari. 2020. Convergence of machine learning and robotics communication in collaborative assembly: Mobility, connectivity and future perspectives. *Journal of Intelligent & Robotic Systems* 98 (2020), 541–566.

[89] F. A. Alqurashi, F. Alsolami, S. Abdel-Khalek, E. Sayed Ali, and R. A. Saeed. 2022. Machine learning techniques in Internet of UAVs for smart cities applications. *Journal of Intelligent & Fuzzy Systems* 42 (2022), 3203–3226.

[90] J. Wang, C. Jiang, H. Zhang, Y. Ren, K.-C. Chen, and L. Hanzo. 2020. Thirty years of machine learning: The road to Pareto-optimal wireless networks, *IEEE Communications Surveys & Tutorials* 22 (2020), 1472–1514.

[91] A. Kumar, S. Bhatia, K. Kaushik, M. Gandhi, G. Devi, D. Pacheco, et al. 2021. Survey of promising technologies for quantum drones and networks. *IEEE Access* (2021).

[92] P. S. Bithas, E. T. Michailidis, N. Nomikos, D. Vouyioukas, and A. G. Kanatas. 2019. A survey on machine-learning techniques for UAV-based communications. *Sensors* 19 (2019), 5170.

[93] S. Vahdat and S. Shahidi. 2020. D-dimer levels in chronic kidney illness: A comprehensive and systematic literature review. *Proceedings of the National Academy of Sciences, India Section b: Biological Sciences* 90 (2020), 911–928.

[94] M. Esmailiyan, A. Amerizadeh, S. Vahdat, M. Ghodsi, R. I. Doewes, and Y. Sundram. 2021. Effect of different types of aerobic exercise on individuals with and without hypertension: An updated systematic review. *Current Problems in Cardiology* (2021), 101034.

[95] F. A. Zadeh, D. O. Bokov, G. Yasin, S. Vahdat, and M. Abbasalizad-Farhangi. 2021. Central obesity accelerates leukocyte telomere length (LTL) shortening in apparently healthy adults: A systematic review and meta-analysis. *Critical Reviews in Food Science and Nutrition* (2021) 1–10.

[96] S. Vahdat. 2022. Clinical profile, outcome and management of kidney disease in COVID-19 patients - a narrative review. *Eur. Rev. Med. Pharmacol. Sci.* 26 (Mar. 2022), 2188–2195.

[97] A. Koubâa, A. Ammar, M. Alahdab, A. Kanhouch, and A. T. Azar. 2020. DeepBrain: Experimental evaluation of cloud-based computation offloading and edge computing in the Internet-of-Drones for deep learning applications. *Sensors* 20 (2020), 5240.

[98] L. Yang, H. Yao, J. Wang, C. Jiang, A. Benslimane, and Y. Liu. 2020. Multi-UAV-enabled load-balance mobile-edge computing for IoT networks. *IEEE Internet of Things Journal* 7 (2020), 6898–6908.

[99] Y. Su, S. Wang, Q. Cheng, and Y. Qiu. 2021. Buffer evaluation model and scheduling strategy for video streaming services in 5G-powered drone using machine learning. *EURASIP Journal on Image and Video Processing* (2021), 1–18.

[100] D. Wei, J. Ma, L. Luo, Y. Wang, L. He, and X. Li. 2021. Computation offloading over multi-UAV MEC network: A distributed deep reinforcement learning approach. *Computer Networks* (2021), 108439.

[101] A. Al-Hilo, M. Samir, C. Assi, S. Sharafeddine, and D. Ebrahimi. 2020. UAV-assisted content delivery in intelligent transportation systems-joint trajectory planning and cache management. *IEEE Transactions on Intelligent Transportation Systems* (2020).

[102] B. Yang, X. Cao, C. Yuen, and L. Qian. 2020. Offloading optimization in edge computing for deep-learning-enabled target tracking by Internet of UAVs. *IEEE Internet of Things Journal* 8 (2020), 9878–9893.

[103] K. Li, W. Ni, E. Tovar, and M. Guizani. 2020. Joint flight cruise control and data collection in UAV-aided Internet of Things: An onboard deep reinforcement learning approach. *IEEE Internet of Things Journal* (2020).

[104] C. Zhang, M. Dong, and K. Ota. 2021. Deploying SDN control in Internet of UAVs: Q-learning-based edge scheduling. *IEEE Transactions on Network and Service Management* 18 (2021), 526–537.

[105] M. F. Al-Sa'd, A. Al-Ali, A. Mohamed, T. Khattab, and A. Erbad. 2019. RF-based drone detection and identification using deep learning approaches: An initiative towards a large open source drone database. *Future Generation Computer Systems* 100 (2019), 86–97.

[106] L. Meng, T. Hirayama, and S. Oyanagi. 2018. Underwater-drone with panoramic camera for automatic fish recognition based on deep learning. *IEEE Access* 6 (2018), 17880–17886.

[107] D. Hernández, J.-C. Cano, F. Silla, C. T. Calafate, and J. M. Cecilia. 2021. AI-enabled autonomous drones for fast climate change crisis assessment. *IEEE Internet of Things Journal* (2021).

[108] I. Dasgupta, J. Saha, P. Venkatasubbu, and P. Ramasubramanian. 2020. AI crop predictor and weed detector using wireless technologies: A smart application for farmers. *Arabian Journal for Science and Engineering* 45 (2020), 11115–11127.

[109] A. Barnawi, P. Chhikara, R. Tekchandani, N. Kumar, and B. Alzahrani. 2021. Artificial intelligence-enabled Internet of Things-based system for COVID-19 screening using aerial thermal imaging. *Future Generation Computer Systems* (2021).

[110] M. Ghazal, T. Basmaji, M. Yaghi, M. Alkhedher, M. Mahmoud, and A. S. El-Baz. 2020. Cloud-based monitoring of thermal anomalies in industrial environments using AI and the Internet of Robotic Things. *Sensors* 20 (2020), 6348.

[111] K. Madasamy, V. Shanmuganathan, V. Kandasamy, M. Y. Lee, and M. Thangadurai. 2021. OSDDY: Embedded system-based object surveillance detection system with small drone using deep YOLO. *EURASIP Journal on Image and Video Processing,* vol. 2021 (2021), 1–14.

[112] E. K. Wang, C.-M. Chen, F. Wang, M. K. Khan, and S. Kumari. 2020. Joint-learning segmentation in Internet of Drones (IoD)-based monitor systems. *Computer Communications* 152 (2020), 54–62.

[113] H. Genc, Y. Zu, T.-W. Chin, M. Halpern, and V. J. Reddi. 2021. Flying IoT: Toward low-power vision in the sky. *IEEE Micro* 37 (2017), 40–51.

[114] G. Tian, J. Liu, and W. Yang. 2021. A dual neural network for object detection in UAV images. *Neurocomputing* 443 (2021), 292–301.

[115] M. Ł. Pawełczyk and M. Wojtyra. 2020. Real world object detection dataset for quadcopter unmanned aerial vehicle detection, *IEEE Access* 8 (2020), 174394–174409.

[116] Y. Li, Y. Chen, S. Yuan, J. Liu, X. Zhao, Y. Yang, et al. 2021. Vehicle detection from road image sequences for intelligent traffic scheduling. *Computers & Electrical Engineering* 95 (2021), 107406.

[117] J. Yao and N. Ansari. 2021. Secure federated learning by power control for Internet of Drones. *IEEE Transactions on Cognitive Communications and Networking* (2021).

[118] G. Faraci, A. Raciti, S. A. Rizzo, and G. Schembra. 2020. Green wireless power transfer system for a drone fleet managed by reinforcement learning in smart industry. *Applied Energy* 259 (2020), 114204.

[119] W. Xu, H. Lei, and J. Shang. 2021. Joint topology construction and power adjustment for UAV networks: A deep reinforcement learning based approach. *China Communications* 18 (2021), 265–283.
[120] J. Yao and N. Ansari. 2021. Wireless power and energy harvesting control in IoD by deep reinforcement learning. *IEEE Transactions on Green Communications and Networking* 5 (2021), 980–989.
[121] A. Mukherjee, P. Mukherjee, D. De, and N. Dey. 2021. iGridEdgeDrone: Hybrid mobility aware intelligent load forecasting by edge enabled Internet of Drone Things for smart grid networks. *International Journal of Parallel Programming* 49 (2021), 285–325.
[122] K. Li, W. Ni, E. Tovard, and A. Jamalipour. 2020. Online velocity control and data capture of drones for the Internet of Things: An onboard deep reinforcement learning approach. *IEEE Vehicular Technology Magazine* 16 (2020), 49–56.
[123] T. Hong, Q. Yang, P. Wang, J. Zhang, W. Sun, L. Tao, et al. 2021. Multitarget real-time tracking algorithm for UAV IoT. *Wireless Communications and Mobile Computing* 2021, (2021).
[124] J. Tanveer, A. Haider, R. Ali, and A. Kim. 2021. Reinforcement learning-based optimization for drone mobility in 5G and beyond ultra-dense networks. *CMC-Computers Materials & Continua.* 68 (2021), 3807–3823.
[125] F. Qi, W. Li, P. Yu, L. Feng, and F. Zhou. 2021. Deep learning-based BackCom multiple beamforming for 6G UAV IoT networks. *EURASIP Journal on Wireless Communications and Networking* 2021 (2021), 1–17.
[126] L. He, A. Nabil, and B. Song. 2020. Explainable deep reinforcement learning for UAV autonomous navigation. *arXiv preprint arXiv:2009.14551,* 2020.
[127] S. F. Abedin, M. S. Munir, N. H. Tran, Z. Han, and C. S. Hong. 2020. Data freshness and energy-efficient UAV navigation optimization: A deep reinforcement learning approach, *IEEE Transactions on Intelligent Transportation Systems* (2020).
[128] M. S. Shokry, D. Ebrahimi, C. Assi, S. Sharafeddine, and A. Ghrayeb. 2020. Leveraging UAVs for coverage in cell-free vehicular networks: A deep reinforcement learning approach. *IEEE Transactions on Mobile Computing* (2020), 1–1.
[129] M. Singh, G. S. Aujla, and R. S. Bali. 2020. A deep learning-based blockchain mechanism for secure Internet of Drones environment. *IEEE Transactions on Intelligent Transportation Systems* (2020).
[130] A. Gumaei, M. Al-Rakhami, M. M. Hassan, P. Pace, G. Alai, K. Lin, et al. 2021. Deep learning and blockchain with edge computing for 5G-enabled drone identification and flight mode detection. *IEEE Network* 35 (2021), 94–100.
[131] S. Sarkar, S. Khare, M. W. Totaro, and A. Kumar. 2021. A novel energy aware secure Internet of Drones design: ESIoD. In *IEEE INFOCOM2021-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*. 1–6.
[132] B. Xie, S. Li, F. Lv, C. H. Liu, G. Wang, and D. Wu. 2022. A collaborative alignment framework of transferable knowledge extraction for unsupervised domain adaptation. *IEEE Transactions on Knowledge and Data Engineering* (2022).
[133] T. Li, W. Liu, A. Liu, M. Dong, K. Ota, N. N. Xiong, et al. 2021. BTS: A blockchain-based trust system to deter malicious data reporting in Intelligent Internet of Things. *IEEE Internet of Things Journal* (2021).
[134] S. Al-Emadi, A. Al-Ali, and A. Al-Ali. 2021. Audio-based drone detection and identification using deep learning techniques with dataset enhancement through generative adversarial networks. *Sensors* 21 (2021), 4953.
[135] W. Y. B. Lim, J. Huang, Z. Xiong, J. Kang, D. Niyato, X.-S. Hua, et al. 2021. Towards federated learning in UAV-enabled Internet of Vehicles: A multi-dimensional contract-matching approach. *IEEE Transactions on Intelligent Transportation Systems* (2021).
[136] G. Luo, Q. Yuan, J. Li, S. Wang, and F. Yang. 2022. Artificial intelligence powered mobile networks: From cognition to decision. *IEEE Network* 36 (2022), 136–144.
[137] A. Li, D. Spano, J. Krivochiza, S. Domouchtsidis, C. G. Tsinos, C. Masouros, et al. 2020. A tutorial on interference exploitation via symbol-level precoding: Overview, state-of-the-art and future directions. *IEEE Communications Surveys & Tutorials* 22 (2020), 796–839.
[138] A. Li, C. Masouros, A. L. Swindlehurst, and W. Yu. 2021. 1-bit massive MIMO transmission: Embracing interference with symbol-level precoding. *IEEE Communications Magazine* 59 (2021), 121–127.
[139] B. Dai, B. Zhang, Z. Niu, Y. Feng, Y. Liu, and Y. Fan. 2022. A novel ultrawideband branch waveguide coupler with low amplitude imbalance. *IEEE Transactions on Microwave Theory and Techniques* 70 (2022), 3838–3846.
[140] Y. Feng, B. Zhang, Y. Liu, Z. Niu, Y. Fan, and X. Chen. 2022. A D-band manifold triplexer with high isolation utilizing novel waveguide dual-mode filters. *IEEE Transactions on Terahertz Science and Technology* (2022).

Received 20 December 2021; revised 26 September 2022; accepted 2 November 2022