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# A Comprehensive Survey on Artificial Intelligence for Unmanned Aerial Vehicles

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**ABSTRACT** Artificial Intelligence (AI) is an emerging technology that finds its application in various industries. Integration of AI in Unmanned Aerial Vehicles (UAVs) can lead to tremendous growth in the field of UAVs by improving flight safety and efficiency. Machine learning algorithms can enable UAVs to make real-time decisions in complex environments and reach the optimal solution that aims to fulfill a mission's requirements within the hardware constraints such as battery and payload. Several recent works in UAVs employed a variety of machine learning algorithms to enhance the capabilities of UAVs and assist them. Although several reviews have been published examining the various aspects of AI for UAVs, they are all pertaining to particular applications or technologies. Addressing this research gap, we present a comprehensive and diversified review to enable researchers to analyze the current and future requirements and develop the latest solutions utilizing AI. We have classified the reviewed works based on three different classification schemes: 1) application scenario-based, 2) AI algorithm-based, and 3) AI training paradigm-based. We have also presented a compilation of frameworks, tools, and libraries used in AI-integrated UAV systems. We identified that the integration of AI in UAVs has a wide array of applications ranging from path planning to resource allocation. We have observed that Reinforcement Learning based algorithms are more often used in AI-integrated UAV systems than other AI algorithms. Further, our findings reveal that UAV frameworks employing federated learning and other distributed machine learning paradigms are quickly emerging. Furthermore, we also have put forth several challenges and potential applications of AI-integrated UAV systems.

**INDEX TERMS** UAVs, machine learning, artificial intelligence, applications, AI algorithms, AI training paradigms.

## I. INTRODUCTION

Artificial Intelligence (AI) refers to the field of study focused on creating intelligent agents or devices that possess the ability to comprehend their surroundings and make suitable decisions to maximize their chances of accomplishing predefined goals [1]. Rapid progress is being made in the realm of AI, and efforts are being made for its infusion into different utilities to improve the efficiency of operations and achieve far-reaching goals. UAVs have witnessed remarkable growth in recent years with advancements in artificial intelligence (AI) and machine learning. Researchers have applied various artificial techniques to enhance the capabilities and functionalities of UAVs. The incorporation of Artificial Intelligence in UAVs renders autonomy to UAVs. It is estimated that the autonomous Unmanned Aerial Vehicle(UAV) market would cross an expected market value of USD 15634.7 million in 2023 and would cross a valuation of USD 91304.8 million by the end of 2033. [2]. Multiple sectors, including transportation and surveillance, have seen a drastic change as a result of autonomous UAV technology. Modern UAVs are equipped with advanced sensors and AI-based algorithms, enabling them to function autonomously without any human

**TABLE 1. Related Surveys**

| Year | Author | Contributions |
|---|---|---|
| 2019 | Bithas et al. [6] | Presented a comprehensive examination of various Machine Learning(ML) algorithms employed to facilitate UAV-based communication. |
| 2021 | Wilson et al. [10] | Presented the latest advancements in embedded sensors, communication technologies, computing platforms, and machine learning methods, which have been employed in UAVs for smart sensing tasks while simultaneously achieving high power efficiency. |
| 2021 | Munawar et al. [13] | Presented an integrated approach for post-disaster flood management via the use of cutting-edge technologies and UAVs. |
| 2021 | Thakur et al. [12] | Surveyed the artificial intelligence techniques in smart cities surveillance using UAVs. |
| 2022 | Rezwan et al. [7] | Conducted a thorough assessment of various research works involving the use of AI for UAV navigation and also highlighted some of the major future problems. |
| 2022 | Fu et al. [8] | Investigated methods to solve the problem of low energy efficiency in wireless UAV networks using a deep learning approach. |
| 2022 | Puente et al. [9] | Surveyed various AI algorithms which facilitate autonomous path planning in UAV swarms. |
| 2023 | Tang et al. [14] | Presented a review on swarm intelligence algorithms for multiple unmanned aerial vehicles collaboration. |
| 2023 | Cheng et al. [11] | Presented an extensive review of integration of AI in various UAV-focused IoT(Internet of Things) functions. |
| 2023 | Sai et al. | Presents a comprehensive and diversified review of AI-integrated UAV systems and demonstrates most of the latest trends in technologies and potential fields for improving UAV applications by using AI. |

intervention. The efficacy and precision of autonomous UAVs enable them to navigate through complicated environments, collect data, and execute complex tasks. Such UAVs are being inducted for a variety of real-life purposes, such as monitoring traffic patterns, conducting aerial inspections [3], [4], or delivering packages. In agriculture, they help in crop monitoring and spraying and provide farmers with invaluable insights into their fields. In disaster management, they are used for damage assessment, survivor localization, and the delivery of aid to inaccessible regions.

AI algorithms are incorporated in several applications of UAVs, as discussed later in Section III. Path planning, UAV control systems, and UAV swarm coordination are some of the important applications. Path planning plays a crucial role in UAV operations, ensuring safe and efficient navigation. ML algorithms, such as Reinforcement Learning (RL), are commonly employed to train UAVs to compute optimal paths based on environmental factors and mission objectives. UAV control systems employ AI techniques to ensure a stable flight and precise maneuvering. Proportional-Integral-Derivative (PID) controllers adjust UAV movements based on error signals between desired and actual states. Machine Learning(ML) algorithms like Deep Learning Neural Networks (DLNNs) have been employed to enhance control systems by learning complex flight dynamics and adaptive control strategies. Further, AI algorithms enable the coordination of multiple UAVs and facilitate collaborative operations. Swarm algorithms, such as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), enable UAVs to communicate and cooperate, leading to efficient task allocation [5] and collective decision-making.

Modern UAV power system has seen rapid upgradation with the development of efficient batteries that provide longer flight time. High-resolution cameras and other sensors are able to capture real-time data during flight, which enables the decision-making process and enhances situational awareness.

### A. RELATED SURVEYS

In the section, we start by briefly describing the already undertaken works in areas related to our topic and differentiate our work from them. The related surveys have been summarized in Table 1. Bithas et al. [6] put forth a comprehensive examination of various Machine Learning(ML) algorithms employed to facilitate UAV-based communications. Rezwan et al. [7] conducted a thorough assessment of various research works involving the use of AI for UAV navigation and also highlighted some of the major future problems. Fu et al. [8] investigated methods to solve the problem of low energy efficiency in wireless UAV networks using deep learning approaches. Puente et al. [9] surveyed various AI algorithms such as reinforcement learning, which facilitate autonomous path planning in UAV swarms. They also highlighted the prospective future challenges and their potent solutions. Wilson et al. [10] presented the latest advancements in embedded sensors, communication technologies, computing platforms, and machine learning methods which have been employed in UAVs for smart sensing tasks while simultaneously achieving high power efficiency. Cheng et al. [11] presented a review of the integration of AI in various UAV-focused IoT(Internet of Things) functions.

Although several reviews have been published examining the various aspects of AI for UAVs, they are all pertaining to particular applications or technologies like path planning [9], smart city surveillance [12], flood management [13], and Internet of Things(IoT) [11], swarm intelligence [14]. There is no comprehensive survey covering various applications, AI algorithms, AI paradigms, tools, and libraries used in AI-integrated UAV frameworks, etc. Addressing this research gap, we present a comprehensive and diversified review to enable researchers to analyze the current and future requirements and develop the latest solutions utilizing AI. The major contributions of our work are:

1) For the first time, we present a comprehensive survey on Artificial Intelligence for UAVs.
2) We categorize the existing research works based on three criteria–a) application scenario, b) AI algorithm, and c) AI training paradigm.
3) We cover a broad range of applications of AI in UAVS, ranging from path planning to resource allocation.
4) We present a detailed discussion on how different AI algorithms are employed in UAV applications.
5) We present a compilation of tools and libraries used in building AI-integrated UAV systems.
6) We showcase challenges in integrating AI in UAVs. We also illustrate a number of future directions for research.

### B. ORGANIZATION OF THIS ARTICLE

The rest of the article is organized as follows. In Section II, the methodology we have utilized for studying and analyzing

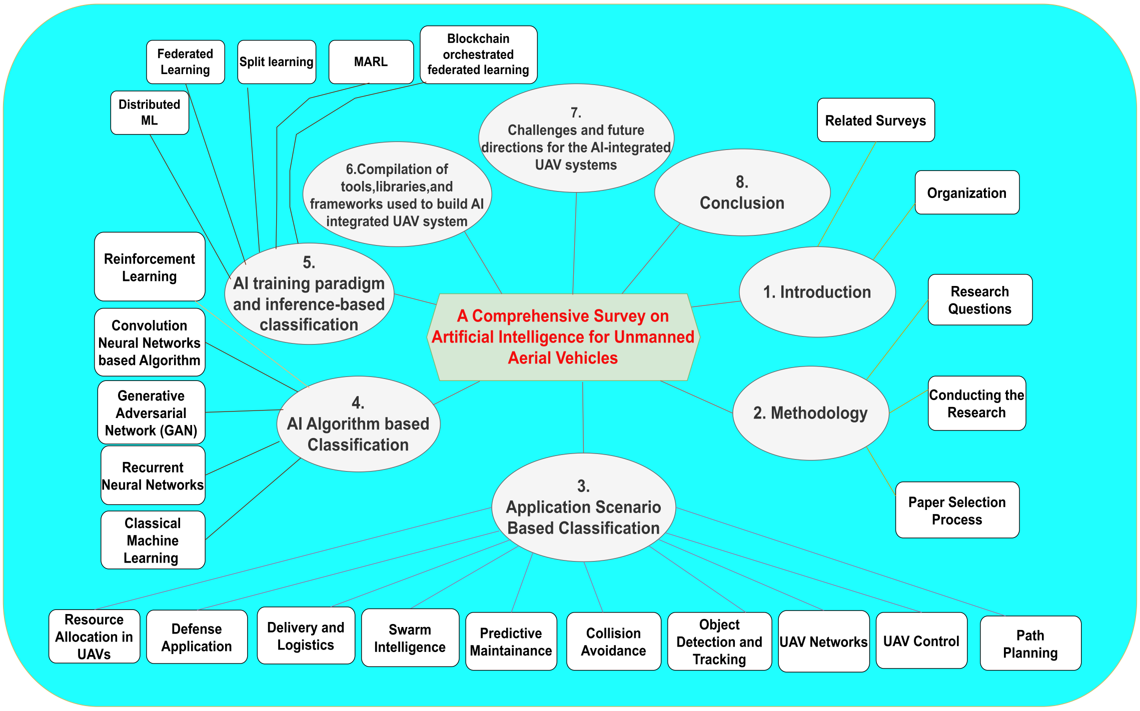


**FIGURE 1.** Survey map.

the papers has been described. In Section III, we mention various applications of infusion of AI into UAVs and elaborately describe each application. In the next section(Section IV), multiple AI algorithms have been elaborated, which have been used in a variety of applications in UAVs along with their usage in UAV systems. Section V categorizes the existing research works based on different AI paradigms. We present several challenges and future works associated with the integration of AI in UAVs in Section VII. Finally, we conclude our work in Section VIII. An overview of the survey is presented in Fig. 1.

## II. METHODOLOGY

In this section, we describe the article selection procedure and the protocols followed while preparing this review.

### A. RESEARCH ISSUES

We put forth four primary questions and attempt to solve them through our analysis in this review. 1) What are the various applications of AI in Unmanned Aerial Vehicles(UAVs)? 2) What are the roles of specific AI algorithms in the corresponding applications? 3) What are the present and anticipated issues in the incorporation of these techniques in UAVs? 4) What is the scope for future research, and what are the existing challenges in the field?

### B. REVIEW

We have used renowned scientific databases such as IEEE Xplore, Science Direct, MDPI, Elsevier, and ACM for the purpose of choosing the most relevant papers to solve the posed questions and include them in our study. We searched for relevant papers using carefully chosen search phrases and strings. We paid importance to choose papers from the aforesaid sources to ensure presenting high-quality scrutinized articles that have been published in reputed conferences, journals, and workshops. We have chosen the latest papers to ensure presenting updated and accurate information. We have utilized two search strings - Artificial Intelligence for UAVs and Machine Learning for UAVs.

### C. SELECTION OF PAPERS

After examining the search databases, we only chose the papers with the most relevance to our theme and rejected the other papers. The chosen papers were then analyzed in the next step, which comprised thorough reading of the abstracts and conclusions. This enabled further sorting of the relevant papers, and only the most relevant papers were considered to be utilized for our review. The papers selected in this step were read and analyzed thoroughly. We have utilized 166 papers for our study.

## III. APPLICATION SCENARIO-BASED CLASSIFICATION

In this section, we outline different applications in the integration of AI and UAVs and present the papers in each of these applications. Table 2 enlist and summarize these applications. Fig. 4 presents the same pictorially.

### A. PATH PLANNING

Path planning is one of the most critical components of a UAV flight. It refers to the computing of a geometrical path from the source to a final destination in the most efficient way. UAVs are often employed to work in unknown environments whose precise mathematical models may not be known beforehand. Pham et al. [15] presented a technique using reinforcement learning to operate in such generic conditions. This technique involved training a quadrotor to maneuver to the target using a proportional–integral–derivative (PID) controller based on Q -learning algorithm (PID+Q-learning algorithm). This eliminates the necessity of a mathematical model. They also suggested a stochastic learning model for real-world implementation of the UAV account for environmental uncertainties like wind [16], [17]. Wang et al. [18] suggested using deep reinforcement learning(DRL)-based method for the UAVs to navigate in extensive and intricated environments. Their technique delineates the UAV's crude sensory data into flight control signals and enables autonomous maneuvering.

Collision avoidance is an important constituent of the path-planning mechanism of any algorithm. To address the issue of collision with traffic or any other obstacle while planning the path, Lin et al. [19] suggested sampling rooted path-determining method based on the closed-loop swiftly-exploring random tree algorithm. They also developed three alterations of this algorithm by i) simplifying the trajectory computation procedure, ii) employment of medial waypoints iii) prediction of collision by making use of a reachable set. Their technique was successful in creating collision-averse trajectories in real time for a variety of UAVs when the obstacles differed in quantity, angles of approach, and speeds. Shiri et al. [20] explored the self-directed management of large unmanned aerial vehicles (UAVs). Ensuring their swift movement and minimal motion energy while avoiding mid-air collisions amidst windy conditions presents a challenging control task that necessitates significant communication energy to exchange states of UAVs on a rapid and real-time basis. However, their approach leads to considerable computational energy usage, particularly with multi-dimensional UAV states. The study's numerical evaluations prove that the proposed ML-assisted mean-field game approach effectively avoids collisions while minimizing communication energy and acceptable computational energy. Q learning and neural network-based strategies have been suggested by Yijing et al. [21]. Their approach for improving the learning rate in UAV path learning and obstacle avoidance involves utilizing a neural network for continuous state space fitting and proposing a trap-escape strategy for the UAV to escape difficult situations. They evaluated the effectiveness of their method, including the Adaptive and Random Exploration approach (ARE), by simulating four separate maps comprising walls, blocks, bricks, and traps and achieved satisfactory results. The ARE method allows the UAV to explore the environment and take actions based on current evaluation, with a random mechanism to redirect it to a safe path when close to obstacles. This technique reduces learning errors and facilitates accurate computation of the route.

### B. UAV CONTROL

UAV control refers to the techniques used to control the movements of a UAV. This includes controlling the flight path, altitude, speed, orientation of the UAV, and various sensors to enable safe and efficient UAV flights capable of completing a required task. UAVs can be broadly controlled manually by a human or autonomously using artificial intelligence algorithms.

Autopilot is usually employed to achieve stability and navigation during the flight. Proportional-Integral-Derivative (PID) control is a common autopilot system that is known to work quite satisfactorily in stable external environments. Problems posed by unknown and harsh environments need to be addressed. Koch et al. [22] investigate the use of Reinforcement Learning algorithms to train the autopilot system responsible for altitude control in UAVs. To check the correctness of their model, they trained a quadrotor flight controller using RL. After this, they compared the performance of RL and PID controllers to determine if the RL method was better in terms of precision in flight control, and their analysis yielded satisfactory results. Similarly, Moe et al. [23] suggested a Deep Reinforcement Learning (DRL) based controller that addresses the problem of nonlinear attitude control in fixed-wing UAVs. The researchers designed a controller utilizing the proximal policy optimization (PPO) algorithm and confirmed that it could stabilize a fixed-wing UAV to reference roll, pitch, and airspeed values from a wide range of initial conditions. They compared the trained RL controller with a PID controller and discovered that it outperformed the PID controller in most cases and had similar performance. Furthermore, they demonstrated that the RL controller is highly adaptive to unseen disturbances such as wind and turbulence.

Kumar et al. [24] developed an autopilot system that can regulate speed and altitude using an electronic throttle control system (ETCS) and elevator, respectively. To control the throttle position for the suitable flow of air mass, a DC servo motor is employed in the design of the ETCS. The study employs AI-based controllers to create a stable autopilot system. The simulations prove that these suggestions yielded the goal of attaining a wider range of airspeed, improvising energy efficiency and fuel economy, and reducing pollutant emissions, by employment of the throttle, speed, and altitude controls, to satisfactory levels and paving the way for future work in this direction.

### C. UAV NETWORKS

UAV networks are a type of network that continue multiple UAVs that coordinate among themselves and with a ground control station. In a UAV network [25], each drone can act as a node in the network and can communicate with other drones and with the ground control station using wireless communication technologies such as Wi-Fi, Bluetooth, or radio waves. The drones can also share data and collaborate

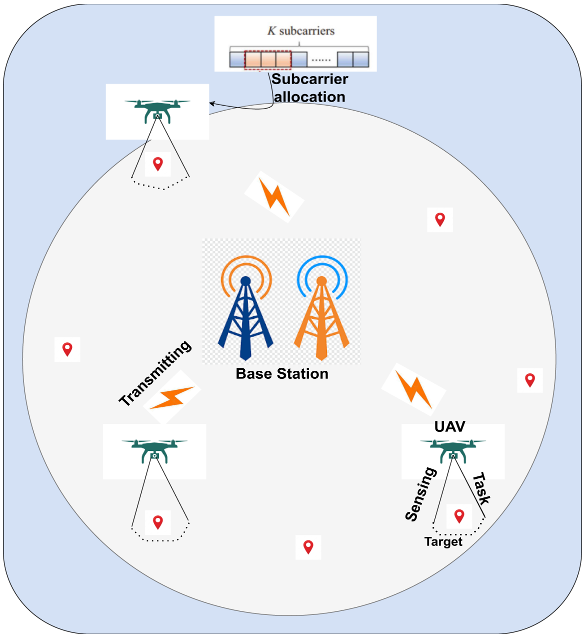


**FIGURE 2. Cellular networks of UAVs.**

to perform tasks such as surveillance, mapping, and sensing. Zhang et al. [26] focused on a cellular Internet of UAVs, which involves UAVs performing sensing tasks along with transmission, which minimizes the age of information (AoI). Designing the UAV trajectories for sensing and transmission is challenging since they are closely intertwined. To address this issue, they suggested a distributed sense-and-send protocol wherein UAVs select tasks and locations for sensing and transmission from a discrete and continuous set, respectively. Simulation results indicate that cooperative UAVs are capable of attaining a reduced AoI than non-cooperative UAVs by dividing tasks.

To address the difficulty in achieving three-dimensional (3D) coverage in the UAV communication process, Zeng et al. [27] put forth a novel solution utilizing deep reinforcement learning (DRL). They utilized the advanced dueling double deep Q network (dueling DDQN) with multi-step learning. In this approach, the action-value function of the navigation policy is trained directly using the signal measurement obtained by the UAV. This approach facilitates the creation of simulated UAV trajectories and the prediction of their anticipated returns. These predictions are then employed to train the DQN using the Dyna technique [28], thereby significantly improving the learning efficiency. Wireless communications are often faced with threats such as interference and cyber attacks. To address this problem, Saad et al. [29] proposed an approach that presents a path-planning technique designed for a network of UAVs connected to cellular networks. Fig. 2 shows the pictorial representation of this approach. The objective of each UAV is to balance the maximization of energy efficiency while simultaneously achieving low wireless latency and interference on the ground network along its path.

In the context of object detection [30], AI can be applied to UAVs for:

1) Real-time object detection: The images captured by UAVs' cameras can be processed with AI algorithms to detect objects in real time. 2) Tracking moving objects: UAVs can be used to track moving objects accurately. 3) Image recognition: AI algorithms can be trained to autonomously recognize objects or patterns of interest using the images captured by the UAV. 4) Autonomous flight: AI algorithms can be used to enable autonomous flight of UAVs.

Rohan et al. [31] proposed a system that uses a Convolutional Neural Network(CNN)-based object detection algorithm that captures the target object's center positions and encloses it within a bounding box. A Gain-Scheduled PID controller-based algorithm has been developed for object tracking, which can effectively follow the detected object even when its speed is changing. Based on the experimental results, it has been demonstrated that the object detection algorithm can accurately detect and categorize objects while consuming less power and achieving a high fps. Avola et al. [32] presented their method to address the problems posed by the variable movement of the target, visual obstructions, disarranged background, and too low or high brightness in the images captured by UAVs for the purpose of tracking and detecting their targets. To imitate a multi-scale image analysis, various kernel sizes are utilized on each stream. The suggested framework is employed as the foundation for the Faster-R-CNN pipeline, creating an MS-Faster R-CNN object detector that can reliably detect objects in video sequences. Afterward, this detector is combined with Deep Association Metric (Deep SORT) algorithm to be able to track objects in real time using the images captured by UAVs.

The image captured by the UAV contains small and closely packed objects, which can result in missed detection errors. To combat this issue, Tian et al. [33] suggested using a dual neural network review technique that can rapidly identify missed targets in one-stage detection by categorizing the secondary characteristics of the suspected area of interest. This approach can lead to accurate detection of small targets with high precision.

### D. COLLISION AVOIDANCE

Collision avoidance is critical to safe UAV flights. UAVs are prone to colliding with obstacles in their flight path, such as terrain and traffic.

Some major methods implemented to avoid such collisions [34] of UAVs include:

1) GPS: Ground Positioning System can be used to avoid obstacles by identifying them during the flight and re-routing the UAV's flight path. 2) Obstacle detection and avoidance sensors: Light Detection and Ranging (LiDAR), sonar, or radar systems can be used to detect obstructions in the flight path and avoid them. 3) Computer vision: Cameras can be used to view and subsequently analyze the external environment of the UAV to identify and avoid obstacles. 4) Flight planning: The path of UAVs can be planned optimally using

AI algorithms which can bypass any obstacle in the path and also optimize other parameters such as flight time. 5) Communication and coordination: UAVs can communicate with each other and with other aircraft to avoid collisions. This technique is particularly useful in situations where multiple UAVs are operating in the same airspace.

Joshi et al. [35] examined how the performance of UAVs in Deep Reinforcement Learning (DRL)-based waypoint navigation and obstacle avoidance is impacted by measurement uncertainty. This uncertainty arises due to sensor noise, which affects the accuracy of obstacle detection. The Gaussian probability distribution, characterized by an unknown non-zero mean and variance, is assumed to model the measurement uncertainty or noise. They further refined the noise element using a Kalman filter. Making further use of DRL, Lai et al. [36] proposed a You Only Look Once (YOLO) algorithm while employing a mononuclear camera simultaneously to detect obstacles swiftly and accurately.

Singla et al. [37] introduced a novel approach for facilitating a quadrotor UAV with a monocular camera to avert collision with obstacles autonomously in unspecified indoor environments. Existing control methods that use monocular images for collision avoidance rely heavily on the specifications of the surroundings and do not fully utilize the vast amount of information available for decision-making. The researchers put forth a deep reinforcement learning-based approach that addresses this issue by utilizing the concept of partial observability, enabling the UAV to store useful details about the environment to make better maneuvering decisions. Their technique employs RNNs and has a high rate of inference while simultaneously reducing power consumption by significantly reducing the UAV's oscillatory motion.

### E. PREDICTIVE MAINTENANCE

Predictive maintenance in UAVs refers to analyzing data from sensors and flight history to forecast potential mechanical issues. By identifying patterns and anomalies in these observations, maintenance can be scheduled proactively, ensuring UAV reliability and minimizing downtime. This will reduce the threat of sudden failures of UAVs during a mission and would also help in extending the lifespan of UAVs and optimizing maintenance schedules. In the long run, this would lead to lower operation costs and better safety. It is possible to detect anomalies, monitor the UAV's health, and predict failures of UAV systems such as battery, propulsion, and structure. The RUL (Remaining Useful Life) of the propulsion system can be predicted using neural networks.

Based on the above concepts, Zahra et al. [38] put forth a system in which Inertial Measurement Unit (IMU) sensors are installed on the motor to monitor vibrations that are induced by the motor in the propulsion system. Then, this vibration data is analyzed using vibration signal analysis, which yields five time-domain features which depict the attributes of the input signals. Utilizing these features, it becomes possible to assess whether the motor is currently in a normal or abnormal condition. An abnormal state hints at an upcoming failure of the motor. To better judge the time until the motor's failure, RUL prediction involves calculating the HI(Health Indicators) of the motor for a future time period. It involves a sequence of transformation algorithms- Principal Component Analysis, Exponentially Weighted Average, and scaling. The output HI is a numerical value that falls within the range of zero to one. A reading of one indicates complete failure and a reading of zero implies that the motor is in perfect condition.

To avert the drone's motor from achieving undesirable temperatures during operation, Lu et al. [39] developed a system that records the motor temperature using DS18B20 sensors. Afterward, the Raspberry Pi processing unit assesses if the motor is working unusually using reinforcement learning. To monitor the activity of Raspberry Pi, a custom-designed user interface is available on a tablet. This system enables the drone to land itself when the temperature of the motor goes beyond a threshold temperature, thus preventing mid-flight motor failures and other technical problems. The academia is intensively exploring better ways of anomaly detection in UAVs. Wang et al. [40] proposed a method for detecting anomalies in UAVs. Their method involves the use of a Recurrent Neural Network called Long Short Term Memory (LSTM). A predictive model is first established by utilizing a training dataset consisting of normal data. This can be used to predict data for the future. This is followed by estimating the uncertainty of these predictions. Comparing the predicted data with the range of uncertainty identifies the anomaly.

### F. SWARM INTELLIGENCE

The ability of multiple UAVs to form a group and work together autonomously is referred to as swarm intelligence. The UAVs in a swarm work in a properly coordinated manner to achieve a specific task. The idea for implementing swarms in UAVs came by observing insects such as ants and bees, which are known to work in groups. The UAVs in a swarm are capable of collaborating and communicating with each other in real time. The synchronization among the UAVs is endowed using advanced AI and ML algorithms. This technology has enabled researchers to perform tasks such as search and rescue and delivering parcels using UAVs and has paved the way for further research in the areas of using UAV swarms in various fields such as agriculture and transportation. Swarm technology provides better resilience and scalability as compared to using individual drones for the same mission. It also allows the UAV swarms to cover bigger areas of operations and perform complicated tasks by dividing a single large task among several UAVs.

Breathing in ambient air is crucial for the existence of life on Earth. As a result, the deteriorating air quality has become a major concern. It is, therefore, pertinent to predict and keep track of the air quality index in real-time. Tanwar et al. [41] suggest an approach to Federated Learning that is both distributed and decentralized, which can be implemented within a swarm of UAVs. In their approach, the air quality data collected by the sensors is fed into a Long Short-Term Memory (LSTM) model for analysis. Every UAV in the swarm utilized the data it had collected on its own to train a model. Subsequently, each UAV sent its locally trained model to the central base station. Once the central base station has received the locally trained models from all the participating UAVs, it aggregates the models' weights to generate a single master model. This master model is subsequently sent back to all the UAVs involved in the Federated Learning process during the following cycles. As a result of this process, the UAVs become capable of estimating the air quality in a given region in the future.

Zeng et al. [27] introduced an innovative structure for executing distributed federated learning (FL) algorithms utilizing a group of UAVs comprising a foremost UAV and various trailing UAVs. This approach helps to resolve the problem of the lack of consistent connections between the UAV swarm and ground-based stations (BSs), which makes it challenging to utilize centralized machine learning when dealing with a substantial amount of data. Every trailing UAV generates its own delimited FL model from the data it has gathered, which it then transmits to the leading UAV. The leading UAV then processes each of the models it retrieves from its followers and generates a master model, which is returned to every trailing UAV. Zeng et al. [27] further bring forth a joint power allocation and scheduling design which aims at improving Federated Learning's rate of convergence by considering the requirements for energy and the control system's delay specifications.

Rahman et al. [42] dealt with the issue of communication among swarms of UAVs during search-and-rescue operations using methods based on machine learning. They introduced a technique for determining path loss in UAV swarms using machine learning, and it also forecasts the strength of received signals. At the outset, a random forest model is trained using the information retrieved from the received signal to create the path-loss profile. Afterward, K-means clustering was utilized to forecast the cluster parameters for the UAV swarms. Finally, to acquire accurate swarm formation, the dendrogram of all varieties was examined.

### G. DELIVERY AND LOGISTICS

UAVs have been witnessing rapid growth in the areas of flight time and autonomous operations. This makes them highly useful for being implemented for the purpose of delivering goods. They can deliver parcels in a fast and efficient manner even to remote areas which are hard to access by any other mode of transport. Modern and advanced technology capable of enabling longer and safer flights is needed to achieve the goal of goods delivery using UAVs reliably. UAVs need to be able to carry heavier goods with better and more efficient batteries and navigation systems capable of preventing collisions and computing optimum flight paths. Using UAVs for commercial purposes such as goods delivery has to be done under strict compliance with government regulations to ensure safety. This is why companies that want to incorporate UAVs for delivery purposes are required to obtain the necessary permits and certifications. For the correct delivery of goods, proper determination of flight paths is required. A strong network of ground personnel is also required to coordinate timely and correct deliveries. Software based on AI algorithms is needed, which can compute the optimum flight paths and track the parcels on a real-time basis.

Dorling et al. [43] created a cost function that considered factors such as energy consumption and UAV reuse. This function was then simulated in practical scenarios to find optimal and workable solutions. This is a solution to the problem of multi-trip vehicle routing [44] and reducing delivery time and cost of operation. Kong et al. [45] presented a new autonomous learning technique called the attention-based pointer network (A-Ptr-Net), which aims to optimize drones' delivery trajectories. The A-Ptr-Net model, which incorporates an attention mechanism, has proven to be capable of automatically adjusting to new drone trajectory data without the need for an explicit distance matrix. The authors further create convex function constraints that pertain to the nonlinear energy consumption of drones and other crucial factors, including customer demands. The constraints developed are subsequently utilized to optimize the drone logistics delivery through the A-Ptr-Net model.

Owing to the limitations of their batteries, drones are most appropriate for last-mile delivery, which refers to the delivery of goods from the package distribution centers (PDCs) to the customers. Khamidehi et al. [46] examined the problem of dynamic drone assignment while aiming at guaranteeing high Quality of Service (QoS) standards. They utilize a queueing theoretic methodology to model the customer-service parameter. Additionally, they employ a deep reinforcement learning technique to acquire a strategy that facilitates the dynamic redistribution of drones. This ensures that the waiting-queue duration of the packages never crosses an upper bound, thus helping the supplier and consumer alike. Simulations prove that this approach is indeed effective and further help in reducing the required number of drone for an operation.

### H. DEFENSE APPLICATIONS

The integration of artificial intelligence (AI) in UAVs can greatly enhance their effectiveness in border security applications.

Some ways AI-powered UAVs can be used for border security are listed below: 1. Surveillance and Reconnaissance: UAVs with AI technology can patrol along the borders for surveillance. Objects such as vehicles and people can be detected using ML techniques, and this will help the security personnel to eliminate threats in a timely and efficient method. 2. Threat Detection: Cameras fitted in UAVs can capture images of a large area and can then process them using ML and AI techniques to identify potential threats, such as smugglers. 3. Autonomous Operations: UAV's capability to operate autonomously will enable efficient patrolling of the border areas and assist ground personnel in recognizing and correcting security issues. UAVs can also provide better information related to threats because they can continue surveillance silently and without getting noticed. 4. Communication and

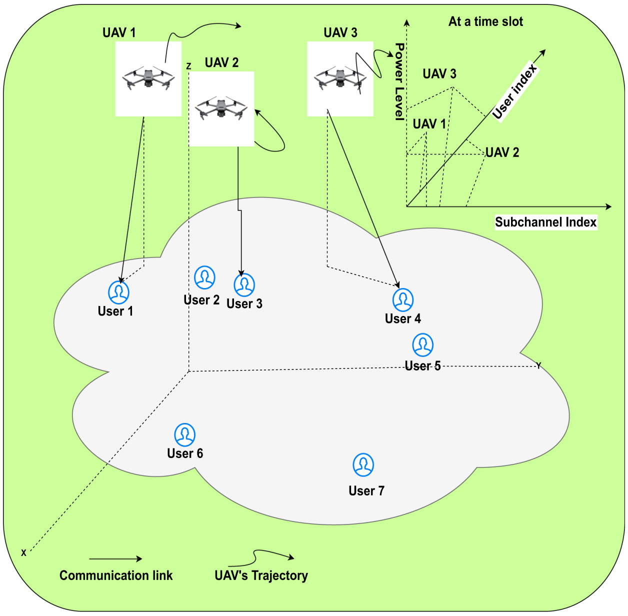


**FIGURE 3.** **Multi-UAV communication networks.**

Coordination: AI-powered UAVs can also be used to enhance communication and coordination between border patrol agents and UAV operators. UAVs can provide real-time information to border patrol agents, allowing them to respond to potential threats more quickly and effectively. 5. Rapid Response: UAVs with AI implementation can provide quick and effective assistance in emergency operations with enhanced situational awareness. This can include delivering essential life-supporting goods to disaster-struck regions which might be inaccessible easily by other means of transport.

Aguilar et al. [47] designed a strategy for enabling autonomous micro-UAV flights for detection and surveillance missions. The authors suggested YOLO-based neural network algorithms for achieving the aforesaid purpose. The testing and analysis revealed that the algorithms were successful in accurate real-time object and human recognition in different landscapes and environments. The improved wireless network stability and improved physical maneuverability of UAVs have led to further work in the direction of military surveillance using UAVs.

Afifi et al. [48] aimed to solve the problem of exact three-dimensional location determination detection of UAVs to enable accurate and swift military operations such as tactical autonomous flights. The authors employed the pre-existing 5G network instead of Ground Positioning System(GPS) for this. They suggested two machine learning approaches involving deep neural networks and reinforcement learning to utilize the 5G network for exact location calculation in real time.

### *I. RESOURCE ALLOCATION IN UAVS*

The distribution of resources among a group of unmanned aerial vehicles (UAVs) has become an important issue that researchers have devoted significant attention to in recent times. This is indispensable for the quick, safe, and reliable operation of UAVs. These UAVs are capable of autonomous flight or remote control and find application in diverse areas, including surveillance, reconnaissance, communication, and delivery. Research allocation in networks driving the UAVs aims at the optimal distribution of limited resources such as spectrum, power, and bandwidth. This will help to improve the UAVs' potential. However, this is faced with a number of challenges based on UAV mobility since even very minute changes in the UAV's position coordinates change the entire network topology. This complicates the process of real-time resource allocation. The finitude of all the crucial resources is another major issue. UAV batteries are usually low-powered with a very limited operational period. This lack of unrestricted energy supply limits the physical maneuverability of the UAVs, communication, and computational power.

There have been various methods suggested to tackle the issue of assigning these resources in networks of UAVs. These methods can be generally categorized into two groups: centralized and decentralized. The centralized approaches pertain to a central controller that takes care of distributing resources among various UAVs. In comparison to decentralized approaches, these methodologies exhibit higher efficacy levels due to their consideration of the overall network state. However, they are associated with increased complexity and communication overhead requirements. Decentralized approaches, conversely, pertain to individual UAVs making autonomous determinations regarding resource allocation depending on local data. Such approaches possess greater scalability and resilience due to their independence from a central controller. Their efficacy may still not match that of centralized approaches as they lack access to global network information.

Resource allocation to UAVs by base stations also plays a critical role in augmenting coverage and surveillance area in the context of UAV-assisted networking. As such, the task of resource allocation assumes the utmost significance, given the aforementioned factors. Various techniques involving artificial intelligence and machine learning have been employed to tackle these challenges. These include reinforcement learning, which enables the UAV to allocate resources based on data obtained in real-time. Game theory [49] is another approach to solving these issues, wherein the resource allocation is projected as a task to be solved between the participating UAVs.

There are some other major applications of AI in UAVs which offer a huge potential for research and development, like precision agriculture. It involves using cameras and sensors to monitor crop health, predict yields, and optimize input application. In bridge inspection, AI analyzes high-resolution images and thermal data from UAVs to detect structural defects, enhancing safety and efficiency in maintenance.

Chen et al. [50] presented a solution to solve the issue of combining caching and resource allocation in a network of UAVs equipped with caches, which provide wireless service to ground users via the licensed and unlicensed bands of the LTE network. The authors utilized a technique that

**TABLE 2. Summary of the Applications of AI in UAV**

| Application scenario | Target issue | Reference(s) | Purpose of using AI |
|---|---|---|---|
| Path Planning | Path learning and collision avoidance | [19], [20] | Using deep reinforcement learning, ML techniques, neural networks to avert collision |
| | Environmental uncertainties | [18] | Deep reinforcement learning(DRL)-based method for the UAVs to navigate in extensive and intricated environments. |
| UAV Control | Autonomous attitude control | [22], [23] | To train the autopilot component responsible for attitude control in UAVs |
| | Speed control | [24] | An autopilot system that can regulate speed and altitude using an electronic throttle control system (ETCS) and elevator, respectively. |
| UAV Networks | Sensing and transmission | [26], [27] | Focused on a cellular Internet of UAVs with the implementation of deep learning |
| | Threats such as interference and cyber-attacks | [29] | Deep reinforcement learning algorithm that uses echo state network (ESN) cells |
| Object detection and tracking | Variable movement of the target, and navigation through visual obstructions, disarranged background | [31], [32], [33] | Detection and tracking of targets using AI algorithms |
| Collision Avoidance | Navigation and obstacle avoidance | [35], [37], [36] | Use Deep Reinforcement Learning to reduce measurement uncertainty and detect obstacles swiftly and accurately |
| Predictive maintenance | Reducing the risk of unexpected breakdowns or failures, optimize maintenance schedules and extend the lifespan of the UAV | [38], [39], [40] | Monitoring of motor vibrations and temperature and using ML techniques |
| Swarm intelligence | Monitoring air quality | [41] | Using Federated Learning in a swarm of UAVs to monitor and estimate air quality of an area |
| | Lack of consistent connections between the UAV swarm and ground-based stations | [27] | Using distributed federated learning (FL) algorithms to improve connections between the UAV swarm and ground-based stations and enable joint power allocation |
| | Communication among swarms of UAVs during search-and-rescue operations | [42] | Using machine learning for determining path loss in UAV swarms, and also forecast the strength of received signals |
| Delivery and Logistics | Route planning | [43], [45] | Using ML and AI to compute optimal UAV trajectory |
| | Dynamic drone assignment | [46] | Using deep reinforcement learning techniques to reduce the required number of drone for an operation. |
| Defense Applications | Detection and surveillance missions | [47], [48] | Using ML techniques to detect the exact location of a target in real-time |
| Resource Allocation in UAVs | Optimal distribution of limited resources such as spectrum, power, and bandwidth | [50], [51], [52] | Using ML algorithms which enables UAVs to select the most effective resource allocation methodologies |
| | Facilitate emergency communications | [53] | To enable search and rescue operations in disaster situations |
| | Forest fire detection | [54] | Using Internet of Things(IoT) sensors to monitor and detect forest fires |

relies on a liquid state machine (LSM). The LSM algorithm can enable the cloud to anticipate the distribution of content requests from users, even with only partial information on the states of the network and users. With this, the UAVs can select the most effective resource allocation methodologies, which aim to maximize the number of users with steady queues. By analyzing the distribution of user association and content requests, the algorithm calculates the ideal content to be cached by UAVs and the optimal resource allocation strategy. Duan et al. [51] created Internet Of Things (IoT) [55] uplink transmission systems with high capacity by integrating nonorthogonal multiple access (NOMA) with UAV communication. The k-means clustering algorithm is utilized to cluster IoT nodes into subsystems that correspond to the number of UAVs.

For proper resource allocation in UAVs to facilitate emergency communications in disaster-struck regions, Duong et al. [53] proposed a rapid user clustering model based on the K-means algorithm, along with an optimized allocation of power and time for transfer. In disaster situations, UAVs would work as flying base stations and help in the facilitation of communications, which can be used for search and rescue operations. Sun et al. [54] put forth a method to identify localized patches of forest fire using UAVs based on the Industrial Internet of Things (IIoTs). When using IoT sensors to monitor various aspects of forest fires, taking into account the priority constraints between sensors can ensure a prompt response in forest fire monitoring. A cooperative particle swarm optimization algorithm that uses learning and is based on a Markov random field decomposition strategy has been suggested as a means of finding the most efficient allocation strategy for UAV resources. Chang et al. [52] focused on a multi-UAV system and employed machine learning techniques to tackle the issues of resource allocation and trajectory planning. To tackle the challenges related to the vast number of dimensions in the state space, the authors put forward an algorithm for strategic resource allocation based on deep learning and reinforcement learning. The authors used deep Q-network was utilized to incorporate dynamic optimization.

## IV. AI ALGORITHM-BASED CLASSIFICATION

In this section, we present the reviewed papers based on the AI algorithm incorporated. Fig. 5 shows the diagrammatic representation of the AI algorithms used in AI-integrated UAV systems, and Table 3 summarizes the reviewed papers under each algorithm.

### A. REINFORCEMENT LEARNING

Reinforcement learning (RL) is a method in which an agent interacts with a dynamic environment in a trial-and-error fashion to learn to respond in a way that optimizes the reward [56]. At each stage of interaction, the agent receives sensory

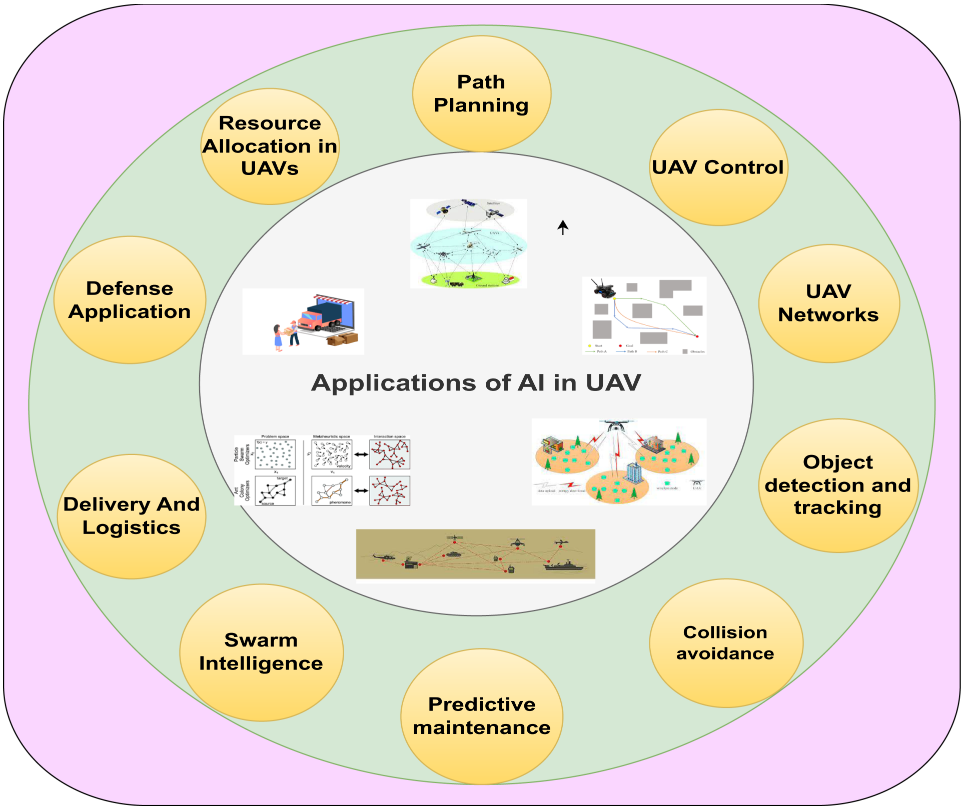


**FIGURE 4.** Overview of applications of AI in UAVs.

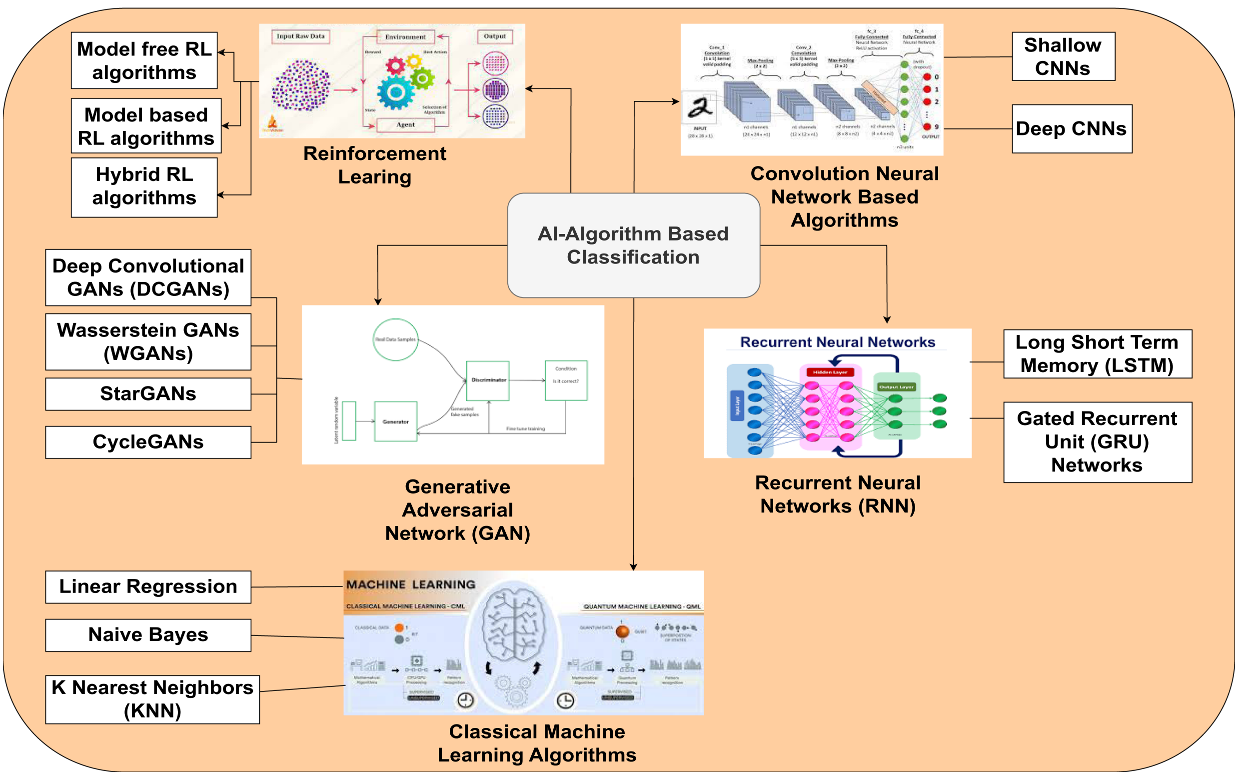


**FIGURE 5.** AI algorithm-based classification.

**TABLE 3.** Summary of AI Algorithm-Based Classification

| AI algorithm | References(s) | Target issue |
|---|---|---|
| Policy-based Reinforcement Learning | [22], [57] | Address the limitations of PID control |
| Value-based Reinforcement Learning | [58], [59]<br>[60]<br>[21] | Long-term resource allocation<br>Inefficiency of existing route planning algorithms<br>UAV navigation and obstacle avoidance |
| Imitation RL learning | [61]<br>[62]<br>[63] | To detect the precise motions necessary to lead the UAV along the trajectories<br>Enhancing UAV tracking performance<br>UAV deployment strategy to maximize UAV owner profit and on-ground user benefits |
| Inverse reinforcement learning | [115], [65] | To track a multirotor UAV's path |
| Model-ensemble based Hybrid RL algorithms | [66]<br>[67]<br>[68] | To predict wheat output using UAVs in the winter<br>To evaluate total nitrogen concentration in water<br>Coordination among several UAVs traveling over a vast region |
| LeNet Shallow Convolutional Neural Networks | [70], [71]<br>[116] | For spreading deep neural networks (DNNs) within unmanned aerial vehicles and to adjust the system to the UAV's dynamic movement and network fluctuation (UAVs)<br>Incorporating machine learning (ML) capabilities into small UAVs |
| AlexNet Shallow Convolutional Neural Networks | [78] | To automatically detect damage to wind turbine blade surfaces |
| Deep Residual Learning Network (ResNet) | [81] | For real-time UAV identification |
| InceptionNet | [83] | To aid UAV-based surveillance operations that include the collection of movies using a mobile camera |
| Deep Convolutional GANs (DCGANs) | [90] | To enable 5G-enabled maritime UAV communication employing millimeter wave (mmWave) for the air-to-surface link |
| Wasserstein GANs (WGANs) | [93] | To enhance wireless signal-based detection of unauthorized UAVs |
| StarGANs | [117] | Transmitting emotions using 3D hand and full-body motion |
| CycleGANs | [96] | To reduce wildfire damage |
| Long Short-Term Memory (LSTM) in recurrent neural networks (RNNs) | [102]<br>[103]<br>[104] | Resource allocation issue for UAVs<br>UAV anomaly detection<br>UAV communication for future wireless networks |
| Gated Recurrent Unit (GRU) networks | [107]<br>[108]<br>[109] | Forecasting UAV direction<br>To analyse UAV flight data impacted by motor or wind vibration<br>To enhance UAV spectrum sensing performance |
| Linear regression | [111]<br>[112] | Fault detection in UAV systems<br>To find the best place to attach four gas sensors and a Particle Number Concentration (PNC) monitor to a hexacopter as part of a UAV system for evaluating point source emissions |
| Naive Bayes | [118] | To detect and classify dangers of malicious attacks like GPS spoofing |
| K-Nearest Neighbors (KNN) | [119]<br>[111] | A method for human-swarm interaction that employs full-body action recognition to manage an autonomous flock of UAVs<br>Identifying contextual errors in UAVs |

input that provides some indication of the current state of the environment, and then the agent chooses an action to send as output. The agent receives a singular scalar reinforcement input based on the value it places on the altered condition of the environment. To maximize the sum of reinforcement signal values over time, the agent makes decisions that lead to such outcomes. Over time, it learns this via trial and error and other strategies.

### 1) MODEL-FREE RL ALGORITHMS

Model-free RL algorithms adapt their policy based on the outcomes of their actions without estimating or using the dynamics of the environment. There are two types of model-free RL algorithms, as described below:

*a) Policy-based algorithms:* Without explicitly estimating or modeling the underlying dynamics of the environment, a policy-based algorithm is able to learn a policy, which is a mapping from states to actions. Finding the best policy is the primary emphasis of policy-based techniques rather than attempting to estimate the value function or the action-value function (Q-function). Gradient ascent algorithms are often used for this purpose since they update parameters in the direction of the gradient of an objective function that stands for the anticipated return.

Research on intelligent flight control systems is ongoing, and RL has recently been used to address the limitations of PID control. Using state-of-the-art RL algorithms like the Deep Deterministic Policy Gradient and Proximal Policy Optimisation, Koch et al. [22] studied the efficacy and accuracy of the inner control loop that controls altitude. They developed a simulator to train a flight controller using RL and then used it to evaluate the effectiveness of PID and RL in maintaining a constant altitude. Using a Gauss-Markov random model, Liu et al. in [57] analyzed a mobile edge computer network that included a UAV. The issue is formulated as an optimization of a Markov decision process, with the UAV trajectory and UAV-TU association serving as the parameters. To maximize system reward, it proposes to devise a quality-of-service (QoS)-based action selection strategy using a double deep Q-network.

*b) Value-based algorithms:* An algorithm that bases its decisions on an estimate of a certain value function or action-value function (Q-function) is known as a value-based algorithm. The algorithms look for the value function to maximize the anticipated cumulative payoff. Estimates are continually updated using techniques like temporal difference learning based on the difference between the actual and predicted values.

Cui et al. in [58] addressed the long-term resource allocation issue as a stochastic game for maximizing predicted rewards, where each UAV acts as a learning agent, and each resource allocation solution is an action executed by the UAVs. The authors here developed a Q-learning-based framework for MARL, in which agents work together to learn the best way to act given a set of local observations but make decisions independently. Similarly, the authors of [59] proposed a MARL-based path planning method for UAVs, claiming the advantage of it over traditional Q-learning as it gathers both global and local information, significantly improving performance by using two layers in the algorithm. One layer deals with local information, and the other lower layer deals with global information, considering it a long-term stride. Qu et al. created the reinforcement learning-based grey wolf optimizer method (RLGWO) in [60] to address the inefficiency of existing route planning algorithms, especially when confronted with a three-dimensional, complex flying environment. The authors of [21] used an Adaptive and Random Exploration (ARE) strategy to successfully accomplish the UAV navigation and obstacle avoidance objectives. Also, search techniques to help the UAV getaway on the right track were used.

#### 2) MODEL-BASED RL ALGORTIHMS

Model-based Reinforcement Learning (RL) algorithms combine learned models of the environment with RL techniques to make informed decisions. These algorithms simulate possible actions and their outcomes, thus enabling better exploration and optimal policy determination compared to trial-and-error approaches.

Model-based algorithms use transition functions to estimate the optimal policy.

*a) Imitation learning:* Model-based imitation learning [61] is a group of reinforcement learning algorithms that may be used to rapidly suggest an approximation of a solution to a given control problem, often in robotics. According to the theory, either a person or a machine might do a variety of vocations, such as performing home tasks for domestic robots. Imitative learning is used because it is often difficult to recognize the exact movements required to guide the robot along the trajectories, but they may be learned by utilizing a model of the robot's dynamics. Liang et al. in [62] proposed a new learning-based system that automatically enhances UAV tracking performance via learning. This algorithm can be trained alone; however, it is part of the model-based learning paradigm, and so it improves with guidance from control methods. This method was developed for use when adhering to the reference trajectory would be overly forceful or otherwise counterproductive to system dynamics. To maximize UAV owner profit and on-ground user benefits, [63] proposed a multi-agent imitation learning-enabled UAV deployment strategy. Agent rules for online scheduling with imperfect information were developed, trained, and run in a distributed manner with a guaranteed -Nash equilibrium by modeling the actions of related experts using CNNs, GANs, and a gradient-based policy [64].

*b) Inverse reinforcement learning:* Inverse reinforcement learning (IRL) refers to the challenge of deducing an agent's reward function from its policy or observed behavior. In order to track a multirotor UAV's path, the authors of [65] used IRL Control. An expert's numerous demonstrations were collected in the first step, and then a hidden Markov model (HMM) and dynamic time warping (DTW) were used to generate a representative trajectory from the collected dataset. The multirotor used this information to replicate the flight path. The optimum controller for minimizing the trajectory tracking error was then built using IRL to learn the quadratic hidden reward function.

#### 3) HYBRID RL ALGORITHMS

*a) Model-ensemble based:* Model ensemble learning is a technique for developing a single learning model capable of making inferences on supplied data by combining different learning models, such as Logistic Regression and Naive Bayes classifiers. To predict wheat output using UAVs in the winter, Li et al. [66] utilized an ensemble-based learning and hyperspectral-based approach, with the latter being used to assess crop attributes due to the fact that hyperspectral data may give rich spectral information. Boruta feature selection and the Pearson correlation coefficient (PCC) are two examples of the kinds of feature selection techniques used to filter out data with unusually high spectral indices. By integrating linear ridge regression, random forest, and decision trees, the authors here were able to create an ensemble-based learning model that could predict wheat production. Total nitrogen concentration in water was evaluated by the authors of [67] using a hyperspectral and ensemble-learning-based framework applied to emergent plants using a drone. The authors of the article conducted a hypothesis test using four different types of machine learning models. The results of the regression analysis were then used to inform the development of a decision-level fusion (DLF) model that would allow for the extraction of Total Nitrogen (TN) concentration in water.

In [68], Perron et al. addressed a patrolling problem issue, which is an issue of coordination among several UAVs traveling over a vast region. Thus, in the article, the authors proposed a method for combining reinforcement learning with multi-agent simulation, which enabled the herd of UAVs to find nearby optimal solutions in real geo-referenced virtual environments, implying that they can automatically find patterns of patrolling in an area even when there are unknown obstacles and moving targets. The authors employed Coordination Learning in Multi-Agent Framework (COLMAS) framework to create their proposed hybrid strategy.

### B. CONVOLUTION NEURAL NETWORK (CNN) BASED ALGORITHMS

An Artificial Neural Network(ANN) has several layers, beginning with the input layer, followed by a number of hidden layers, and finally, the final output layer. CNNs are similar to the ANNs in that the neurons in the learning process self-optimize. There are no significant differences between classic ANNs and CNNs, except that CNNs are mostly employed for pattern identification inside pictures, as this becomes a job targeted with images, reducing the modeling parameters. As a result, CNNs are successful in overcoming the most significant drawback of classical ANNs, namely their computational complexity [69]. CNNs have emerged as a viable tool for enhancing UAV perception and decision-making. The creation of effective and precise algorithms based on CNNs will be crucial in boosting the capabilities of UAVs in many applications as the use of UAVs continues to grow, much like for object identification and semantic segmentation. CNNs are deep neural networks with the ability to segment as well as categorize pictures. Although there are many layers in CNN architectures–some of which have already been mentioned–they may be divided into Shallow CNNs and Deep CNNs. There are several applications for each of the categories; thus, the discussion of the same focus follows.

### 1) SHALLOW CNNS

Few convolutional and pooling layers make up the neural network design known as shallow CNNs because they contain fewer layers than deep CNNs and are often utilized for straightforward image recognition tasks. These networks are easier to train and more computationally effective. Tasks involving picture categorization also make use of them. LeNet and AlexNet are two examples of shallow CNNs that are also commonly utilized in UAVs.

*a) LeNet:* LeNet [70], developed by LeCun et al. in 1998 for recognizing handwritten digits, is one of the first and best-known shallow CNNs. LeNet has seven layers, comprising three fully connected layers, two convolutional layers, and two subsampling layers. Each layer is made up of a group of trainable parameters, such as weights or filters, which are optimized during training to raise the model's accuracy. LeNet is still often used in UAVs today for a variety of objectives. An innovative method for spreading deep neural networks (DNNs) within UAVs is presented in the article [71] in order to speed up data categorization in devices with limited resources and prevent delays caused by server-based approaches. The suggested approach formulates an optimization problem that accounts for the UAV's resource limitations as well as their mobility model as part of air-to-air communication. In order to adjust the system to the UAV's dynamic movement and network fluctuation, mobility prediction [72] is also added. The authors used a simulation on a high-performance computing (HPC) cluster to assess the effectiveness and benchmark of the suggested solutions. Thus, the suggested methodology came out to be a viable option for UAV-based data categorization in contexts with limited resources. The authors rigorously assessed the performance of their system in the simulation using two different CNN models, the Lenet and VGG-16 [73], each with seven and eighteen layers, respectively. The system was used specifically to deal with scenarios involving pedestrian monitoring, which entailed classifying large-scale RGB photos (595326) taken from the Stanford Drone Data Collection [74]. The limited energy and payload capacity finds the challenge to incorporate ML capabilities into small UAVs. Within the limited UAV hardware and software, the authors of [75] proposed a scalable and modular framework for evaluating vision-based ML challenges. In this study, the authors compared and contrasted two alternative systems that rely on vision for navigation. In the first setup, an autonomous landing site identification system was built and evaluated using two different models based on LeNet-5 and MobileNetV2. As a consequence, the UAV may change its trajectory to get closer to the designated landing area. In the second configuration, the authors tried out a person detection model using a customized MobileNetV2 network. It is shown that the system can quickly learn from its environment and respond appropriately, even when faced with constrained computational resources. The article also showed that moving from cloud to edge computing [76] might significantly reduce energy consumption without compromising service quality.

*b) AlexNet:* For picture categorization using the ImageNet dataset, Krizhevsky et al. introduced the [77] network in 2012. A total of 60 million parameters are contained in the five convolutional layers and three fully linked layers that makeup AlexNet. It employs numerous methods to boost performance, including local response normalization, dropout regularisation, data augmentation, and the use of rectified linear units (ReLU) as activation functions. The usage of AlexNet in UAVs demonstrates the network's adaptability and capacity to carry out challenging visual tasks in circumstances with limited resources. The authors of [78] describes a cutting-edge method for leveraging deep learning to automatically detect damage to wind turbine blade surfaces using UAVs. In particular, a 21-functional sub-layer, 8-layer AlexNet, is built and parameterized to categorize photos of blade surfaces taken by a 4-rotor UAV. With an outstanding average accuracy of 99% in damage identification, the AlexNet was evaluated on a different dataset of 350 photos after being tested on a dataset of 10,000 images during training. The authors showed that deep learning classifiers developed on UAV image capture data are capable of automatically detecting damage to wind turbine blades that are already in operation.

### 2) DEEP CNNS

Deep CNNs are multi-layered neural networks that are frequently employed for computer vision applications like image identification [79] and classification. Because they frequently have many more layers than conventional neural networks–some models have hundreds of layers–they are referred to as "deep" neural networks. Deep CNNs have the benefit of learning complicated and abstract features automatically from raw image data, eliminating the need for human feature engineering, which was a time-consuming and error-prone procedure in the past. The following is a description of a few well-known deep CNN architectures that are often utilized in UAVs.

*a) Deep Residual Learning Network (ResNet):* A deep convolutional neural network (CNN), Residual Network was initially presented by He et al. [80] in 2015. This network employs a novel design based on skip connections, or "residual blocks," which allow for direct information transfer across layers to address the problem of vanishing gradients in extremely deep neural networks. By using these expedients, the network may learn residual mappings that are appended to the output of previous layers, making it easier for the network to understand the essential features of the data.

Using micro-Doppler signatures (MDS) shown on radar spectrogram images, a deep learning-based classification algorithm is proposed in [81] for real-time UAV identification. In this case, a frequency-modulated continuous wave (FMCW) radar was used to capture five LSS targets across a range of environments, including three kinds of unmanned aerial vehicles (UAVs) and two types of human activities. The signals were then converted into visual spectrograms through the Short-time Fourier transform (STFT). After analyzing the ResNet-18 model, a new model named ResNet-SP was developed to improve upon it in terms of computation, accuracy, and stability. Dataset expansion and refinement led to the creation of the radar spectrogram dataset.

*b) InceptionNet:* Google engineers developed a deep CNN architecture in 2014 dubbed GoogleNet, sometimes known as InceptionNet [82]. The network was designed to outperform conventional CNNs by improving accuracy with fewer parameters. This architecture is often used for picture classification and identification, combining convolutional filters of varying sizes in parallel to capture features at varying scales,

The study by Chriki et al. [83] proposed an implementation of novel anomaly detection algorithms to aid UAV-based surveillance operations that include the collection of photos using a mobile camera. Strong features were extracted from UAV videos using a combination of a pre-trained CNN and two well-known hand-crafted approaches (HOG [84] and HOG3D [85]). Specifically, the authors used an unsupervised classification method called One-Class Support Vector Machine (OCSVM). Extensive testing on a dataset of videos recorded by a UAV keeping watch over a parking lot confirmed the efficacy of the proposed methods. A pre-trained CNN based on the popular GoogLeNet (or inception v1) was also used [82]. The 2014 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC14) demonstrated that GoogleNet is superior to state-of-the-art classification and detection approaches.

### *C. GENERATIVE ADVERSARIAL NETWORK (GAN)*

A Particular kind of deep learning model called generative adversarial networks, or GANs [86], produce new data that closely mimics a given training dataset. A generator and a discriminator are their two basic parts. In order to trick the discriminator, which has been taught to differentiate between authentic and fraudulent data, the generator produces fresh samples. The two models are trained simultaneously as the discriminator improves its ability to discriminate between actual and false data using the technique of adversarial training The generator creates replica samples of the training data using random data as input. It is taught to use a loss function such as mean squared error or binary cross-entropy to minimize the gap between the generated samples and the true data. The discriminator is trained to determine whether incoming data is genuine or fake and is optimized for this task. One potential use of GANs in UAVs is the generation of high-quality images for use in training object recognition algorithms. It is possible to categorize them based on their architecture, intended purpose, or use case.

In order to limit the damage caused by droplet drift caused by rotor flow fields, an innovative method has been proposed in [87]. This approach combines deep learning and flow field approaches via the deployment of a GAN prediction model. While the discrimination network can distinguish between real and fake images, the generative network can learn the properties of the flow field in order to uncover hidden structures. This model studies training data to determine features of the flow-field distribution, which it then uses to generate a predictive model for flow-field prediction.

#### 1) DEEP CONVOLUTIONAL GANS (DCGANS)

In DCGANs [88], CNN is used as a generator and discriminator. CNNs are useful for creating images because they can identify regional spatial relationships. DCGANs create pictures from random noise using a number of deconvolutional layers in the generator. To assess if a picture is real or false, the discriminator employs a number of convolutional layers. DCGANs have been utilized to produce high-quality pictures in applications, including image and video production. The 5G wireless network [89] is crucial for allowing marine UAV communication. For important applications, great dependability and low latency are necessary. As a result, it's essential to have a fast data rate and trustworthy communication, all of which depend on the state of the channel. A channel mode for 5G-enabled maritime UAV communication employing millimetre wave (mmWave) for the air-to-surface link was thus proposed by the authors in [90]. The channel model's mmWave channel state information (CSI) is intended to be included in the channel estimation method. An LSTM-Distributed Conditional Generative Adversarial Network (DCGAN) was used to implement the strategy across all beamforming directions. To expand the usefulness of the training channel model, a UAV network based on LSTM-DCGAN was developed. Simulation results based on resilient local training errors show that the proposed LSTM-DCGAN-based network is effective.

#### 2) WASSERSTEIN GANS (WGANS)

The Wasserstein distance is employed as the objective function in WGANs [91] as opposed to the conventional binary cross-entropy loss in normal GANs. It has been established that the binary cross-entropy loss is less stable than the Wasserstein distance, which quantifies the separation between two probability distributions. Weight clipping is another technique used by WGANs to impose the Lipschitz constraint [92], which prevents the gradients of the discriminator from exploding or disappearing. Applications like picture synthesis and text creation have both employed WGANs. The study [93] explores the viability of enhancing wireless signal-based detection of unauthorized UAVs using GAN. In order to increase classification accuracy using the discriminative model, a sizable dataset is built without the need for manual annotation. The model works well in outdoor settings and produces outstanding results with little datasets. For multi-class UAVs, an enhanced Auxiliary Classifier Wasserstein GANs (AC-WGANs) model is created, and it is integrated with the USRP B210 SDR for real-time classification.

#### 3) CYCLEGANS

CycleGANs is a sort of GAN that can learn to translate across multiple domains. Unpaired training data is not required for CycleGANs [94]. To learn the mapping between the two domains, CycleGANs employ two generators and two discriminators. Images are mapped from one domain to the other by one generator, then from the second domain back to the first domain by the other generator. Whether the created pictures are phony or real is determined by the two discriminators. CycleGANs have been applied to domain adaptation and picture style transfer, among other things. An UAV-based wildfire [95] detection system was proposed in [96] to reduce wildfire damage. In the deep learning-based categorization of wildfire images, data imbalance between wildfire- and forest-image data is a frequent issue that affects performance. In order to correct data imbalances, the authors of this article suggested a DenseNet-based architecture and created wildfire pictures using CycleGAN. The framework obtained an F1 score of 98.16% and an accuracy of 98.27%. The trained model showed great wildfire identification [97] accuracy when used with high-quality drone photos of wildfires [98].

### D. RECURRENT NEURAL NETWORKS (RNN)

RNN is a type of neural network which deals with sequential data. RNNs have the capacity to process sequential data of variable lengths and employ feedback loops to preserve knowledge about previous inputs [99]. RNNs comprise several layers of neurons, each of which receives input from the layer above and produce its own output. It also has a hidden state sent back into that layer in the following time step. Backpropagation through time (BPTT), a variation of the backpropagation method that considers the temporal character of the input data, can be used to train RNNs. To update the network weights, BPTT computes gradients for each time step of the input sequence and propagates these gradients backward through time [100].

Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are one of the types of RNNs.The major motive of the aforesaid networks is created to solve the issue of “vanishing gradient”.

#### 1) LSTM

Long Short-Term Memory (LSTM) [101] architectures in RNNs are capable of detecting dependencies of temporal nature. Such dependencies arise in sequential data. The LSTM’s input, output, and forget gates monitor and enable selective control of the information flow of a particular memory cell. This information, passing through the output gate moves into the network, while the same information flows into the memory cell through the input gate. Deletion of the data is controlled by forget gates. LSTM is particularly useful for tasks involving the processing of sequential input with gaps in time, such as voice recognition and text processing. Its ability to selectively remember or forget information over long periods of time makes it a great fit for tasks that require recalling past events, such as language translation or handwriting recognition. The LSTM has found a number of uses in UAV-based deployments.

The resource allocation issue for many UAVs serving M2M communications is investigated by Xu et al. in [102]. Uncertainty in a stochastic setting is modeled after a Markov game. To better monitor and predict mobility, leading to higher network rewards, an LSTM with GANs architecture is proposed as a solution to the UAV mobility issue in this article. The results here are superior to those of the more common LSTM and DQN algorithms. Bae et al. in [103] described a novel approach for UAV anomaly detection in the distributed AI environment utilizing deep learning models. Due to the high computational demands of anomaly detection, the embedded system-based UAV environment is not ideal for settings that use standard AI. LSTM-AE(Auto Encoder) and AE models are utilized in distributed AI with DPS and MAS for UAV anomaly detection. Experimental findings indicate that the suggested technique performs well for anomaly identification in the UAV environment. Another article [104] using LSTMs, focus on UAV communication. Future wireless networks will benefit from the use of UAVs as significant communication platforms, particularly in temporary and emergency situations. The capacity for data flow through an UAV is impacted by the its location. The location of a UAV that optimizes system performance and user throughput is determined in this study using MLP and LSTM techniques. For accurate findings, the suggested system is assessed using TensorFlow packages and contrasted with alternative methods.

#### 2) GATED RECURRENT UNIT (GRU) NETWORKS

RNNs containing GRUs are used to represent sequential data. Cho et al. in [105] proposed it as an alternative to the LSTM architecture. GRU is designed to circumvent some of the limitations of the LSTM architecture while maintaining the same degree of performance. GRU, like LSTM, allows one to choose which memories to retain or discard. GRU only makes use of two gates, the reset gate and the update gate, whereas LSTM makes use of three [106]. How much of the new information should be stored is determined by the update gate, while how much of the old information should be deleted is determined by the reset gate. The simplified design allows for faster GRU training.

Typically horizontally organized, the polarisation compass used by UAVs for navigation causes notable heading mistakes as a result of inevitable tilts during flight. Heading errors are increased when the body axis tilt and the solar meridian angle are coupled. Utilizing a GRU neural network, an extensive investigation of attitude angle factors has been performed, creating a brand-new heading error modeling and compensating technique in [107]. In terms of forecasting UAV direction, their solution fared better than cutting-edge algorithms. The use of defect detection to improve system stability is important in UAV systems. Credible defect detection is accomplished using data-driven approaches, although the efficacy of standard techniques may be hampered by time series noise. In order to analyze UAV flight data impacted by motor or wind vibration, an upgraded GRU approach is thus proposed in [108]. A GRU model is constructed to estimate sensor data after the raw data is denoised and normalized to enhance the analysis. The approach employs thresholds and residuals to reduce wildfire damage. The efficiency of the approach is assessed using simulation data from UAVs, and defect detection is determined to be successful. Traditional approaches struggle to withstand the impacts of noise uncertainty since the power of noise and the channel's SNR are unpredictable. This is due to the UAV environment's continual change. Luo et al. in [109] integrated machine learning and data preprocessing to enhance UAV spectrum sensing performance. The satisfactory simulation proves the superiority of their GRU-based approach over LSTM networks.

### *E. CLASSICAL MACHINE LEARNING ALGORITHMS*

In machine learning, the techniques used to train models to make predictions or judgments based on data are known as classical algorithms. UAVs may be equipped with traditional machine learning techniques to boost performance and give them the ability to make more informed judgments. A summary of some of the most popular traditional machine learning algorithms and the UAV-related works employing them is given below.

#### 1) LINEAR REGRESSION

Finding the best-fit line or hyperplane that illustrates the connection between the dependent variable and the independent factors is the aim of linear regression [110]. Both simple and multivariate regression analyses may be performed using linear regression. In a straightforward regression analysis, there is only one independent variable, and a straight line is used to describe the connection. Multiple independent variables are used in multiple regression analysis, and a plane or hyperplane in higher dimensions is used to describe the connection. The following list of UAV-related applications has used linear regression. Alos et al. introduced a novel method in [111] for contextual fault detection in UAV systems that makes use of the intricate linear correlations between UAV properties, such as sensor data and orders. An UAV system is a complicated system because of the control, aerodynamics, and communication systems that go into its design. This method uses dynamic linear regression to estimate the values of a particular characteristic in order to detect any potential flaws that might arise from a faulty sensor reporting false values. Using a K-NN (Nearest Neighbour) classifier, the estimation error values at each time step are obtained and divided into two categories, namely normal and abnormal. Potential flaws are shown by the anomalous spots. The article [112] proposes to find the best place to attach four gas sensors and a Particle Number Concentration (PNC) monitor to a hexacopter as part of a UAV system for evaluating point source emissions. There were two studies done to determine how well the gas sensors worked and how the air flowed. After determining that the best place to attach the sensor was adjacent to the UAV, they utilized a linear regression model to analyze the effect of sensor location on our pollutant concentration data. This research provides guidelines for developing reliable UAV systems for evaluating emissions from stationary sources.

#### 2) NAIVE BAYES

The Naive Bayes algorithm [113] is a frequently used algorithm for classification purposes. The Bayes theorem [114], a linchpin of probability theory, serves as its theoretical basis. The Naive Bayes approach assumes that the presence of one characteristic in a class does not rely on the existence of any other qualities. This is known as the "naive" assumption because it improves the method's computational efficiency and simplicity of estimating probability. The Naive Bayes method must first be trained on a collection of labeled data before it can be used for classification. The algorithm determines the conditional probability of each feature given a class label during the training phase. The number of times each feature appears in each class in the training data is counted to achieve this. The posterior probability of each class, given the observed characteristics, may be used to predict the class label of incoming data once the algorithm has been trained. The anticipated class label is then chosen from the class with the highest likelihood.

As the number of ways in which UAVs may be deployed grows, security becomes a key issue. UAVs rely heavily on civilian GPS signals for finding and navigation. However, these transmissions may be intercepted and manipulated by malicious attacks like GPS spoofing. Several techniques, such as supervised machine learning, have been proposed by researchers in [118] to detect and classify these dangers. However, no research in this area has focused on unsupervised models. When comparing the results of supervised and unsupervised models, this research found that the Decision Tree model was the most successful in detecting and classifying GPS spoofing attempts. Getting data during live missions is difficult; thus, a simulator is used to mimic the three tiers of mental exertion required for SAR operations. Several physiological markers are used as characteristics in

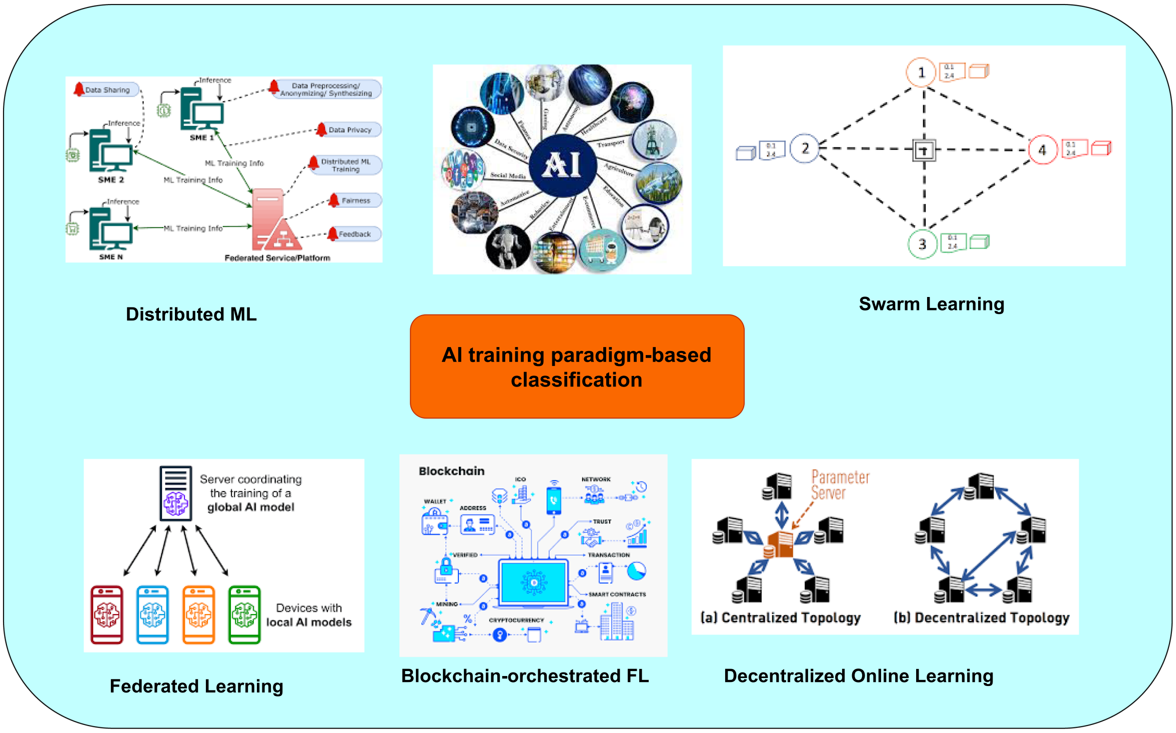


**FIGURE 6. AI training paradigm-based classification.**

identifying mental exertion. Using the eXtreme Gradient Boosting (XGBoost) method and the Shapley Additive exPlanations (SHAP) score, as described in the article [120], a recursive feature elimination strategy is used to choose the most informative features.

### 3) K-NEAREST NEIGHBORS (KNN)

Machine learning algorithms like KNN are utilized for classification and regression problems. It is a straightforward method that relies on the similarity concept. Similar items tend to cluster together, which is the fundamental tenet of KNN. The input data for KNN are points in a multidimensional space. The size of the space corresponds to the number of characteristics in the data, and each point represents a single instance of the data. KNN searches the space for the K closest data points to a new input data point when one is provided. The class of the majority of these KNNs then determines the algorithm's output [121] [122].

Insecure situations where people interact closely with robot swarms necessitate intuitive control. Maintaining the swarm's autonomy while providing adequate tools for the human operator to affect the robots' decision-making process is required in such activities. The work [119] presents a method for human-swarm interaction that employs full-body action recognition to manage an autonomous flock of unmanned aerial aircraft. The KNN algorithm is used to classify human actions and estimate the full-body position of the human operator. The swarm bases its objective direction on the identified activity. A multi-stage experimental design to assess the system's resilience and prediction accuracy shows how useful this technique is. The research by Alos et al. [111] suggests a novel method for identifying contextual errors in UAV systems. Control, aerodynamics, and communication systems are all used in UAV design. The suggested method takes advantage of intricate linear correlations between several UAV characteristics, including sensor readings and orders. Dynamic linear regression is used to estimate the values of a particular attribute, and each time step includes a calculation of the estimation error. The values of the estimation error are divided into two categories–normal and abnormal–using the KNN classifier.

## V. AI TRAINING PARADIGM AND INFERENCE-BASED CLASSIFICATION

In this section, we classify the papers based on the AI training paradigm employed. Fig. 6 shows the diagrammatic representation of the AI training paradigms, and Table 4 summarizes the reviewed papers under these AI training paradigms.

### *A. DISTRIBUTED ML*

The use of machine learning algorithms that function in a distributed fashion is referred to as distributed machine learning. This method enables UAVs to communicate their models with other UAVs or a central server for increased accuracy while learning from data collected in their local settings.

A distributed optimization approach using an adaptive fuzzy PID-UAV attitude controller is proposed in [123] to solve the issues of membership value and expert knowledge dependency in the control effect. Fuzzy PID has advantages

**TABLE 4. Summary of AI Training Paradigm and Inference-Based Classification**

| AI training paradigm | References(s) | Target issue |
|---|---|---|
| Distributed ML | [123]<br>[50] | To solve the issues of membership value and expert knowledge dependency in the control effect<br>Shared caching and resource allocation |
| Federated learning | [126], [126], [127]<br><br>[128] | To provide Federated Learning-based wireless networks<br><br>To allow for the safe sharing of local model changes |
| Split learning | [131], [132] | To detect the presence of fire on city streets by surveillance UAVs |
| Multi Agent Reinforcement Learning(MARL) | [134]<br><br>[135]<br><br>[136] | To examine the difficulties of processing data on IoT nodes owing to a lack of computing power<br><br>To address the user association issue in a multi-UAV aided network for uplink-downlink decoupled (UDDe) transmissions<br>To resolve a simultaneous optimization issue of UAV trajectory design, multidimensional resource scheduling, and user access strategy |
| Blockchain orchestrated federated learning | [137], [138], [139], [140]<br>[141], [142] | To use blockchain technology in B5G-enabled UAV communication<br><br>Studies the impact of employing drones for edge intelligence in smart settings, including security and decentralisation |

over traditional PID when learning how to acquire continuous square wave instructions. The system's tracking and anti-interference skills are greater, it can reach stable control faster, and it has excellent dynamic and static characteristics. The results of the experiments reveal that the UAV can reach and maintain a stable altitude of 2 meters within 6 seconds after takeoff using a single PID controller. The control system's high precision and simplicity of installation contrast sharply with the fuzzy controller's advantages, which include decreased overshoot and transient response and the ability to develop precise and rapid behavior management. For a network of cache-enabled UAVs serving wireless ground clients on the LTE licensed and unlicensed bands, the problem of shared caching and resource allocation has been addressed in the article [50]. The proposed solution is a distributed approach using the liquid state machine (LSM) machine learning architecture that allows the cloud to predict the distribution of user content demands and UAVs to autonomously choose the appropriate resource allocation methods. Simulation results on real-world datasets show that the proposed method drastically decreases convergence time by as much as 20% compared to two baseline methods, Q-learning with cache and Q-learning without cache.

### B. FEDERATED LEARNING (FL)

Federated Learning is a distributed machine-learning technique that permits the creation of a machine-learning model on a swarm of UAVs. In the beginning, each UAV trains a local model with its own data. After that, a central server gathers the locally trained models to produce a global model. Because raw data is not shared with other UAVs in the swarm, data privacy and security are maintained. FL is divided into two categories: horizontal FL and vertical FL [124], [125]. The former is the commonly used type of FL, which is applicable to scenarios with various samples but comparable characteristics. The vertical, on the other hand, is employed in situations where participant samples are available as scattered datasets.

The article [126] suggests UAV communications for long-lasting FL. The topic of how to include FL in wireless networks, which is complicated by mobile users' low battery capacities, has been addressed here. In order to provide long-lasting FL-based wireless networks, this article suggests using UAVs for wireless power transfer. The goal is to simultaneously optimize transmission time, bandwidth allocation, power control, and UAV positioning in order to increase the efficiency of UAV transmit power. The connection of the variables makes it difficult to directly answer the specified problem. As a result, the authors create an effective method called UAV for sustainable FL (UAV-SFL) using the decomposition technique and a sequential convex approximation approach.

Pham et al. recommended UAV communications for permanent FL in [126]. This article discusses how to implement FL in wireless networks. The issue of permanent Fl is made more difficult by the limited battery life of mobile devices. Thus, it employs UAVs for wireless power transfer to enable long-lasting FL-based wireless networks. Improving UAV transmission efficiency requires optimizing many factors at once, including transmission time, bandwidth allocation, power control, and UAV position. The interdependence of the factors prevents us from providing a simple solution to the given issue. In light of this, we use the decomposition method in conjunction with a sequential convex approximation strategy to develop a practical solution we name UAV for sustainable FL (UAV-SFL).

An FL-based method was also proposed in [127]. A hybrid power allocation and scheduling solution was presented to optimize the convergence rate of FL while taking into consideration wireless characteristics and energy consumption. In addition, a thorough convergence study was carried out for FL. Applying traditional AI models to UAV sensing data may raise concerns about data utilization and privacy. Even while FL is a solution, there are still concerns about privacy and safety. In order to develop a Mission Control System(MCS) with the help of UAVs, the article [128] proposes using an SFAC or secure federated learning architecture. SFAC uses a blockchain-based UAV collaborative learning architecture to allow for the safe sharing of local model changes and validation of contributions without the need for a central curator. To further ensure that freshly updated local models remain private, local differential privacy is then used. An RL-based reward system is used to incentivize the sharing of high-quality models. Many simulations show that SFAC greatly improves UAV usefulness, promotes the sharing of high-quality models, and guarantees privacy.

### C. SPLIT LEARNING

Split Learning [129] is another approach to train a global learning network. Without disclosing the original data, the training can be performed. This approach divides the ML model into a number of smaller sub-models, which are subsequently trained in a distributed manner by a number of clients and a server. The output of an intermediate layer is disseminated by the client and sent through forward propagation to the server [130]. The privacy of the original data is protected by the server's backward propagation of gradients to the clients.

In the article [131], a spatiotemporal split learning is used to detect the presence of fire on city streets by surveillance UAVs. Autonomous surveillance UAVs are used to monitor the city's streets for any suspicious activity and to gather a large amount of data. The fire classification model is globally trained, allowing fire stations to recognize the presence of a fire in the neighborhood quickly. The article also investigates the network architecture, client and data ratios, and a sufficient number of clients for split learning in this UAV environment to enhance communication resilience. Rapid fire detection and fireman deployment require effective communication between the UAV and the central server.

Concerns concerning privacy have been raised by the rise of personal monitoring devices, such as dash cams and cycling helmet cameras. A team has created SASSL [132], a secure aerial surveillance drone that utilizes split learning to find fires the streets of a secure aerial surveillance drone that uses split learning to detect fires on the streets in order to address this issue. The drone records CCTV footage, which is then sent to a nearby server, where a deep neural network is used to instantly detect the presence of fire. The drone only processes the feature map on the cloud server after running the deep neural network up to the first hidden layer in order to protect the privacy of citizens' data. Additionally, the UAV may also capture any abnormal activity in a suburb and analyze the data using its built-in deep neural network or by sending it to a server.

### D. MULTI AGENT REINFORCEMENT LEARNING(MARL)

The single-agent RL algorithm based on a centralized approach is capable of solving non-convex or time-dependent optimization issues. On the other hand, MARL is a widely utilized technique in UAV swarm networks [133]. The number of UAVs will greatly expand the action space and state space of the single-agent RL algorithm when used in UAV swarms. Consequently, there will be more information overhead, training will be more difficult, and convergence speed will slow down. As a result, it is necessary to create a distributed RL approach that may be used by several devices to run RL simultaneously [130].

The article [134] examines the difficulties of processing data on IoT [143] nodes owing to a lack of computing power and how mounting mobile edge servers on UAVs can offer mobile edge computing services that are available on demand. For integrated optimization of job offloading, resource allocation, UAV mobility, and online decision-making process is necessary. For decentralized implementation, a multi-agent DRL approach is suggested, in which several intelligent UAVs collaboratively choose their computations and communication strategies without centralized coordination. The proposed paradigm has the potential for creating IoT networks that self-organize. Its decentralized learning technique works better than current DRL systems, according to numerical findings.

The user association issue in a multi-UAV (refer Fig. 3) aided network for uplink-downlink decoupled (UDDe) transmissions is covered in the study [135]. The authors provide rate-splitting multiple access (RSMA) rules that boost spectral efficiency by using rate splitting and sequential interference cancellation (SIC). They propose a non-convex joint optimization problem for UL-DL association and beamforming and employ a multi-agent deep reinforcement learning (MADRL) and resilient partly observable Markov decision process (POMDP) for distributed optimization. Also suggested is an enhanced clip and count-based proximal policy optimization (PPO) technique. The simulation results demonstrate that the suggested technique performs better than the alternatives.

The article [136] suggests a Multi-UAV aided communication technique employing Multi-Agent Reinforcement Learning to resolve a simultaneous optimization issue of UAV trajectory design, multidimensional resource scheduling, and user access strategy. A proximal policy optimization method, centralized training distributed execution, and a hybrid game model of users and UAVs are used in the algorithm. The implementation is enhanced by a beta policy A wide array of simulations are carried out to confirm the efficacy of the algorithm. The strategy intends to compensate for the limitations of present wireless communication by supporting integrated space-air-ground communication.

### E. BLOCKCHAIN-ORCHESTRATED FEDERATED LEARNING(BCFL)

Blockchain-orchestrated Federated Learning (BCFL) combines Federated Learning, which trains AI models across decentralized devices, with blockchain technology to securely manage model updates. BCFL ensures transparent tracking of contributions from multiple devices while maintaining data privacy and integrity through blockchain's immutable ledger. In a BCFL, multiple UAVs operate together in a collaborative ML process that is governed and protected by a blockchain-based network. Several benefits come with using blockchain technology in B5G-enabled UAV communication, including flexibility, scalability, immutability, transparency, and quick and efficient delivery services with privacy and security [137] [138]. Blockchain offers a safe and dependable communication environment for UAV networks by storing data in a timestamped, sequential, and immutable fashion. Additionally, due to the shared ledgers' non-alterability and the use of GCS satellites, B5G-enabled UAV-UAV communication is safe from any adversary assaults [139].

Unmanned aerial vehicles (UAVs) equipped with 5G network connectivity may benefit from blockchain technology, as discussed in [140]. Instead of relying on a single server for federated learning, the suggested method makes use of a decentralized horizontal federated learning architecture to verify the legitimacy of UAVs flying in different domains using multi-signature smart contracts. The experimental evidence demonstrates the excellent efficiency and accuracy of this method. The article [141] explores the advantages and disadvantages of employing drones for edge intelligence [141] in smart and secure settings. To solve the issues of security and decentralization and enable environmentally friendly, sustainable settings, the authors suggest an integrated approach of FL and blockchain. They discuss the theoretical and technological components of the proposed method as well as the difficulties, possibilities, and trends of the future.

To provide intelligent connectivity and services to aerial and ground-connected devices, the authors [142] present a system that integrates the capabilities of both UAVs and Unmanned Ground Vehicles (UGVs). UAVs can adapt how they serve their customers. The cooperative approach accounts for the power and mobility constraints of individual nodes, while FL is used at the network's periphery to provide timely, accurate service providing. Blockchain is used to decentralize provisioning and control while providing authenticity and integrity. Extensive simulations confirm that the method proposed significantly improves connectivity, service availability, and UAV energy.

## VI. TOOLS, LIBRARIES, FRAMEWORKS FOR BUILDING AI-INTEGRATED UAV SYSTEMS

In this section, we discuss the tools, libraries, and frameworks that are utilized to build AI-integrated UAV systems.

### A. MACHINE LEARNING-BASED TOOLS, LIBRARIES, FRAMEWORKS FOR BUILDING AI-INTEGRATED UAV SYSTEMS

Scikit-learn(SkLearn) [144] is a widely used open-source machine learning package. Classification, regression, clustering, and dimensionality reduction are just some of the many tasks that may be accomplished using the many techniques and tools provided. In addition, it provides tools for testing and deploying models. In [142], authors have implemented the proposed algorithm using SkLearn to solve the UAV power management issue. The approach here takes into account the mobility and power limitations of the nodes. The authors of [145] use SkLearn to predict how long it will take for each frame in the dataset to complete all of them. In this work, SkLearn is used to employ four different machine learning models–Kernel-Ridge Regression, SVR-RBF, Gaussian-handle Regression, and Random Forest Regression–to handle data. Training time, prediction latency, root mean square error, and mean absolute error are some metrics that the authors extracted with the help of the SkLearn tool. With the use of machine learning, this work aims to propose a dynamic computation offloading approach that is both energy-efficient and effective for multi-UAV systems with high-resolution cameras.

The primary use of the open-source machine learning framework PyTorch [146] is in the creation and training of neural networks. For activities like data manipulation, layer definition, and the implementation of frequently used operations, PyTorch offers a wealth of pre-built modules and utilities. In [135], the authors trained two neural networks, an "actor network" and a "critic network" on a Python 3.6 platform using PyTorch, which makes up the proposed MADRL-based joint optimization technique. The authors of [129] have also trained their RL agents using Pytorch. In this study, the MASAC algorithm is suggested as a method to maximize efficiency while minimizing power usage.

Keras [147] is a Python-based open-source deep learning framework. It offers a high-level, user-friendly interface for constructing and training neural networks. It comes with a plethora of pre-built layers, activation functions, and optimization algorithms, making it simple to build complicated neural network structures. Keras has both sequential and functional APIs, enabling users to build models of varying complexity. In [148], Keras-Retinanet was used to simulate aerial data from micro-aerial vehicles. Another implementation of a Keras-based deep neural network for real-time UAV position prediction is provided in the article [149]. This article proposes a mathematical framework for predicting the ground radar look angle, together with data preprocessing and a deep learning model based on a long short-term memory autoencoder (LSTM-AE). The raw historical dataset is preprocessed using the TensorFlow and Keras libraries for accurate depiction.

### B. UAV-RELATED TOOLS, LIBRARIES, FRAMEWORKS FOR BUILDING AI-INTEGRATED UAV SYSTEMS

ArduPilot [150] is a flight control system, and the ArduCopter [151] plugin is an add-on module for it. Drones and other unmanned aerial vehicles (UAVs) may be piloted with the help of ArduPilot, a free and open-source autopilot software package. The ArduCopter plugin prioritizes multirotor copters' administration and control, including quadcopters, hexacopters, and octocopters. It gives capabilities allowing the UAV to operate independently in the air. Koch et al. [22] used the ArduCopter plugin in their UAV-based framework. A remote health monitoring system (HMS) based on UAVs is presented in the study [152]. Using IoMT technology [153], it takes readings of vital signs and transmits them wirelessly to doctors for remote analysis. The device provides video surveillance in an effort to reduce hospital stays and readmissions. In this study, the authors used the Ardupilot, a kind of embedded airplane powered by the Arduino IDE. This Ardupilot's autopilot function and GSM connectivity allow it to pilot the UAV. Information transmission in this concept was implemented using a fly-by-wire scheme.

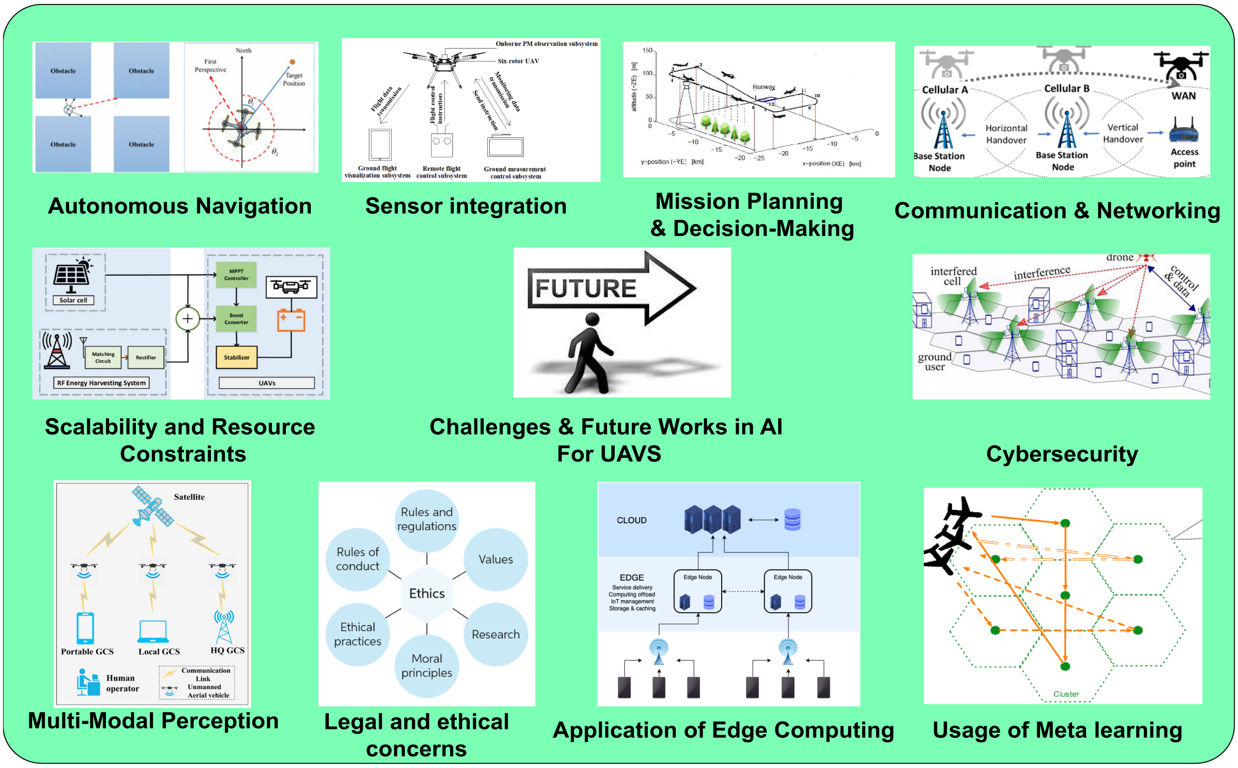


**FIGURE 7.** **Challenges and future works.**

GymFC [154] is an open-source reinforcement learning system that was developed primarily for training and assessing flight controllers in simulated scenarios. It is based on the OpenAI Gym [155] toolbox and includes a series of settings and tools designed specifically for flight control tasks. GymFC provides several flight control settings that model various circumstances and dynamics, such as fixed-wing aircraft, multirotor copters, and other aerial vehicles. Another research study [22] examines the accuracy and precision of attitude control in RL-created AI flight controllers. This study aims to use cutting-edge RL algorithms, including DDPG, TRPO, and PPO, to design controllers for the Iris quadcopter [156]. To solve the problem of quadcopter attitude control using deep reinforcement learning, the authors [157] implemented their idea in GymFC, a flight controller environment based on the OpenAI Gym API.

## VII. CHALLENGES AND FUTURE DIRECTIONS

In this section, we outline several challenges and possible future works in AI-integrated UAV systems. Fig. 7 illustrates various challenges and areas for future developments.

### A. AUTONOMOUS NAVIGATION

The development of AI algorithms for enabling autonomous navigation and path planning presents one of the biggest challenges that the industry is trying to address. UAVs need to operate and maneuver effectively in intricate and ever-changing environments, evade obstacles, and promptly respond to sensor data by making real-time decisions to enable autonomous navigation. Also, most of the current studies in this area suggest path-planning protocols by assuming fully and homogeneously connected networks without discontinuities in the links. Future works may include the development of light-computation-based algorithms for achieving route prediction in the three-dimensional space on a real-time basis.

### B. SENSOR INTEGRATION

UAVs generate reactions to the stimuli received from onboard sensors, such as cameras, radar, and GPS, to perceive their surroundings. Integrating data from multiple sensors to compute external environmental awareness presents a complex task. Hajiyev et al. [158] suggested Robust Kalman Filter(RAKF) address the faults in the sensors of UAVs. RAKF acclimatizes itself in the presence of faults, ensuring accurate data interpretation even in the presence of sensor failure. Deep learning techniques, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), can be used to process and analyze data from various sensors.

### C. MISSION PLANNING AND DECISION-MAKING

One of the most crucial aspects of an autonomous flight is a UAV's ability to make real-time decisions while on a mission. However, addressing factors such as weather conditions, real-time information, and mission parameters while designing algorithms is a major challenge. UAVs also need to adapt to changing circumstances and unexpected events. As a part of future work, we propose the employment of genetic algorithms, which involves improving the aptness and accuracy of possible solutions to approach a particular decision-making problem, thereby improving the efficiency of the mission too.

### D. COMMUNICATION AND NETWORKING

UAVs operating in swarms need an efficient and quick communication system devoid of latency for collaborating and sharing information to accomplish complex missions. Establishing such networking ability among UAVs while maintaining reliable connectivity in dynamic environments is challenging. The communication links are also extremely susceptible to failures owing to cyber-interventions and environmental factors. ML techniques that can be incorporated infuse the link and path lifetime as an important parameter in computing flight paths, thus improving the lifetime of the link and reducing the loss of connectivity.

### E. SCALABILITY AND RESOURCE CONSTRAINTS

UAVs are faced with limitations on computational power and memory due to size, weight, and power constraints. Efficient algorithms and hardware are required to enable the UAVs to operate within these limitations and to make AI solutions viable on UAV platforms. Robust AI algorithms are needed to prevent accidents or failures by detecting and mitigating errors, handling unexpected scenarios, and maintaining system integrity. We also need to replace the existing computationally heavy task-specific algorithms with their optimized counterparts and develop high-performance and low-weight UAV memory chips.

### F. ENERGY EFFICIENCY

UAV batteries are also faced with limitations in size and capacity due to operational constraints. This restricts the flight time and payload-bearing capacity of the UAVs, thus rendering them incapable of being employed as full-scale agents, such as in the goods delivery industry. The idea of a hydrogen fuel cell battery supplemented with lithium-ion batteries, which can be used after the former has run out of charge, can be used for the mission needs to be continued. We also propose the incorporation of ML and DL algorithms that can compute energy-efficient flight paths by considering environmental factors such as wind, which highly affect the aerodynamics of the UAV and the fuel demand of the UAV propellers.

### G. CYBERSECURITY

UAV communications are susceptible to cybersecurity threats, such as unauthorized access(man-in-the-middle), data breaches, and potential hijacking of control systems. Xiao et al. [159] suggested an anomalous-behavior detection system for UAV networks using Recurrent Neural Network. We propose the induction of physical security keys as an industry standard for facilitating UAV authentication. Also, ML techniques need to be employed to calculate secure and optimal flight paths, which minimize the risk of issues like jamming attacks.

### H. MULTI-MODAL PERCEPTION

Incorporating meaningful data from multiple external sensors, including radar, cameras, and infrared sensors, for the apprehension of the UAV's operational environment presents a complicated problem for the industry and researchers alike. Samaras et al. [160] have elaborated various deep-learning techniques for solving this issue. The development of effective algorithms for the proper infusion of data into the computations for creating accurate situational awareness is needed and presents a positive area for future work.

### I. AVAILABILITY OF RELIABLE AND HIGH-QUALITY DATA

The computational backbone of all machine learning algorithms uses extensive data to train mathematical models. Sourcing high-quality and diversified accurate data is still problematic. All training datasets used in the industry should be updated and labeled regularly and tested regularly to filter out spurious data. This will eventually help achieve better abilities in the UAVs in terms of better object detection, recognition of images, and anomaly detection.

### J. LEGAL AND ETHICAL CONCERNS

The heavy usage of AI in UAVs has paved the way for unprecedented applications of UAVs in our lives, directly or indirectly. However, this has drawn persistent criticisms in terms of infringements on privacy, data security, and accountability. Robust algorithms need to be developed to address each of these concerns, and educational awareness should be spread regarding the technological advances being made in this area to reduce the concerns potential UAV users and customers might be having.

### K. APPLICATION OF EDGE COMPUTING

Achieving optimal performance in UAVs within the bounds of available resources has been a major problem in the path of the development of UAVs. Edge computing [161] presents a possible solution to address these issues by enabling real-time processing of the collected data while simultaneously reducing the need to transfer data to cloud servers continuously. It also ensures the transmission of only the relevant data within the UAV network to reduce the wastage of network bandwidth and also increases the privacy and security of sensitive information. This can enable the formation of UAV swarms and be employed for purposes like search and rescue missions.

### L. APPLICATION OF COGNITIVE LEARNING

Making quick and real-time decisions based on changes in external stimuli is one of the most crucial aspects of autonomous UAV flights. However, developing UAVs with human-like cognition ability is inexpedient. Employing cognitive learning to address this challenge can improve path planning, resource allocation, and reaction to previously unseen situations for the UAVs, owing to a better ability to acquire more knowledge, improvise strategies and optimize performance gradually.

### M. USAGE OF META-LEARNING IN THE FIELD OF UAVS

Meta learning is a technique where AI models learn how to learn. It involves training models on various tasks to develop adaptable strategies, enabling them to quickly adapt and excel when faced with new, unfamiliar tasks.

The continuously growing number of UAV users necessitates the need to increase the computational speed and accuracy of UAVs. Meta-learning [162] can be employed to improve the learning speeds of algorithms to adapt to training models so that better efficiency can be obtained in applications such as UAV swarms and multipath planning.

## VIII. CONCLUSION

Autonomous UAVs rely heavily on AI technology for their operation. UAVS can now perform autonomous path planning, obstacle avoidance, object detection, and tracking, among other tasks, which require very fast decision-making ability in real time. Recent review papers on AI-integrated UAV systems have mostly focused on certain specific applications or technology, but no thorough and comprehensive survey existed which demonstrates most of the latest trends in technologies and potential fields for improving UAV applications by using AI. Our survey addresses this research gap and presents a comprehensive and diversified review of AI-integrated UAV systems.

We have classified the reviewed papers based on three criteria - 1) the application scenario, 2) the AI algorithm employed, and 3) the AI training paradigm employed. We have also presented a compilation of tools, libraries, and frameworks employed in building AI-integrated UAV systems. We have also highlighted several challenges and potential future improvements in AI-integrated UAV systems, which aim at optimizing flight safety and efficiency. Finally, our survey showcases that application of AI in UAVs has been fruitful and will see further diverse applications in the future. Our review will act as a guide to the technical teams and researchers working in building AI-integrated UAV systems.

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