Future UAV/Drone Systems for Intelligent Active Surveillance and Monitoring

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The rapid development of the Internet of Things (IoT) has fueled the widespread adoption of Unmanned Aerial Vehicles (UAVs) or drones across various fields, including their use in applications such as surveillance and monitoring. UAVs flight capabilities allow to effortlessly access previously inaccessible locations, providing real-time, high-resolution data – images and videos – of any desired area or target. Furthermore, the growth of Artificial Intelligence (AI), and edge computing technologies has empowered UAVs with high computational capabilities, making them suitable for diverse applications such as agriculture, transportation and border security. These technology advancements also equip UAVs with powerful on-board processing for sophisticated decision-making that enhances UAV activeness and intelligence. This survey explores the promising areas of UAVs for intelligent active surveillance and monitoring across diverse applications. First, the various levels of UAV activeness within applications are discussed; second, prior research is examined to identify the key technologies and architectures that power intelligent UAV systems; and third, several UAV applications in surveillance and monitoring, ranging from basic tasks to highly intelligent operations are explored. Finally, the survey concludes by discussing emerging research challenges and outlines a guiding road map for future research of highly interdisciplinary and emerging areas in UAV-based systems for surveillance and monitoring.

Additional Key Words and Phrases: UAVs; Drones; Surveillance and Monitoring; Intelligent and Active UAV Systems.

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1 Introduction

Unmanned Aerial Vehicles (UAVs) or drones are compact aerial vehicles designed for operation without an onboard human pilot. These UAVs can either be operated remotely or function autonomously and they have gained significant momentum due to their adaptability to diverse and complex scenarios. For instance, they have been employed in applications such as agriculture, search and rescue operations, surveillance systems, and mission-critical services. This is largely attributed to their technological and practical advantages, including their high mobility, the ability to extend wireless coverage, and access to areas that are otherwise unreachable [1]. In addition, these vehicles can come equipped with advanced imaging technologies, including high-resolution or infrared cameras. Global Positioning Systems (GPS) and various types of sensors can be integrated within UAVs to enhance their capabilities. Moreover, these UAVs can perform simple or complex surveillance and monitoring tasks due to their ability to fly high, covering large and difficult-to-access areas while reducing mission costs and potential casualties [2]. To understand the classification of UAVs, **Figure 1** illustrates two main groups. Based on the flying hardware, UAVs are mainly classified as fixed-wing, fixed-wing hybrid, single-rotor, and multi-rotor [3]. In addition, UAVs can be classified with different levels of autonomy. The drone autonomy is the system's ability to operate without direct human decisions based on a set of predetermined commands that are dictated for each operation. Autonomous classification can be leveled based on the involvement of the pilot in controlling the vehicle. These can be described as **Level 0** - *No Automation*, **Level 1**- *Low Automation*, **Level 2** - *Partial Automation*, **Level 3** - *Conditional Automation*, **Level 4** - *High Automation* and **Level 5** - *Full Automation* [4]. These main classifications are important for selecting the right UAVs based on rotor type, wing configuration, and flight endurance, ensuring optimal performance for specific tasks. It also aims in mission planning by highlighting autonomy levels, human involvement, and automation, which influence network design, communication needs and helps tailor UAV systems to diverse applications.

It is worth mentioning that within these classifications, recent UAV models are enhanced with advanced sensors, Artificial Intelligence (AI), and edge computing, thereby providing improved features, decision-making, and strategic planning capabilities. Their proficiency in onboard and cloud-based data processing allows for real-time face recognition and movement detection, adapting their location and flight paths intelligently to environmental conditions [5]. This autonomy can also enhance their effectiveness in surveillance and monitoring tasks. In this context, the concept of the Internet of Drones (IoD) emerges as a networking architecture that exploits the interplay between UAVs and wireless communication technologies. The networked drones within the IoD can unlock disruptive scenarios across diverse applications. However, to fully leverage their potential, accurate modeling techniques are necessary to capture the complexities of UAV features, wireless communications, and networking protocols [6]. In the following, we describe the different applications, and further explain UAV classification, and characteristics.

Surveillance: Surveillance is a systematic method for observing people, places, objects, or environments, and serves various purposes including information collection, activity detection, law enforcement, and research [7]. It can involve human observers, cameras, or other technologies, and ranges from individual monitoring of homes to large-scale urban surveillance by government entities. With the integration of Internet of Things (IoT) devices, surveillance techniques have evolved significantly [8]. The incorporation of AI, cloud, and edge computing has enhanced capabilities like object recognition, event, anomaly detection, and automated decision-making [9]. Thereby, this evolution is making surveillance increasingly prevalent across diverse industries and applications.

Monitoring: In urban areas, the growing need for surveillance combined with monitoring is driving technological advancements aimed at enhancing service efficiency, sustainability, and strengthening public safety and security. For instance, in smart cities, video surveillance and analytics play a crucial role in real-time traffic flow control management, pollution reduction, and improving transportation efficiency [5]. Networked cameras, combined with video analytics, are also useful in remote areas or in natural events like flooding, where they are used for

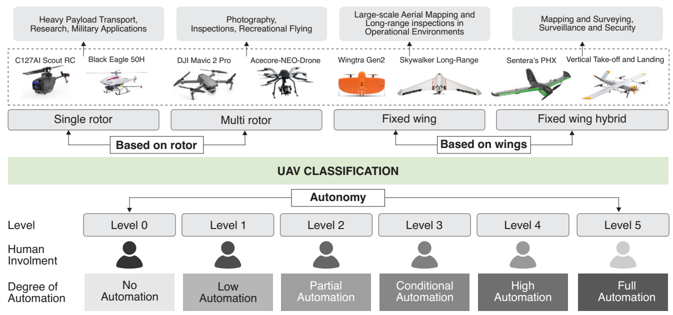

Fig. 1. This figure illustrates a detailed classification of UAVs by rotor type, wing configuration, flight endurance, and typical applications. It also highlights varying levels of autonomy, human involvement, and degrees of automation, alongside specific use cases categorized by rotor and wing types.

monitoring environmental conditions to detect potential safety hazards. Similar to the surveillance process, the monitoring process also involves the real-time gathering and analysis of data to enhance the efficiency of a particular system or process. It is usually performed for industrial, commercial, and infrastructure maintenance purposes [10]. Advanced monitoring techniques exploit data processing and computing to make real-time decisions and bring automation to the process being monitored. The implementation of AI-powered surveillance and monitoring systems facilitates predictive maintenance, anomaly detection, and automated responses, resulting in improved system scalability, adaptability, and efficiency. Although the characteristics of advanced monitoring are similar to surveillance in terms of real-time data collection and analysis, there are several crucial differences between them. **Table 1** describes typical differences between surveillance and monitoring practices. Surveillance is characterized by continuous observation across broad environments or multiple subjects, typically for security, behavioral analysis, or intelligence purposes. This approach frequently involves the collection of sensitive personal data, raising substantial privacy and regulatory concerns. On the other hand, monitoring focuses on periodic or real-time tracking of specific system parameters or processes, often aimed at optimizing performance, ensuring operational integrity, or detecting malfunctions. Monitoring activities are generally small-scale, target specific devices or systems, and involve less sensitive, operational data, thus posing fewer privacy concerns. Based on the

Table 1. Key characteristics distinguishing surveillance from monitoring, highlighting differences in data collection methods, scale, focus, data sensitivity, and privacy implications.

Characteristic	Surveillance	Monitoring
Data Collection	Continuous observation over time	Periodic or real-time tracking of specific parameters
Scale	Broad, large-scale deployments across areas/subjects	Focused, small-scale targeting specific systems
Objects	Multiple subjects or environments	Specific systems, processes, or devices
Data Sensitivity	High potential for sensitive, personal data	Typically operational or technical, less personal
Privacy/Security	Significant privacy concerns, regulatory implications	Minimal privacy issues, focused on system integrity

deployment of sensors for data collection, analysis and decision making, we can categorize the surveillance and monitoring systems as either passive or active [11, 12]. The characteristics of active and passive surveillance and monitoring are summarized in **Figure 2**, and can be described as follows:

Passive Surveillance and Monitoring: Passive surveillance and monitoring mainly refers to the collection of data with fixed or non-real-time deployment or observing patterns. This can involve cameras, microphones, or other sensors that are deployed in a pre-scheduled manner. The decision-making of the devices are typical

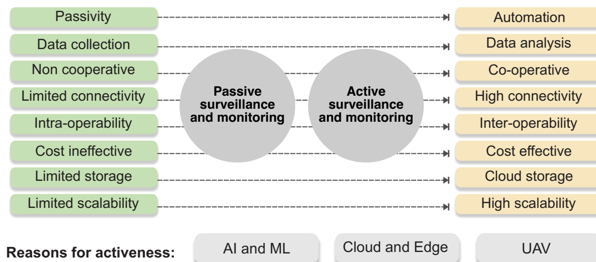

Fig. 2. Distinction between passive and active surveillance and monitoring methods. Passive approaches involve collecting data without the subject's awareness, while active methods involve the subject being aware they are being monitored. Both can be applied for surveillance (observation for security or information gathering) and monitoring (data collection for system optimization).

inactive and non-real-time. In such a process, most devices are fixed at a location to keep collecting required data. Decisions are made later based on the collected data. This type of surveillance and monitoring can have many objectives such as recording the movement of objects (vehicles or people), detecting smoke, or surveying an area for changes in land use over time [13]. The main characteristics of passive surveillance and monitoring include passivity, non-cooperativity, and limited connectivity. The passive surveillance and monitoring systems work in the background without interfering with the events being monitored. Some examples of these systems include the collection of environmental data (temperature, humidity, and atmospheric pressure), monitoring of infrastructure, health monitoring, network monitoring, and inventory monitoring.

Active Surveillance and Monitoring: Active surveillance and monitoring, in comparison, refers to the active engagement of the surveillance or monitoring agents to decide the data collection process dynamically and based on the real-time needs of the surveillance agents. For example, equipped with proper detection algorithms, the surveillance or monitoring agents may actively adjust the data collection focus or schemes and re-orient more resources to certain areas or objects of interests. If surveillance or monitoring agents involve moving ground vehicles or UAVs, then the deployment of the surveillance and monitoring can be adjusted flexibly in real time. Monitoring, on the other hand, involves the periodic or real-time tracking of specific system parameters or processes, with a focus on optimizing performance, ensuring operational integrity, or detecting malfunctions. While monitoring may overlap with surveillance in certain contexts, it is generally more focused on system functionality and less on individual behavior or security. Integrating intelligence with sensors brings activeness to surveillance and monitoring operations by enabling real-time data collection, processing, and facilitating prompt decision-making. As another example, in the context of traffic monitoring, deep learning methods can be employed to train cameras to autonomously detect events like accidents or criminal activities. This allows authorities to respond quickly by dispatching aid to the affected areas. Further, analyzing real-time and historical traffic data allows authorities to predict peak times of traffic and prepare accordingly. UAVs play a crucial role in enabling active surveillance and monitoring. Several key factors such as the flexibility of UAVs, advancements in AI and ML techniques, and the development of communication technology support the UAVs to easily collect, store, process, and analyze the data to make decisions during the operations.

In this survey, we introduce a novel categorization of surveillance and monitoring systems based on two dimensions: activeness and intelligence. Unlike traditional passive/active distinctions, we propose three categories: semi-active (periodic checks), active (real-time engagement), and proactive (anticipating and preventing events). These dimensions are interrelated, and we discuss how they influence UAV capabilities in surveillance.

Individually Semi-active Surveillance and Monitoring: These types of surveillance and monitoring involve UAVs with limited or conditional activeness. These UAVs are assigned specific tasks, such as reaching a location

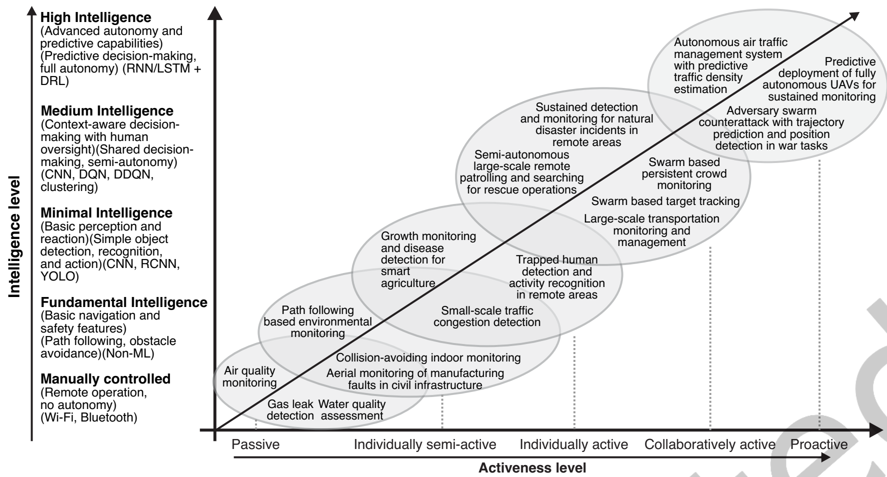

Fig. 3. Applications of UAVs in intelligent active surveillance and monitoring based on their intelligence level (degree of autonomy and decision-making capabilities) and activeness level (frequency of interaction with the environment); This illustration helps to identify the right UAV for specific tasks by considering the level of automation and interaction required [14].

or following an object. These devices can also be outfitted with intelligence for obstacle avoidance, enabling them to identify and avoid objects in their trajectory. This feature becomes particularly vital when a UAV operates at low altitudes, whether it be in indoor or outdoor environments.

Individually Active Surveillance and Monitoring: In the case of individually active surveillance and monitoring, one or more UAVs are individually deployed for the operations. These UAVs are capable of making individual decisions based on their onboard intelligence and sensors. These UAVs can decide their own path during the operation, fly autonomously, and make decisions about the given target. These UAVs are mostly used in vision-based applications.

Collaborative Active Surveillance and Monitoring: In collaborative surveillance, UAVs are increasingly deployed in swarms, enabling cooperative missions through shared data and communication. These UAVs display different levels of autonomy. Some operate independently within a multi-agent system, responding to environmental changes and shared data. Others follow a hierarchical model, where primary UAVs lead and secondary UAVs follow their directives. This collaboration enhances mission efficiency, reducing time and expanding coverage area compared to solitary UAV operations.

Proactive and Predictive Surveillance and Monitoring: These methods of surveillance and monitoring entail the use of UAVs outfitted with sensors, edge computing technology, and learning-based algorithms to proactively predict and detect occurrences or irregularities in a monitored area. These UAVs operate cooperatively, collaborating to share the data they collect. Learning models then process this data, discerning patterns and making predictions about forthcoming events. These predictive insights empower proactive decision-making during operations.

Our Survey Motivation: UAVs have emerged as a valuable tool for surveillance and monitoring, drawing the attention of numerous researchers. Despite this growing interest, there is a lack of comprehensive and systematic surveys on this topic. Existing reviews on UAVs primarily focus on specific areas such as civil applications, deployment, security, and miscellaneous applications [15–19]. Authors in [15] survey the UAVs' civil applications in wireless coverage, remote sensing, civil infrastructure inspection, search and rescue operations, surveillance and monitoring, and precision agriculture. Authors in [16] and [17] review the security threats, related issues, and different attacks in UAV applications. In [18], authors analyze bio-inspired algorithms for the deployment and routing in UAV-based Flying Ad Hoc Networks (FANET). Yazdi et al. in [19] provide the classification of UAVs based on their size, range, rotor, and aerodynamics, and then discuss UAV-enabled services and applications including UAV-enabled mobile edge computing architectures. While these existing works have covered various aspects of UAV systems and applications, a critical gap remains in the comprehensive exploration of UAVs' surveillance and monitoring capabilities in the literature. This gap is particularly concerning given the diverse levels of intelligence and activeness required for effective UAV-based surveillance and monitoring.

Our Survey Contributions: To bridge this gap, we present a comprehensive survey aimed at enhancing the understanding of the key factors involved in UAV-based intelligent active surveillance and monitoring. The key contributions of this survey are outlined as follows:

- To the best of our knowledge, this survey is the first to comprehensively examine the role of UAVs in intelligent active surveillance and monitoring. We provide an in-depth analysis of the key enabling technologies, architectures, and applications driving this field, along with the associated research challenges and future trends.
- We introduce innovative dimensions of activeness and intelligence to categorize and analyze UAV systems. This dual-dimensional approach distinguishes our survey from existing literature and provides a systematic understanding of UAV capabilities in surveillance and monitoring. It is important to note that while activeness and intelligence are distinct, they are interdependent to some extent, as noted in our analysis of their relationships.
- This survey presents a unique classification system for UAV applications in surveillance and monitoring, structured around the introduced dimensions of activeness and intelligence. This classification offers novel perspectives on UAV deployment in various surveillance tasks, ranging from basic monitoring to complex, intelligent operations, with an emphasis on how different levels of activeness and intelligence interact in practice.
- Beyond the current state-of-the-art, this survey identifies potential synergies between emerging technologies, such as AI, edge computing, LLMs, and UAV systems. We discuss how these advancements can further enhance the activeness and intelligence of UAVs, offering key insights and directions for future research in intelligent UAV-based surveillance and monitoring.

Visual Summary and Structural Overview: Figure 3 provides a comprehensive categorization and visual summary of various UAV surveillance and monitoring applications based on the two new dimensions of activeness and intelligence levels. Specifically, the X-axis of the figure represents different levels of UAVs' activeness during the mission, ranging from passive to proactive. The Y-axis represents the varying levels of required intelligence in UAVs for mission completion, from low to high. Central to the figure are the main surveillance and monitoring applications strategically positioned in a cluster based on their corresponding x- and y-coordinates. This visual representation clearly illustrates that the more activeness we need, the higher intelligence at UAVs is required, and the more complex and demanding the application becomes. The first cluster closer to the origin encompasses simple applications of data collection where the activeness of the UAVs is passive or mostly determined by the human controller. In the second cluster, individually semi-active UAVs exhibit fundamental intelligence in applications like path following or collision avoidance. A set of low intelligence such as object detection and recognition, as in the third cluster, is required for UAVs to work actively and individually for applications like traffic congestion detection, human detection, or disease detection in smart agriculture. Medium intelligence as shared decision-making is required at collaboratively active UAVs in the fourth cluster for large-scale surveillance and monitoring of natural disasters, transportation, multiple targets, and crowds. Highly complex applications in the fifth cluster such as air traffic management and war-related tasks require UAVs to be proactive and show full autonomy with high intelligence of predictive decision-making capabilities. A comparative summary of this survey's scope and coverage in relation to existing UAV and SAGINs/ground-aerial network studies is provided

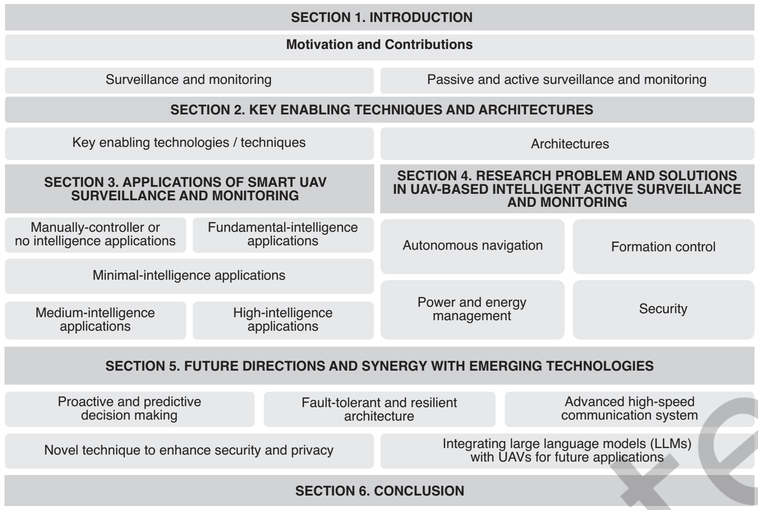

Fig. 4. Detailed structure of the survey. A comprehensive categorization and visual summary of various UAV surveillance and monitoring applications based on the two new dimensions of activeness and intelligence levels.

in **Table 2**, emphasizing the unique integration of activeness and intelligence dimensions that distinguish this work from prior surveys.

Table 2. Comparison of this survey with representative prior works. (✓= Addressed; ✗= Not addressed; Partial = Partly addressed.)

Study	Focus Area	Application Scope	Activeness	Intelligence	SAGIN Focus	Architecture
Fahlstrom et al. (2022) [20]	UAV systems classification	General UAV applications	✗	✗	✗	✓
Lu et al. (2023) [21]	UAV routing in SAGINs	Routing and connectivity	✗	Partial	✓	✓
Xiao et al. (2024) [22]	6G SAGIN architecture	Communication & resources	✗	✗	✓	✓
Our Work	UAV surveillance/monitoring	Activeness-Intelligence mapping	✓	✓	Partial	✓

The organizational structure of this survey is as follows: In Section 2, we discuss the key enabling techniques and architecture. Section 3 covers the different applications of smart UAVs for surveillance and monitoring. Section 4 brings forward recent research problems in active surveillance and monitoring and their solutions. Section 5 explains the future direction as well as the synergy with emerging technologies. Finally, we conclude this survey in Section 6. The structure of the survey is illustrated in **Figure 4**.

2 Key enabling techniques and architectures

To enhance the intelligence of UAV-based surveillance and monitoring, several key enabling technologies and techniques have played a important role. These include Artificial Intelligence (AI), Machine Learning (ML), Edge Computing, Cloud Computing, and Color Mapping techniques. Together, these technologies enable advanced data processing, decision-making, and real-time analysis. A summary of these critical technologies and techniques along with relevant architectures for efficient UAV-based surveillance and monitoring is presented in **Table 3**. Following this overview, each technique and architecture is further detailed. In addition, to evaluate the effectiveness of UAV systems for surveillance and monitoring, it is essential to consider several key performance and Quality of Service (QoS) criteria. These criteria provide a common framework for comparing different architectures, technologies, and applications. A summary of the primary evaluation criteria is presented in **Table 4**, providing readers with a structured lens for assessing UAV system designs. Each of these criteria influences the architectural choices and enabling technologies discussed in this section. For instance, centralized architectures may face higher latency and energy costs but achieve better data fusion, while decentralized systems may prioritize scalability and robustness at the expense of integration complexity.

Table 3. Key enabling technologies, techniques, and architectures for UAV-based surveillance and monitoring, including AI, ML, edge and cloud computing, and color mapping.

Technique/Architecture	Subsections
2.1 AI and Genetic GA	Object Detection, Recognition, and Terrain Analysis
	Unsupervised and Reinforcement Learning-Based Capabilities
	Genetic Algorithms and Time Dependent Traveling Salesman Problem (TSP) Capabilities
2.2 Cloud and Edge Computing	Roles of Edge and Cloud Computing
	Synergistic Roles of Edge and Cloud Computing
2.3 Dynamic Pattern Characterization	Colormap or Heatmap-Based Technique
2.4 UAV Architectures for Surveillance and Monitoring	Architecture Based on Cooperation
	Independent or Non-Cooperative Architecture
	Cooperative Architecture
	Architecture Based on Control and Data Processing Location

Table 4. Key evaluation criteria for UAV research, outlining essential performance metrics such as communication delay, energy efficiency, coverage, and resilience, which are critical for ensuring effective and scalable UAV operations across diverse mission scenarios.

Criterion	Definition	Relevance
Latency	Delay in data/control transmission	Vital for timely mission response and real-time ops
Reliability	Success rate of task completion	Ensures mission safety and dependability
Energy	Power use per task/mission	Limits endurance and flight range
Throughput	Effective data rate	Impacts video and high-data-rate tasks
Coverage	Area that can be monitored/covered	Defines operational reach
Scalability	Ability to handle more UAVs/traffic	Enables large-scale/swarms
Robustness	Resistance to failure/disruption	Ensures operation in harsh conditions

2.1 Artificial Intelligence (AI) and Genetic Algorithms (GA)

AI and GA techniques encompass a wide spectrum of tasks in UAV-based surveillance and monitoring, ranging from basic flight management to advanced decision-making. These techniques are essential in empowering UAVs to autonomously and efficiently execute complex tasks. Supervised learning algorithms, the foundation of object detection and recognition in UAV flights, are meticulously trained on labeled data. This training process equips them with the essential knowledge to accurately identify specific objects or classes of interest during real-time operations [23, 24]. Various unsupervised learning algorithms can also assist UAVs in anomaly detection [25], and clustering tasks in surveillance and monitoring applications. Thus, these algorithms can analyze large datasets from UAV-captured images and videos, recognizing regularities and identifying anomalies, while also grouping similar instances without the need for labeled data. In addition, network edge orchestration can utilize both offline and online learning-based approaches to achieve pertinent selections of network protocols and video properties in multi-drone-based video analytics [26].

For UAVs to conduct surveillance and monitoring operations in an active and intelligent manner, they need to possess specific capabilities that can be categorized as follows:

Object detection, recognition, and terrain analysis: Object detection and recognition are crucial in UAV surveillance and monitoring, enabling UAVs to autonomously identify and categorize objects. Convolutional Neural Networks (CNNs) play a significant role in image recognition and processing for identifying objects, people, or scenes in aerial images. CNN's layered architecture, based on trained data, recognizes patterns and features with high accuracy [27]. Similarly, terrain and geographic analysis are essential, utilizing Support Vector Machines (SVMs) for classifying land covers and identifying roads, buildings, and other geographic features in complex environments [28].

Prediction and Forecasting: Prediction and forecasting capabilities in surveillance and monitoring empower UAVs to not only predict the future positions and states of observed objects but also to proactively adapt to dynamic environmental changes. Long Short-Term Memory (LSTM) algorithms are useful in forecasting or predicting the movement of objects during surveillance and monitoring. LSTMs can analyze sequences of images or sensor data to predict future positions or states of observed objects [29].

Unsupervised learning-based capabilities: Unsupervised learning is highly effective for identifying unusual patterns or anomalies in data, which is crucial for surveillance and monitoring. Unsupervised learning involves training the model with unlabeled and categorized data. The unsupervised learning-based algorithms enable the following capabilities in UAVs.

Pattern Recognition and anomaly detection: Pattern recognition involves identifying regularities or patterns in UAV collected data during the surveillance and monitoring. Autoencoders are effective in detecting anomalies or changes in environmental patterns, such as unexpected landscape changes or areas affected by environmental degradation [30]. They learn to reconstruct normal data and can detect anomalies by identifying data points that have high reconstruction errors.

Clustering or grouping: Clustering algorithms help in identifying patterns and structures in data that are not explicitly labeled. In surveillance and monitoring, this is crucial for understanding and categorizing various elements within the data, such as differentiating between types of vehicles, crowds, or geographical features. The clustering algorithm can also simplify the collected data by segmenting it into more manageable groups. This makes it easier to analyze and interpret the data

Reinforcement learning-based capabilities: Unlike supervised or unsupervised learning, reinforcement learning techniques do not use pre-existing data to make decisions. These techniques consider UAVs as training agents to make sequences of decisions through trial and error. In this process, UAVs receive rewards for desirable outcomes and penalties for undesirable ones. Over time, the UAV develops a strategy or policy that maximizes these rewards, leading to the maximized cumulative reward [31]. Reinforcement learning-based algorithms enable the following capabilities in UAVs:

Optimal Path Planning and Collision Avoidance: Reinforcement learning optimizes UAV path planning and collision avoidance. DQN algorithms guide UAVs in learning efficient routes, considering distance, time, energy, and safety [32]. Simultaneously, these algorithms enable UAVs to identify and avoid obstacles, updating strategies based on action outcomes to ensure safe operation [33].

Autonomous decision-making: Reinforcement Learning (RL) algorithms, such as policy gradient methods, equip UAVs with the capability to independently make decisions. This is based on the data they gather and their accumulated learning experiences, eliminating the necessity for continuous human oversight. These methods are beneficial for autonomous decision-making as they allow the UAV to learn complex behaviors based on the cumulative reward, considering both immediate and future actions.

Cooperative decision-making: In scenarios involving multiple UAVs, reinforcement learning such as Multi-agent Reinforcement Learning (MARL) enables UAVs to coordinate or compete with each other. It allows each UAV to learn its policy while considering the presence and possible actions of other agents [34, 35].

Genetic Algorithm (GA) and Time-Dependent Traveling Salesman Problem (TDTSP) Capabilities: The use of UAVs for crowd control and monitoring applications highlights the need for intelligent and adaptable surveillance strategies. Several works [36] have investigated distributed target monitoring using models suited to the dynamic nature of crowd surveillance, often framed as instances of the Time-Dependent Traveling Salesman Problem (TDTSP). As part of this broader optimization landscape, Genetic Algorithm (GA) heuristics have been explored to address the visit-oriented TDTSP [9], offering scalable solutions for enabling UAVs to periodically monitor groups of moving targets that simulate pedestrian motion in crowded environments.

2.2 Cloud and Edge Computing Technologies

The convergence of edge and cloud computing technologies has transformed modern computing, reshaping how data is processed, stored, and accessed across various industries [37]. Edge computing, characterized by its proximity to data sources, facilitates delay-sensitive and real-time processing and analysis of data. This capability is crucial for applications involving geo-distribution, mobility support, location awareness, content perception, and parallel processing in distributed IoT systems. A series of existing works have been done in effectively allocating and managing edge resources to better serve future IoT applications [38–42]. In the case of UAVs edge computing empowers applications like obstacle avoidance, navigation, event detection, and target tracking by playing critical roles as follows:

Roles of Edge Computing: Edge computing allows UAVs to process collected data onboard or at the edge server, depending on the requirements. Two important benefits of edge computing are as follows: *Real-time Processing:* Edge computing brings computational power closer to the data source for immediate analysis. With the extensive resources of edge servers, UAVs data can be analyzed as it's generated. Processing data locally or near the UAV minimizes the time required to transmit data to a centralized server and receive a response [43]. This reduction in latency is crucial for applications like surveillance, where quick decision-making is essential [44].

Architecture Support and Management: Edge computing is instrumental in supporting and managing different architectures of UAV groups in surveillance and monitoring applications. Managing UAV groups involves coordinating actions, optimizing communication, and ensuring efficient resource usage. Edge computing facilitates communication and information sharing among UAVs within a group. Collaborative decision-making is enabled by exchanging processed data, allowing UAVs to work together in real-time. Cloud computing, essential in modern technology, offers scalable resources, on-demand services, and advanced data management, enhancing sectors like automation, IoT, and healthcare with fast, secure, and cost-effective solutions. It utilizes remote servers for tasks like intensive image and video analysis, playing a crucial role in UAV applications. The roles of cloud computing in UAV applications can be given as follows:

Roles of Cloud Computing: Cloud computing plays a significant role in enhancing UAV-based surveillance and monitoring by offering scalable, centralized processing and extensive storage capabilities. Cloud computing provides the following crucial capabilities for UAV operations:

Data Storage and Remote Access: Cloud computing enables UAVs to offload captured data to centralized cloud storage. This technology allows secure storage and access to large volumes of data, such as high-resolution images and videos, from anywhere.

Data Integration and Analysis: Cloud computing offers a centralized platform for integrating data collected from multiple UAVs, enabling comprehensive analysis and insights. Cloud servers provide high-performance computing resources, facilitating complex analytics and data fusion that may be challenging on individual UAVs due to resource constraints.

The incorporation of cloud and edge computing technologies into UAV-based surveillance and monitoring systems significantly enhances UAV capabilities. The explicit and synergistic roles of edge and cloud computing are discussed as follows:

Synergistic Roles of Edge and Cloud Computing: While edge and cloud computing each have their merits, their synergy offers significant benefits. The integration of these technologies in UAV surveillance and monitoring can strike a balance between real-time responsiveness and in-depth data analysis [45]. This synergy ensures that

UAVs can swiftly respond to immediate challenges while also handling complex analytical tasks. Edge computing reduces the need to transmit large volumes of raw data to the cloud by selectively sending only the most relevant information. This not only conserves bandwidth but also enhances the overall responsiveness and efficiency of the UAV system [46]. By providing a centralized hub for advanced analytics and long-term data retention, cloud computing complements the real-time responsiveness of edge computing, creating a collaborative and adaptive system for UAV-based surveillance and monitoring. The dynamic allocation of processing tasks between edge and cloud computing ensures an optimal balance that adapts to changing mission requirements and scenarios.

2.3 Dynamic Pattern Characterization

Colormap or heatmap-based technique: In UAV-based surveillance and monitoring, color maps or heatmaps are commonly used to visualize the results of automated analysis. While the underlying systems rely on raw data and algorithms to make decisions, heatmaps serve as an effective tool for interpreting complex data and providing human-readable representations of dynamic patterns of objects and events [47]. These techniques graphically represent information using colors, where warmer colors denote higher values and cooler colors indicate lower values. Heatmaps simplify the interpretation of large and complex datasets by highlighting patterns and trends in a way that is easy to understand. Heatmaps are invaluable in intelligent surveillance and monitoring applications by providing an intuitive way for human analysts to identify areas of interest, potential threats, and regions requiring further monitoring. They are instrumental in generating density maps, indicating the concentration of people, vehicles, or other objects in a specific area, which can help identify congested regions and facilitate flow optimization decisions. For instance, as demonstrated in **Figure 5**, heatmaps can visually represent crowd density in a surveyed area at a specific time. In predictive analytics, heatmaps help visualize the results of UAV data analysis, offering predictions and trend forecasts [48].

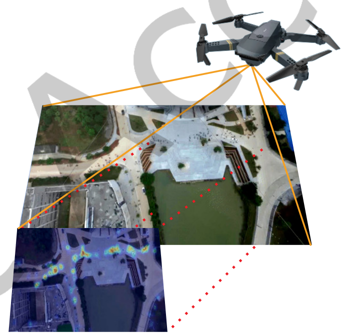

Fig. 5. Crowd density mapping through a heatmap.

2.4 UAV Architectures for Surveillance and Monitoring

The architecture of UAV systems for surveillance and monitoring is shaped by the level of cooperation among UAVs, as well as the locations for control and data processing. In various applications, the architectures of these systems are influenced by the scale of operations, accessibility of computing resources, and data processing strategy. The main architectures of UAV systems in surveillance and monitoring applications and their key techniques are summarized in **Table 5** below.

Architecture based on cooperation: UAV deployment in surveillance varies with operation scale. For small-scale tasks, a single UAV is preferred for its cost-effectiveness and ease of management. In contrast, large-scale operations benefit from multiple UAVs working in a swarm, enhancing collective decision-making and data sharing. Depending on the level of cooperation among UAVs, deployment architectures can be categorized as either independent (non-cooperative) or cooperative.

Table 5. Summary of UAV architectures and associated techniques in surveillance and monitoring.

Type	Architecture	Technique / Technology	References
Based on Cooperation	Non-Cooperative Architecture	Machine Learning (ML)	[49]
	Cooperative Architecture	Deep Reinforcement Learning	[50]
Based on Centralization	Centralized Architecture	Edge/Cloud Computing	[51, 52]
	Decentralized Architecture	ML at the Cloud	[53]
		Machine Learning (ML)	[54]
	Hybrid Architecture	ML and Cloud Computing	[55]
		Cloud Computing	[56]

Independent or non-cooperative architecture: In UAV-based surveillance, the independent architecture involves UAVs operating solo, using only their sensors for tasks like monitoring or IoT data collection [49]. This architecture allows for semi or full-activeness in UAVs, suitable for simple monitoring tasks. Semi-active UAVs mostly focus on basic navigation and obstacle avoidance, while fully active ones leverage machine learning for basic object detection, displaying moderate intelligence.
Cooperative architecture: In cooperative architecture, UAVs work together, coordinating movements and sharing information to enhance efficiency and effectiveness in operations like rescue, environmental monitoring, and disaster response [57, 58]. This collaboration increases surveillance coverage and decision-making efficiency, allowing UAVs to adjust deployment and behavior dynamically, and improving system performance and reliability.
Architecture based on control and data processing location: Depending on the control structure and location of data processing, UAV architectures for surveillance and monitoring can be categorized as centralized, decentralized, or hybrid. **Figure 6** illustrates these architectures and their distinctions in UAV connectivity with a control center or backbone UAV. The choice between these architectures depends on factors such as deployment scale, mission complexity, latency requirements, connectivity reliability, and computational capacity. Centralized architectures are typically suited for small to medium UAV fleets with reliable communication and centralized processing, supporting pre-planned missions with less need for local autonomy. In contrast, decentralized architectures are preferable for large-scale or dynamic missions requiring fast, local decision-making and resilience to communication disruptions, since they distribute control and processing across UAVs. Hybrid architectures combine these approaches, balancing centralized oversight with decentralized flexibility.

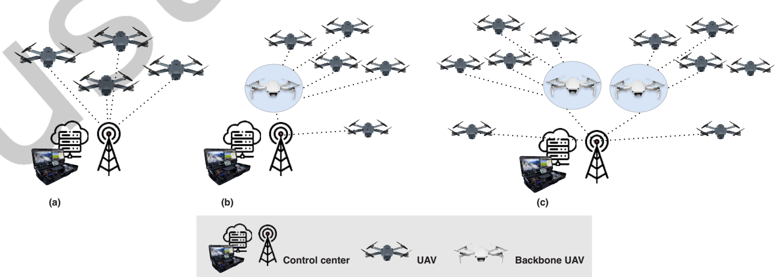

Fig. 6. Illustration to show distinctions of: (a) Centralized architecture; (b) Decentralized or ad-hoc architecture; (c) Hybrid architecture.

The centralized architecture in UAV surveillance uses a central control station (like a ground station or cloud server) to manage UAVs [52]. This station processes data from multiple UAVs, optimizing task allocation and system performance. While it simplifies management, this approach can incur high communication costs and delays in large-scale operations, and centralizing data creates a potential single point of failure. In a decentralized or ad-hoc UAV architecture, each UAV operates with a degree of autonomy, capable of making independent decisions [53]. This architecture typically involves a small group of UAVs, with one designated as the backbone UAV, acting as a communication relay between the ground station and other UAVs. This setup, effective in unpredictable environments, enhances system resilience and processing speed by allowing simultaneous data tasks. However, it faces challenges in data integration and security due to decentralized processing and local storage [54]. The hybrid architecture combines the elements of centralized and decentralized UAV systems, where UAV groups use ad-hoc communication within each group, and backbone UAVs connect directly to a central station for group-specific data transfer. The central station, with its powerful computing resources, performs complex data analysis, extracting valuable insights. Additionally, backbone UAVs from different groups can communicate ad-hoc, with only one connected to the ground station [55]. The hybrid architecture combines the benefits and drawbacks of centralized and decentralized systems. It processes data onboard and then at a central server, cutting communication costs and improving UAV response time. This approach provides wider coverage, vital for intelligence and analysis. However, its semi-centralized structure may limit efficiency in remote areas and slow down processing compared to fully decentralized systems [59]. Also, reliance on a control center may reduce the robustness inherent in decentralized architectures.

3 Applications of smart UAV surveillance and monitoring

The growing intelligence of UAVs has transformed surveillance and monitoring operations, enabling tasks that previously required human intervention. Given the new capabilities of real-time data analysis using AI/ML algorithms, these UAVs can autonomously perceive, decide, and adapt to dynamic changes in their environment. This section categorizes surveillance applications based on UAV intelligence levels. **Table 6** presents a content outline of the section to illustrate the different levels of intelligence in UAV-based surveillance and monitoring applications.

Table 6. Applications of smart UAV surveillance and monitoring.

Applications based on UAV intelligence levels	**Examples**
3.1 Smart UAV Surveillance and Monitoring	Air Quality Monitoring, Water Quality Assessment, Gas Leak Detection
3.2 Fundamental-Intelligence Applications	Pre-decided Path Following Applications, Obstacle-avoiding Applications
3.3 Low-Intelligence Applications	Simple Object Detection, Recognition, and Action-taking Applications
3.4 Medium-Intelligence Applications	Shared Decision-making Applications, Swarm-based Applications, Colormap/Heatmap-based Applications
3.5 High-Intelligence Applications	Proactive Applications

Table 7 provides an overview of intelligence and applications of UAV systems, and details various critical dimensions, their functionality and implementation along with relevant references.

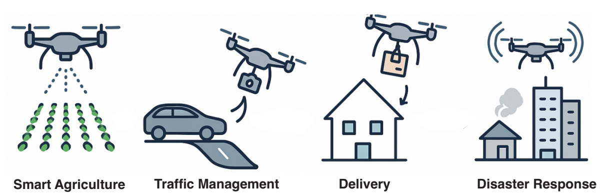

Fig. 7. A visual illustration of the vision of UAVs across diverse surveillance and monitoring applications, mapping example tasks onto intelligence and activeness levels for intuitive understanding.

Table 7. Intelligence and applications.

Level of intelligence	Level of activeness	Intelligence type	UAV applications	Techniques / Technologies	Reference
Manually controlled	Passive	Sensory data collection	Air quality monitoring	Wi-Fi, Bluetooth	[60–62]
			Water quality assessment	Wi-Fi, Bluetooth	[63, 64]
			Gas leak detection	Wi-Fi, Bluetooth	[65]
Basic intelligence	Individually semi-active	Pre-decided path following	Path following based environmental monitoring	Computer vision, waypoint navigation	[66, 67]
			Inspection of power lines and transmission towers	Computer vision, waypoint navigation	[68]
		Obstacle avoidance	Aerial monitoring of manufacturing fault in civil infrastructure	Computer vision, waypoint navigation	[10, 69]
			Collision avoiding indoor monitoring	Edge computing, CNN, YOLO	[70–72]
Low intelligence	Individually active	Simple object detection, recognition and action	Small-scale traffic congestion detection	Edge computing, CNN, YOLO	[73–75]
			Growth monitoring and disease detection for smart agriculture	CNN	[76–78]
			Trapped human detection and activity recognition in remote areas	YOLO 3, YOLO 5	[79–82]
Medium intelligence	Collaborative	Shared decision-making, semi-autonomy	Large-scale transportation monitoring and management	CNN	[83]
			Semi-autonomous large-scale remote patrolling and searching for rescue operations	Edge computing, YOLO 3	[84, 85]
			Sustained detection and monitoring for natural disaster incidents in remote areas	Edge computing, YOLO 3	[86]
			Swarm-based target tracking	DRL, Genetic algorithms	[87–89]
			Swarm-based persistent crowd monitoring	Bayesian method, CNN, heatmap	[90–92]
High intelligence	Proactive	Predictive decision making and full autonomy	Adversary swarm counterattack with trajectory prediction and position detection in defense applications	LSTM, SBLSTM, RNN, DRL	[93–95]
			Predictive decision making for autonomous drone-based delivery systems in dynamic environments, i.e., adjusting flight paths based on traffic, obstacles or weather	LSTM, GMM, DRL	[96–98]
			Predictive deployment of UAVs for real-time monitoring of traffic congestion and accident detection in urban environments	LSTM, CNN, DRL	[99]

As illustrated in **Figure 7**, UAVs are deployed across a wide range of surveillance and monitoring applications, with each application requiring a specific combination of intelligence and activeness levels to achieve mission goals. UAV operational roles range from simple data collection and environmental monitoring to more complex tasks such as smart agriculture, traffic management, delivery services, and disaster response, each demanding appropriate technological capabilities for effective deployment. It is important to note that the intelligence levels in **Table 7** reflects not only specific technologies but also their integration, deployment context, and the scope of autonomy they enable.

Intelligence level classification is determined not only by the listed technologies or algorithms, but also by their operational integration, deployment context, and functional role. For example, YOLOv3 and edge computing, while representing low intelligence in isolated detection tasks, may be categorized as medium intelligence when integrated into collaborative, adaptive, or distributed decision-making systems.

3.1 Manually-controlled or No-intelligence Applications

In surveillance, manually controlled UAVs primarily serve as sensor carriers, gathering data efficiently. These cost-effective UAVs operate remotely via Bluetooth or Wi-Fi, and are suited for basic environmental monitoring.

Air quality monitoring: In air quality monitoring applications, sensor-equipped UAVs can be manually piloted to the desired location to monitor the air or detect the source of pollution in the air. The equipped sensors can collect data on different parameters like particulate matter (PM2.5 and PM10), gases (ozone, nitrogen dioxide, etc.), and meteorological data (temperature, humidity, and wind speed). These data can be processed at the ground station and create a spatial map of air pollution levels in different areas [60, 61].
Water quality assessment: Hyperspectral and multi-spectral cameras are powerful tools for water quality assessment [100, 101]. These cameras can be mounted on UAVs to be transported to the desired water body for the detection of parameters such as turbidity, chlorophyll concentration, dissolved organic matter, and algal blooms. This information is crucial for monitoring water pollution and identifying potential sources of contamination [63]. Additionally, with the help of thermal infrared (TIR) sensors, UAVs can detect cold water areas over groundwater-dominated riverscapes [64].
Gas leak detection: UAVs equipped with specialized gas sensors play a crucial role in the detection and localization of gas leaks from pipelines, storage tanks, or industrial facilities [65]. This capability allows for rapid response, which is essential in preventing potential environmental hazards. The deployment of UAVs for gas detection also addresses a significant safety concern by eliminating the need for direct human contact with gas leaks. These remotely piloted UAVs can efficiently cover large areas and access hard-to-reach locations, making them indispensable tools for ensuring the safety and environmental compliance of such facilities.

3.2 Fundamental-intelligence Applications

As depicted in **Figure 3**, fundamental intelligent UAVs employed in surveillance and monitoring applications typically possess fundamental capabilities such as path following and obstacle avoidance, without involving complex decision-making. In these applications, the UAVs operate in a semi-active manner, individually following given instructions. Some of the main surveillance and monitoring applications of UAVs utilizing fundamental intelligence are categorized as follows:
Pre-decided path following applications: Pre-decided path-following surveillance and monitoring applications are those where the flight path is already decided and UAVs are given the information of waypoints and no-fly zones. During surveillance and monitoring, UAVs follow these pre-decided paths to fly during the missions. Some of these applications are as follows:

Path following based environmental monitoring: Simple environmental monitoring applications require basic intelligent UAVs for aerial photography and videography. In these applications, localization mapping and path planning are performed before UAV deployment with the help of area maps, obstacles, and no-fly zone information. Defining a specific path for UAVs to follow ensures that the UAVs cover the desired area or target systematically and efficiently while reducing the target revisit time and workload [102]. Proper path planning in these applications can reduce the number of UAVs required for mission completion as well as the energy consumption [67].

Inspection of power lines and transmission towers: Regular monitoring of transmission towers and power lines is crucial to ensure the reliability and safety of these critical infrastructure components. Basic intelligent UAVs offer a safer alternative to humans for these monitoring jobs. They can be deployed to fly along predetermined flight paths that cover the entire length of power lines and monitor multiple transmission towers in a single mission. The sensors equipped at UAVs can collect the data during monitoring which can be used to identify any maintenance needs [68].
Obstacle-avoiding applications: Path-following UAVs, typically reliant on GPS and IMU, encounter challenges in environments lacking GPS. Vision-based methods such as SLAM and VO allow for navigation through image analysis [103]. Additionally, obstacle avoidance is crucial for enhancing the safety and effectiveness of UAV missions. UAVs with basic intelligent systems can autonomously navigate and avoid obstacles, with several applications based on these capabilities outlined in subsequent sections.

Aerial monitoring of manufacturing fault in civil infrastructure: Vision-based solutions enable UAVs to avoid obstacles in their flight path. A primary application is the aerial monitoring of faults in civil infrastructure or civil infrastructure health monitoring. UAVs equipped with high-resolution cameras and sensors make it possible to conduct comprehensive inspections of bridges, buildings, pipelines, and other critical structures for the identification of manufacturing defects, such as structural weaknesses, cracks, or material inconsistencies, which might otherwise go unnoticed [10].

Collision avoiding indoor monitoring: Collision avoiding indoor monitoring by UAVs combines sensors and algorithms, using LiDAR, ultrasonic sensors, and computer vision for safe navigation [104]. This technology is crucial for efficient monitoring in places like warehouses or indoor events and allows for automated inspection and data gathering where traditional methods fall short [70, 72].

3.3 Low-intelligence Applications

UAV-based Low-intelligence surveillance and monitoring involves simple decision-making on object detection and recognition. Individual UAVs in these applications utilize diverse machine-learning algorithms to detect objects and adjust their flight strategies. The following section outlines some key applications of this category.

Simple object detection, recognition, and action-taking applications: Object detection and recognition applications typically operate on a small scale, employing a single UAV with onboard intelligence to achieve their objectives. These UAVs function independently, making detection decisions and planning tracking trajectories. These applications hold significance in diverse fields, and the following examples provide specific instances of applications involving object detection and tracking.

Small-scale traffic congestion detection: Integrating intelligent UAVs into traffic object detection and tracking is helpful in many aspects. Utilizing ML approaches, these UAVs can assess the number of vehicles on a specific road and detect occurrences of traffic congestion. In a centralized architecture, the ground station can also use a Convolutional Neural Network (CNN) with You Only Look Once (YOLO) algorithms to compute vehicle density based on captured data [73, 74]. Similar to the detection of vehicles, UAVs can also be deployed to detect roads for tracking path design in traffic monitoring [75].

Growth monitoring and disease detection for smart agriculture: The deployment of intelligent UAVs in smart agriculture has increased in recent years due to their flexibility and the capability to collect image data of crops [76]. Their roles include fertilizer application, seeding, crop and soil monitoring, disease detection, improving harvest quality, and preventing yield loss [77, 105]. ML techniques like CNN or SVMs analyze leaf images for disease, guiding precise pesticide application [78].

Trapped human detection and activity recognition in remote areas: Human activity recognition is key in UAV surveillance, aiding in tasks like search and rescue and traffic management by identifying activities such as falls or walking [79]. During the COVID-19 pandemic, it was vital for monitoring social distancing [106]. CNNs, RNNs, and YOLO algorithms, trained on diverse activity datasets, effectively detect human activities in UAV footage [81]. The YOLO V5 framework, enhanced by GAs, improves detection from high altitudes [82].

3.4 Medium-intelligence applications

A medium level of intelligence in UAVs can be referred to as a moderate degree of cognitive capabilities and decision-making capacity embedded within the UAV systems as illustrated in **Figure 3**. Equipped with AI and ML, these UAVs process information, make decisions and work together in large-scale operations. They share data, collaboratively plan, and execute tasks, enhancing coverage, efficiency, and scalability. Some key medium-intelligence UAV applications are as follows:

Shared decision-making Applications: By incorporating AI, and edge computing technologies, UAVs are capable of processing data in real-time. This enhances their effectiveness in various surveillance and monitoring applications as follows:

Large-scale transportation monitoring and management: Collaborative intelligent UAVs excel in extensive transportation monitoring, with specific regions allocated to each UAV for data collection. Traffic flow and optical flow theories can be employed to accurately estimate traffic flow parameters from the collected data [83]. Furthermore, these UAVs can deliver multimedia content to vehicles, caching and updating it as per demandc̃iteal-hilo2021. They also offer communication and computation services, enhancing vehicle connectivity [107].

Semi-autonomous large-scale remote patrolling and searching for rescue operations: Medium intelligent UAVs boost the effectiveness of large-scale patrolling and SAR missions with their speed, mobility, and cost-efficiency. They navigate difficult terrains using advanced sensors and cameras, offering a budget-friendly alternative to manned aircraft. These UAVs use ML algorithms to detect victims in emergencies such as sea accidents and forest fires, with models identifying humans through mobile signals or IoT devices [84]. Thermal imaging and networks like YOLOV3 enhance survivor detection in thermal images [108].

Sustained detection and monitoring for natural disaster incidents in remote areas: Ensuring sustained detection and monitoring in remote natural disaster scenarios is of paramount importance. In remote natural disasters like forest fires, UAVs are crucial for fire detection and tracking, crucial for evacuation and rescue efforts [86]. Disaster areas often face the challenge of disrupted wireless networks due to infrastructure damage, leaving trapped individuals without the means to request help. To address this issue, intelligent and collaborative UAVs can step in, offering temporary communication services.

Swarm based applications: Aerial swarms utilize distributed and cooperative capabilities to manage both individual and collective movements of UAVs. In a swarm, UAVs collaborate to achieve shared goals or perform specific tasks, drawing inspiration from the collective behavior of social insects like ants or bees. These swarms, equipped with ML algorithms, process data and make decisions onboard, reducing dependence on ground stations and improving efficiency [109]. The applications of swarms in surveillance and monitoring are outlined below.

Swarm-based target tracking: Swarm-based target tracking uses multiple UAVs to analyze sensor data for comprehensive environmental understanding [110]. This involves searching and tracking targets in static or dynamic conditions. In Single or multiple dynamic target-tracking applications, the swarm strives to maintain high-quality tracking for individual targets while simultaneously tracking a larger number of targets. The heatmaps-based approach is helpful in such applications to show the probability of moving targets in a given area [88]. Detection of multiple targets of an unknown number is a much more challenging task than that of a known number where the swarm needs to explore the entire environment to complete the task [89].

Cooperative mapping: In cooperative mapping, UAV swarms collaborate to collect and share data, producing detailed maps more efficiently and accurately than single UAVs. This approach allows simultaneous coverage of different areas, resulting in comprehensive maps of large regions. Such collaborative mapping is crucial for disaster assessment, urban planning, and archaeological exploration.

Colormap/heatmap based applications: Multi-UAV applications are evident in large-scale surveillance and monitoring scenarios such as crowd monitoring at public events, concerts, festivals, and sporting events. In these applications, multiple UAVs are equipped with high-resolution thermal imaging cameras to collect the image data. At the ground station or the edge side, color mapping software can be applied to generate color maps or heatmaps that depict the density of objects in various monitored areas. This information proves valuable for identifying potential safety hazards, like overcrowding in specific zones, and aids in crowd management and evacuation planning. The utilization of color mapping brings significant advantages to the following applications.

Persistent crowd monitoring: Color mapping significantly improves UAV swarm-based crowd monitoring. Using the Bayesian method, UAVs combine multiple data sources into heatmaps for clearer insights [90–92]. The Multiview CNN algorithm further aids in real-time crowd detection by integrating RGB inputs with generated heatmaps [91, 111]. This method helps identify crowd locations, guiding UAVs to optimize flight plans for better coverage or avoid crowded zones.

UAV-assisted uniform area coverage for cooperative mapping: Cooperative UAV mapping aims for a consistent environmental portrayal, facing efficiency and energy challenges due to coverage overlap. Color mapping techniques ensure even coverage, minimizing these issues. Several studies have explored the diverse applications of heatmaps with UAVs in cooperative mappings like uniform delivery path selection and efficient area scanning with optimized energy use, underscoring heatmaps' utility in enhancing UAV efficiency [112, 113].

3.5 High-intelligence Applications

High-intelligence surveillance and monitoring applications require proactive UAVs with predictive decision-making. These applications are highly complex and lie in the topmost cluster in **Figure 3**. ***Proactive applications:*** With the recent developments and implementation of AI and ML techniques such as DRL, recurrent neural network (RNN), and LSTM, the UAVs become potentially capable of predicting the locations of targets or events and proactively planning the actions to be taken. Some important proactive applications are discussed as follows:

Adversary swarm counterattack with trajectory prediction and position detection in war tasks: In war scenarios, where UAV swarms can serve as a medium of attack, predicting UAVs' trajectories becomes crucial for effective counteraction. RNN and LSTM algorithms, specialized in capturing temporal data characteristics, prove highly adept at predicting UAV trajectories. As demonstrated by [93–95], this capability extends to civil aviation systems, aiding air traffic control in collision avoidance among UAVs. To address the challenge of countering adversary UAV swarms, the work in [93] emphasizes the significance of precise position detection. The authors utilize the Neural Relational Inference (NRI) model and mapping table within their framework to predict swarm trajectories. In a complementary approach, the authors of [94] introduce a Sequential Model with Stacked Bidirectional and Unidirectional LSTM (SBULSTM) to predict UAV trajectories. Unlike traditional LSTMs, the bidirectional LSTM in this model leverages future information to enhance current information prediction, enabling UAVs to autonomously navigate complex space environments, avoiding obstacles, and ensuring safe and smooth flight.

Predictive deployment of fully autonomous UAVs for sustained monitoring: Fully autonomous UAV-based sustained monitoring introduces a transformative approach to continuous surveillance and monitoring. UAVs equipped with state-of-the-art sensors and imaging capabilities become indispensable assets for these applications. They navigate complex environments, avoiding obstacles autonomously while adhering to optimized flight paths [114]. Leveraging advanced ML techniques these UAVs play a pivotal role in optimizing deployment strategies [97]. Through predictive modeling of cellular traffic and precise determination of service areas using LSTM and Gaussian mixture models (GMM), UAVs ensure efficient and seamless communication experiences [96]. In the context of wireless communication, the implementation of DRL algorithms plays a crucial role in predicting signal handovers, contributing to the seamless communication experience crucial for sustained monitoring [98]. These comprehensive strategies emphasize the significant impact of ML algorithms in not only optimizing UAV deployment for sustained monitoring but also in fortifying communication reliability [114].

Autonomous air traffic management systems with predictive traffic density estimation: Predicting air traffic density is a critical component of unmanned aircraft system traffic management (UTM). With the help of these predictions, UAVs can ensure safe operations especially when conducting beyond line of sight missions. By analyzing historical and real-time data, UTM systems can forecast air traffic density in specific regions and corridors. Considering the future UTM for delivery applications, a CNN and encoder-decoder LSTM framework can be used to predict the air traffic of UAVs with dynamic flow structures and airspace [99]. This information allows UAVs to adjust their flight paths or schedules to avoid congested areas, reducing the risk of mid-air collisions and enhancing overall airspace safety.

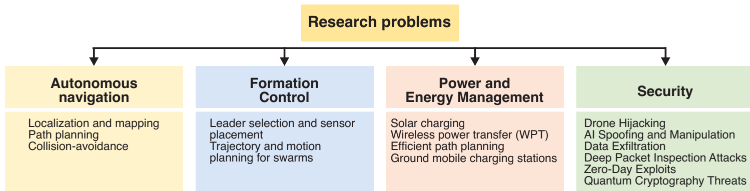

Fig. 8. Key research problems associated with intelligent and active UAV-based surveillance applications.

4 Key research problems and solutions in UAV-based intelligent in active surveillance and monitoring

This section discusses the research problems and the challenges associated with the intelligent and active surveillance applications of UAVs. It also describes the technical limitations of UAVs and explores the current research efforts to overcome these challenges. **Figure 8** summarizes the main research problems related to UAVs in intelligent and active surveillance applications.

4.1 Autonomous Navigation

Autonomous navigation is crucial for intelligent UAVs, allowing them to operate without human help. They use techniques like localization, mapping, path planning, and collision avoidance to safely navigate and perform tasks. UAVs incorporate collision prevention, and in collaboration, they share data for mapping and employ path-planning algorithms for efficient, safe routes [115]. The research problem of autonomous navigation can be divided into the following three sub-problems.

Localization and mapping: Accurate UAV localization in intelligent surveillance systems is essential for effective navigation. Localization and mapping together are the main components of a UAV navigation system. Mapping creates a 2D or 3D environmental layout, highlighting obstacles and features, while localization pinpoints the UAV's location and direction. This process is more complex for UAVs due to three-dimensional space and potential GPS unreliability in challenging environments like indoors or areas with signal obstructions [116]. To overcome these challenges, vision-based methods combining IMU and camera data have emerged. Notably, Visual SLAM (VSLAM) constructs an environmental model while locating the UAV, offering precise indoor navigation [103]. Visual Odometry (VO), using image sequences to estimate motion, suits outdoor navigation but may falter in dynamic settings.

Path planning: In UAV-based surveillance and monitoring, path planning plays a critical role in enabling the UAV to navigate efficiently and effectively through a given area [117]. To ensure safe and efficient navigation, path planning is typically integrated with collision avoidance. Collision avoidance is often referred to as "local path planning" while path planning is referred to as "global path planning". Global path planning generates optimal routes considering the entire environment as one, while local path planning deals with changes in the environment at the moment of detection, performing collision-avoidance maneuvers accordingly [118]. In surveillance and monitoring applications, dynamic environmental changes such as sudden weather changes, object movements, or terrain alterations can make path planning challenging. Another aspect of path panning is performance optimization-based path planning which involves finding the optimal path for a UAV based on different performance metrics such as latency, power consumption, and distance. One more aspect of path planning is covert trajectory planning which involves finding a path for a UAV that minimizes its visibility and detection by potential threats or adversaries [117].

Collision-avoidance: Collision avoidance is critical for UAV-based surveillance to ensure safe flight. It involves two phases: perception using sensors like LIDAR and radar, and action through strategies such as geometric, optimized, force-field, and sense-and-avoid methods [119]. These strategies use velocity, location, obstacle parameters, and real-time detection to maintain safe distances and find efficient paths. Machine Learning (ML) techniques help UAVs avoid collisions with both stationary and moving objects by predicting their locations and movements through methods like RNN-based predictions [120] and the TEXPLORE Reinforcement Learning algorithm [121]. While these techniques often rely on simulations with point-like dynamic obstacles, real-world situations may differ. To address this, [122] introduced a Neural Network Pipeline (NNP) for collision prediction and an Object Motion Estimator (OME) using optical flow to detect and predict moving objects' paths in video feeds. In summary, UAV-based collision avoidance is complex due to the need to avoid both environmental obstacles and swarm members while optimizing performance. ML-driven systems enable UAVs to navigate challenging environments by proactively identifying and avoiding potential collisions.

4.2 Formation Control

Formation control is one of the main aspects of the implementation of UAV swarms. In swarms, formation refers to the geometric arrangement or spatial configuration of multiple UAVs relative to each other. The essential autonomy of UAVs including perception and execution highly depends on the formation control framework [123]. The research problems in formation control can be divided as follows:

Leader selection and sensor placement: Leader selection is a critical aspect of formation control for UAVs. In a swarm, a leader is a UAV that controls the group formation and the other UAVs. The leader can be selected in several ways, depending on the specific application and requirements. In simple applications, typically the UAV with the highest performance characteristics is selected as the leader. Another approach is to have the UAVs in the formation decide the leader through a consensus algorithm. The authors in [124], show that improving the selection of the swarm leader can enhance the performance of the particle swarm optimization (PSO) algorithm. Along with optimal leader selection, choosing the optimal number of leaders is also critical in large UAV groups [125].

Trajectory and motion planning for swarms: Trajectory and motion planning are crucial for the effective operation of intelligent UAV swarms. Trajectory planning determines the optimal path, waypoints, speed, altitude, and orientation for UAVs to follow. In contrast, motion planning determines the actions required for the UAV swarms to navigate through the environment and achieve their goals. Trajectory and motion planning consider various constraints such as obstacles, energy consumption, and mission objectives [126]. Efficient trajectory and motion planning lead to reduced mission time, increased success rate, improved safety, and reduced energy consumption [127, 128]. In order to plan the trajectory and the motion of the intelligent UAV swarms, a centralized approach can be adopted to optimize the overall performance of the swarms. However, it comes at the cost of intensive computation and isn't suitable for large swarms. Instead, a decentralized approach can be used where each UAV in the swarm plans its trajectory and motion based on local information and communication with nearby UAVs. This approach is scalable and adaptable to changing environments, but it may not be able to optimize the overall performance of the swarm.

Recently, bio-inspired algorithms for trajectory and motion planning for UAV swarms are being used showing better performance in complex environments. PSO is one of the most used bio-inspired algorithms in this field [129]. The authors in [130] use the PSO algorithm to design the 3D trajectory of a UAV swarm for surveillance. Their design includes a multi-objective fitness function following energy consumption, flight risk, and surveillance area priority to evaluate the trajectories generated by the planner. In [131], the authors modify the PSO algorithm by developing a novel hybrid particle swarm optimization algorithm, namely, SDPSO that can quickly plan higher quality paths for UAVs in comparison to other bio-inspired algorithms such as dynamic-group-based cooperative optimization (DGBCO), gray wolf optimizer (GWO), and two-swarm learning PSO (TSLPSO) algorithms.

4.3 Power and Energy Management

Large-scale surveillance and monitoring applications require UAVs with extended flight endurance. The primary limitation of UAVs in these applications is high energy consumption. While advancements in battery technology have improved UAV flight times, they still fall short for applications like extensive surveillance and monitoring [132]. To mitigate these limitations, some solutions have emerged. Solar charging, for instance, involves equipping UAVs with onboard solar panels to convert sunlight into electrical energy [133], [134]. This stored power can then support both flight and sensor operations. However, solar-powered UAVs are subject to restrictions as their output is influenced by factors like cloud cover, atmospheric conditions, and sun angle. Additionally, the solar panels add weight and cost to the UAVs, making them less versatile for all applications [135]. Wireless Power Transfer (WPT) technology presents another promising solution for extending UAV endurance. Using flat coil couplers, similar to mobile phone chargers, WPT can recharge UAVs without requiring them to actually land at a base for charging but flying closer to it. This approach enhances the autonomy of UAVs and supports charging other devices. Yet, WPT technology brings its own set of challenges, including the need for precise hovering control, energy-efficient electronic devices, and the potential for electromagnetic interference with onboard equipment [136–138]. Efficient path planning is another means of managing power in UAV-based surveillance and monitoring. By optimizing flight paths and deploying charging stations in the mission area, UAVs can minimize energy consumption and mission duration [139]. Furthermore, ground mobile charging stations, such as cars and buses, are being integrated into UAV operations, allowing for a dynamic approach to UAV battery management by synchronizing UAV and mobile charging station networks. These innovations represent significant steps toward enhancing UAV endurance and operational efficiency [140].

4.4 Emerging Attack Vectors in UAV Security

UAVs can play a vital role in modern surveillance and monitoring systems, but their deployment introduces significant security and privacy challenges. These systems are vulnerable to a variety of sophisticated attacks, targeting both their hardware and software. Ensuring the security and privacy of UAV systems is crucial for maintaining operational integrity, protecting sensitive data, and preventing malicious exploitation. In the following, we explore key attack vectors and the associated countermeasures:

Drone hijacking: One of the most direct threats to UAVs is unauthorized access, commonly known as drone hijacking [141]. Attackers exploit vulnerabilities in communication protocols or authentication mechanisms to gain control over the drone, enabling them to redirect its operations, steal it, or cause intentional crashes. Hijacking attacks often involve spoofing or jamming signals between the UAV and its ground control station. Once communication is disrupted, attackers can inject malicious commands. Techniques to prevent hijacking include implementing secure communication protocols (e.g., end-to-end encryption), real-time anomaly detection, and hardware-based authentication such as tamper-proof modules [142, 143].

AI spoofing and manipulation: UAVs increasingly rely on artificial intelligence (AI) for decision-making and real-time operations. However, this reliance introduces risks, as attackers can exploit vulnerabilities in AI models to manipulate their behavior [144]. Adversarial attacks involve subtly altering sensor inputs, images, or other data to mislead AI algorithms, potentially causing misclassification of objects, navigation errors, or mission failure. Enhancing adversarial robustness during AI model training, validating inputs through multi-sensor fusion, and deploying secure AI frameworks can mitigate these risks [145].

Data exfiltration: UAVs collect and transmit sensitive data, which makes them attractive targets for attackers seeking unauthorized access. Protecting this data is critical to prevent breaches and misuse [146]. Attackers can intercept unencrypted data streams or infiltrate UAV systems to extract sensitive information. This is particularly critical in surveillance missions involving classified or proprietary data. Countermeasures such as end-to-end encryption of communications, secure onboard data storage, and network monitoring tools can mitigate the risk of data breaches. Employing access control mechanisms further enhances data security [143].

Deep packet inspection attacks: UAV communications are susceptible to interception and analysis through deep packet inspection (DPI), enabling attackers to identify patterns or inject malicious payloads [147]. DPI attacks target UAV communication networks by analyzing the metadata and content of transmitted packets to extract information or disrupt operations. To address DPI risks, UAV systems can employ encrypted communication protocols like TLS, regularly rotate encryption keys, and integrate anomaly detection systems to flag unusual traffic patterns [148].
Zero-day exploits: The complexity of UAV systems makes them susceptible to unknown vulnerabilities, known as zero-day exploits [149]. These vulnerabilities, once discovered, can be exploited by attackers before developers issue patches. Zero-day exploits often result from unpatched firmware or software flaws, enabling attackers to gain unauthorized control, disrupt operations, or access sensitive data. Proactive security measures include rigorous code testing, collaboration with ethical hackers, regular updates, and an incident response plan to address emerging threats [150].
Quantum cryptography threats: Advancements in quantum computing pose a long-term threat to traditional cryptographic methods, potentially rendering current encryption standards obsolete [147]. Attackers leveraging quantum computing power can break cryptographic keys used in UAV communication systems, compromising data security. Adopting quantum-safe cryptographic algorithms and hybrid encryption methods ensures resilience against quantum-based attacks. Forward-looking security protocols must integrate these advancements [148].
Wormhole attacks: UAV networks, particularly those utilizing flying ad-hoc networks (FANETs) or mobile ad-hoc networks (MANETs), are susceptible to routing-based attacks, such as wormhole attacks. These attacks disrupt the process of packet routing within the network. In a wormhole attack, the transmission of information between UAVs and ground stations is manipulated in such a way that distant UAVs appear as neighboring UAVs in the network. This misrepresentation significantly impacts the UAVs' decision-making processes, including the selection of the shortest routes even using the same routing [151].

5 Future directions and synergy with emerging technologies

The use of UAVs for intelligent surveillance and monitoring is anticipated to increase in the upcoming years, and new technological developments are likely to emerge. The advancement of edge computing, AI, and ML technologies will make UAVs smarter and more intelligent in terms of decision-making, significantly raising the level of active surveillance and monitoring. **Figure 9** highlights the key future directions for UAV-based intelligent surveillance and monitoring.

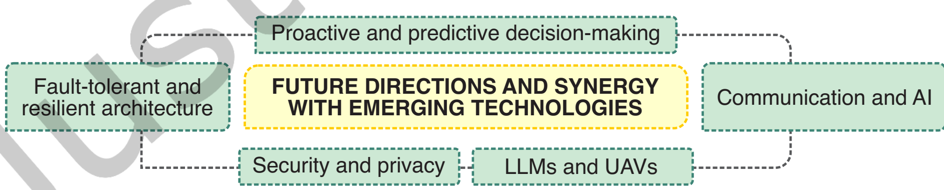

Fig. 9. Proactive and predictive decision-making, fault-tolerant and resilient architecture, communication and AI, security and privacy and LLMs are considered as key emerging technologies to support the future research directions for intelligent surveillance and monitoring.

5.1 Proactive and Predictive Decision-making

High intelligence brings proactiveness to UAVs enabling them to make predictive decisions. However, the current landscape of predictive decision-making in UAVs faces challenges due to constraints in computational power, the complexity of predictive models, and the dynamic nature of environments. To overcome this limitation in future surveillance and monitoring, the implementation of distributed machine learning, such as federated learning, ensemble models, and online learning can allow multiple UAVs to collaboratively train a shared model while maintaining data privacy and decentralization. These approaches facilitate collaborative training of a shared model among multiple UAVs while preserving data privacy and decentralization. The incorporation of such techniques is anticipated to empower future surveillance and monitoring systems to efficiently process vast amounts of information in real-time, supporting predictive decision-making on a large scale. In the future of UAV surveillance and monitoring, the integration of large-scale predictive decision-making holds significant potential across a broad spectrum of applications, with some examples as follows:

Proactive transportation traffic control with pattern and congestion prediction: The vehicular traffic environment, characterized by its highly dynamic nature, can greatly benefit from advanced traffic surveillance and monitoring facilitated by distributed learning models. These models can predict upcoming traffic flow and congestion on a large scale, spanning entire towns or cities. By foreseeing potential traffic bottlenecks and estimating the travel times of vehicles, these distributed learning models can proactively manage traffic flows to optimize transportation efficiency at a city-wide or regional level.

Early warning of natural disasters: Future UAV surveillance and monitoring can also be assisted by the prediction and early warning of natural disasters such as wildfires, floods, or landslides. By monitoring environmental conditions, detecting anomalies, and analyzing patterns, UAVs can provide early alerts and predictions for impending disasters. This can allow authorities to take proactive measures, initiate evacuation plans, and allocate resources in a timely manner. The gathered air quality, water quality, and pollution-related data can help UAVs to predict pollution trends and identify potential pollution sources. This can aid in environmental protection, pollution prevention, and resource management.

5.2 Fault-tolerant and Resilient Architecture

Resiliency in architecture is paramount for the future of UAV surveillance and monitoring, especially when faced with unpredictable and challenging environmental conditions. Harsh and dynamic elements such as temperature fluctuations, humidity, and unpredictable wind speeds can pose significant challenges to UAV deployments. Moreover, during missions, unexpected external forces, heavy rain, or internal incidents may disrupt critical software or hardware components, resulting in degraded performance or a complete inability to fulfill their tasks. To meet these challenges, future UAV-based surveillance and monitoring systems must be dynamic, auto-adjustable, and resilient. They should be able to proactively predict faults and make changes on the fly to minimize the impact of failures or disruptions, thereby reducing downtime and losses. This future fault-tolerant and resilient architecture can be designed in the following ways:

Health and performance improvement through advanced fault prediction models: The development and integration of advanced fault detection and prediction models like SVMs, random forests, CNNs, and RNNs in UAV systems can help to predict faults in UAVs during surveillance and monitoring operations. The fault prediction can enable proactive maintenance safeguarding them from health and performance deterioration. These fault detection models can continuously analyze data from the UAV sensors in real-time to detect deviations from normal operation patterns, which could indicate an impending failure. By reducing the likelihood of in-flight failures, these models can significantly enhance the safety and reliability of UAV operations. This is especially crucial in applications where UAVs are used in hazardous environments.

Extending lifetime through strategic coordination and load balancing: The limited battery and computational power of UAVs pose a challenge to their operational efficiency. Excessive load from data processing on UAVs can easily lead to the failure of their internal components. Load balancing and coordination in UAV swarms are promising approaches to overcome this problem. The future architecture of UAV-based surveillance and monitoring requires such techniques to automatically redistribute tasks among UAVs to avoid situations where components fail or compensate for the loss of a unit. Employing such techniques can ensure the overall progress of the mission without significant degradation.

5.3 Integration of Future Communication and AI with UAV Systems

Maintaining complete communication in real-time during the surveillance and monitoring mission is the first step of a future communication system for UAVs. During the mission, communication issues include communication delays or disturbances between UAVs or with external entities. In the future, the advancement of 6G and satellite communication can play a pivotal role in reducing communication delay and enhancing the reliability of UAV-based surveillance and monitoring communication systems. Some examples are discussed in the following:

Empowerment with 6G and beyond communications: 6G and beyond communications can empower UAV-based surveillance and monitoring. The increased data transfer speeds and low latency of 6G can allow real-time high-definition video streaming from UAVs, providing more accurate and up-to-date information to operators. This means better decision-making can be made in critical situations with quicker response times. Moreover, the enhanced connectivity and network reliability of 6G can improve the communication between multiple UAVs, enabling them to collaborate and cover larger areas more efficiently. The increased network capacity of 6G can also support a greater number of UAVs operating simultaneously, allowing for broader coverage and more effective monitoring of large areas, such as borders, disaster-stricken areas, or crowded events.

Expansion of global reach with satellite backup: To enhance surveillance resilience, future UAV systems can leverage satellite communication, especially in remote areas lacking infrastructure such as oceans, deserts, and mountains. Geostationary satellites (GEO) provide continuous coverage for long-duration missions (e.g., border patrol, oil spills, mountain search and rescue), while Low Earth Orbit (LEO) satellites support low-latency, data-intensive operations. In urban settings, LEO satellites can serve as backup links during communication disruptions. In satellite-UAV communication, UAVs establish Beyond-Line-Of-Sight (BLOS) links via onboard SATCOM terminals operating at mission specific frequencies. These links use mechanically steered or phased array antennas to track satellite beams. Compared to ground-UAV communication, which uses low-latency, high-bandwidth terrestrial links (e.g., LTE, 5G) satellite-UAV communication prioritizes global coverage but faces higher latency, lower data rates, and challenges such as atmospheric attenuation, Doppler shift, and orbital dynamics. Satellite links also require managing handovers and adaptive modulation to maintain reliable control over long distances. Recognizing these differences is critical for designing satellite-reliant UAV systems.

Enhancement of communication reliability with Dynamic Spectrum Allocation (DSA): In the upcoming future, the utilization of UAVs for surveillance and monitoring will continue to expand. Unplanned spectrum allocation in a growing population can result in signal interference and loss during missions, posing potential threats to their success. To face these challenges, DSA schemes can offer a promising approach. By dynamically allocating spectrum resources, these schemes can mitigate the impact of increasing UAV on the spectrum, ensuring efficient utilization and minimizing signal interference. To mitigate the effect of environmental change on UAVs, these systems can feature environment-adaptive backbone UAVs equipped with state-of-the-art communication capabilities. These backbone UAVs can intelligently position themselves to establish and maintain reliable communication links, even in the face of challenging and dynamically changing environmental conditions.

Integration of AI-driven network slicing: Network slicing, a technique enabled by 5G and 6G networks, allows for the creation of multiple virtual networks on a single physical infrastructure, each tailored to specific applications or services. In UAV operations, AI-driven network slicing could be used to allocate network resources dynamically, ensuring that critical tasks, such as real-time video streaming or emergency communications, receive the necessary bandwidth and low latency. Future research could investigate the development of AI algorithms that optimize network slicing for UAVs, balancing the needs of various tasks and maximizing overall system efficiency. This approach could also facilitate the integration of UAVs into broader smart city infrastructure, enabling seamless communication between UAVs and other IoT devices.

Development of Quantum communication channels: Quantum communication, with its potential for ultra-secure data transmission, represents a promising future direction for UAV systems. Quantum key distribution (QKD) could be used to secure communication links between UAVs and ground stations, protecting sensitive data from eavesdropping or cyberattacks. Research in this area could focus on adapting quantum communication technologies for use in UAV systems, including the development of lightweight, energy-efficient quantum communication modules suitable for integration with UAV platforms. Additionally, hybrid systems combining quantum and classical communication could be explored to provide both security and reliability in various operational scenarios.

Real-Time adaptive communication protocols: As UAVs operate in diverse and dynamic environments, the development of real-time adaptive communication protocols will be crucial to maintaining reliable connections. These protocols could automatically adjust communication parameters, such as frequency, power, and modulation schemes, in response to environmental changes, interference, or network congestion. Future research could explore the use of AI and ML algorithms to develop adaptive protocols that optimize communication performance in real-time, ensuring that UAVs remain connected even in challenging conditions. This approach could be particularly valuable in mission-critical operations where uninterrupted communication is essential.

Utilization of High-Altitude Platform Systems (HAPS): High-altitude platform systems (HAPS), operating in the stratosphere, could provide a novel communication infrastructure for UAVs, offering wide-area coverage and persistent connectivity. HAPS could act as aerial communication relays, bridging gaps in satellite and terrestrial networks, particularly in remote or disaster-stricken areas. Future research could focus on integrating HAPS with UAV systems to enhance communication reliability, exploring the potential for HAPS to serve as mobile base stations that dynamically adjust their position to optimize coverage and reduce latency for UAV operations.

5.4 Emerging Techniques to Enhance Security and Privacy

The increased use of UAVs in surveillance and various applications has raised valid concerns about security. One major worry is the potential misuse of UAVs for malicious purposes such as terrorism or spying. UAVs, equipped with cameras, can capture images and videos, leading to worries about privacy violations, especially if done without people's consent. Additionally, there's the fear that UAVs could be used to conduct surveillance on sensitive areas or even carry harmful payloads like explosives. This has prompted a need for effective regulations and security measures to prevent the unauthorized and potentially harmful use of UAVs. As these devices become more commonplace, it is crucial to address both security and privacy concerns through regulations and technological solutions to ensure responsible and safe use. To avoid these situations, new security algorithms for UAVs could be developed when needed. Some example algorithms and technologies are as follows:

Microchip defense mechanism: UAVs, particularly those deployed in critical reconnaissance and surveillance missions, carry sensitive information and data. These UAVs are vulnerable to attacks and can be captured by adversaries, presenting a substantial security risk. Once captured, these UAVs can be reverse-engineered, leading to the potential leakage of sensitive information. This risk increases as UAV designers often depend on third-party intellectual property cores and outsourced elements in the design of integrated circuits (ICs), potentially introducing security gaps at the chip level. Implementing chip-level security is a robust defense against these threats. Integrating security features directly into the microchips that power and control UAVs, and store their data, can significantly secure unauthorized access and the deciphering of encoded information. Microchip defense mechanisms can encompass hardware-based encryption, self-destruct protocols, and authentication mechanisms that deactivate the UAV's functionality when tampering is detected. Such comprehensive security has the potential to not only safeguard the confidential data collected by UAVs but also to protect their physical design and technological advancement from replication via reverse engineering. This approach can ensure a higher level of security, maintaining the integrity of both the information and the technology within these critical aerial assets.

Quantum key distribution (QKD): To safeguard the confidentiality of sensitive data, UAVs can employ Quantum Key Distribution (QKD) during surveillance and monitoring missions to establish highly secure communication channels. QKD enables the creation of encryption keys that are theoretically immune to decryption, ensuring that data transmitted between UAVs and ground stations remains protected from eavesdropping and cyber threats. By leveraging quantum principles, QKD can also detect any interception attempts, making it significantly more resilient than traditional cryptographic methods. As quantum computing continues to advance, rendering some conventional encryption techniques vulnerable, QKD offers a future-proof security solution. This makes it particularly well-suited for missions requiring the highest standards of data security, such as military operations, critical infrastructure surveillance, and other high-stakes UAV applications.

AI-Driven privacy filters: AI-driven privacy filters can be integrated into future UAV-based surveillance and monitoring missions. These filters can automatically detect and redact any personally identifiable information (PII) or sensitive data from images and videos captured during surveillance. Utilizing advanced machine learning algorithms, these filters can accurately identify human faces, license plates, and other sensitive information, ensuring that individuals' privacy is protected, and only relevant data is transmitted to the ground station. Moreover, these AI systems can be trained to comply with various global data protection regulations, making them adaptable to different legal frameworks. The integration of AI-driven privacy filters addresses the growing concerns about privacy in surveillance practices, striking a balance between the need for security and the protection of individual rights.

Neural network-based intrusion detection: Future UAVs can be equipped with highly advanced neural network-based intrusion detection systems. These systems continuously analyze network traffic and communication patterns to detect any suspicious activities or intrusion attempts. By employing deep learning techniques, these neural networks can learn to identify subtle patterns and anomalies that indicate potential security breaches, enhancing their detection capabilities. This capability ensures that the UAV's communication channels and data remain secure during missions. Additionally, these systems can adapt and update their detection strategies in real-time based on new threats, ensuring robust protection against evolving cyber threats. The integration of these advanced systems plays a critical role in safeguarding the integrity and confidentiality of the mission-critical data being handled by UAVs.

Blockchain-based data integrity verification: Blockchain technology can be a powerful tool in ensuring the integrity and authenticity of data collected by UAVs. By leveraging a decentralized and immutable distributed ledger, blockchain records each data entry as a unique block, which is cryptographically linked to the previous block. This method makes it extraordinarily difficult for malicious actors to alter or tamper with the data without detection. As each node in the blockchain network holds a copy of the ledger, any discrepancies between nodes can be identified and corrected, ensuring a high level of data trustworthiness. This capability is particularly crucial in sensitive applications such as environmental monitoring, military operations, and disaster response, where the accuracy and reliability of data are crucial.

Homomorphic encryption: Homomorphic encryption is an advanced cryptographic technique that allows data to be processed while still encrypted, ensuring that sensitive information remains protected even during computation. For UAV operations, where data is often transmitted and processed across various platforms, homomorphic encryption offers a robust solution to maintain confidentiality. Even if intercepted, the encrypted data cannot be understood or misused by unauthorized parties. This method is particularly useful when UAVs are used in scenarios that require the sharing of sensitive data with external entities, such as in collaborative research, law enforcement, or medical supply deliveries. The ability to perform computations on encrypted data also means

that insights can be derived without ever exposing the raw, sensitive information, significantly enhancing the security and privacy of UAV data operations.
Secure boot and firmware updates: Secure boot and firmware update mechanisms are essential security features that protect UAVs from malware, unauthorized software, and other security threats. The secure boot process ensures that the UAV only loads firmware that is digitally signed and verified, preventing malicious software from being executed at startup. Similarly, secure firmware update mechanisms verify the authenticity and integrity of the update package before applying it, safeguarding the UAV from potential vulnerabilities that could be introduced through corrupted or malicious updates. These measures are critical in maintaining the operational integrity of UAVs, especially in mission-critical applications where the reliability of the software is crucial. Regular and secure updates also ensure that UAVs are protected against the latest security threats, maintaining their resilience against evolving cyber threats.

5.5 Integrating large language models (LLMs) with UAVs for future applications

The fusion of LLMs with UAVs holds significant promise for advancing the capabilities of future surveillance and monitoring systems. This integration can benefit future UAV-based surveillance and monitoring systems in several ways.
Natural language interaction and intelligent decision support: LLMs can enable natural language interaction between operators and UAVs. Operators can issue commands, ask questions, or receive status updates through spoken or text-based communication, making the operation of UAVs more intuitive and user-friendly. LLMs can also provide real-time, context-aware decision support to UAV operators. It can analyze the data being collected by the UAVs and offer insights and recommendations to guide operators in making informed decisions during surveillance missions.
Emergency response and alerts: In future UAV-based surveillance and monitoring, advanced technologies, including LLMs, can significantly enhance emergency response capabilities. While language models themselves are not directly used for recognizing critical events or anomalies within data streams, they can play a pivotal role in the subsequent stages of emergency response. Once a critical event is detected by specialized analytical algorithms, language models can be employed to interpret and translate the technical findings into clear, actionable alerts. These alerts can then be automatically communicated to operators or relevant authorities, facilitating prompt and informed decision-making. Language models can assist in organizing information, generating detailed reports, or even drafting initial response strategies based on predefined protocols.
Autonomous mission planning and adaptation: Integrating LLMs with UAVs could enable more sophisticated autonomous mission planning and adaptation. By processing mission objectives expressed in natural language, LLMs can generate detailed flight plans that account for factors such as terrain, weather conditions, and potential threats. During the mission, LLMs can dynamically adjust the plan in response to real-time data, optimizing the UAV's performance and ensuring mission success even in changing or unpredictable environments.
Enhanced object detection and classification: LLMs, when combined with advanced image and signal processing algorithms, can enhance the object detection and classification capabilities of UAVs. By understanding contextual information provided by LLMs, UAVs can prioritize certain objects or events over others, improving the efficiency and accuracy of surveillance tasks. This capability could be particularly useful in complex environments where identifying and tracking specific targets are critical.
Collaborative multi-UAV operations: LLMs can facilitate the coordination and collaboration of multiple UAVs working together on a shared task. Through natural language processing, LLMs can enable UAVs to communicate with each other, share data, and make collective decisions. This approach can lead to more efficient use of resources, improved coverage of large areas, and faster completion of missions. Research in this area could explore the development of decentralized communication protocols and decision-making algorithms driven by LLMs.

6 Conclusion

Due to their flexibility, cost-effectiveness, and support of IoT services, UAVs or drones have drawn great attention in surveillance and monitoring applications. Furthermore, the development of related techniques and technologies such as AI and ML has provided significant advancement to this field in recent years. For instance, the enhanced computational capabilities has enabled UAVs to tackle complex and intelligent applications, including active surveillance and monitoring. In this survey, we studied the core concepts of UAV-based surveillance and monitoring, and described the enabling technologies, architectures and applications within this area. We emphasized various levels of UAV activeness and intelligence, and described how this technology can be adaptable through state-of-the-art AI and ML techniques. Furthermore, we discuss emerging challenges and key research problems and their solutions, and how these developments can influence the UAV performance in diverse application scenarios. Finally, we discussed emerging challenges and future directions, identifying gaps in existing literature, providing ideas for future research. Through this survey, we have thus compiled a comprehensive resource for researchers exploring this rapidly evolving field involving challenges and opportunities in improving UAV-based active surveillance and monitoring applications.

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