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SURVEY

A Survey on Applications of Unmanned Aerial Vehicles Using Machine Learning

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ABSTRACT Unmanned Aerial Vehicles (UAVs) play an important role in many applications, including health, transport, telecommunications and safe and rescue operations. Their adoption can improve the speed and precision of applications when compared to traditional solutions based on handwork. The use of UAVs brings scientific and technological challenges. In this context, Machine Learning (ML) techniques provide solutions to several problems concerning the use of UAVs in civil and military applications. An increasing number of scientific papers on the use of ML in UAVs context have been published in academic journals. In this work, we present a literature review on the use of ML techniques in UAVs, outlining the most recurrent areas and the most commonly used ML techniques in UAV applications. The results reveal that applications in the areas of environment, communication and security are among the main research topics.

INDEX TERMS Unmanned aerial vehicle, machine learning, literature review, UAV applications, neural networks.

LIST OF ACRONYMS

3D	Three Dimensional.
4G	Fourth Generation.
5G	Fifth Generation.
6G	Sixth Generation.
A3C	Asynchronous Advantage Actor Critic.
ACRL	Actor-Critic Reinforcement Learning.
AI	Artificial Intelligence.
AMD	Acid Mine Drainage.
ANN	Artificial Neural Network.
AoI	Age of Information.
BATS	Blockchain and AI-empowered Drone-assisted Telesurgery System.
BS	Base Station.
CCTV	Closed Circuit Television.
CNN	Convolutional Neural Network.
COVID-19	Coronavirus 2019.
CUAV	Cognitive UAV.
DCNN	Deep Convolutional Neural Network.
DDPG	Deep Deterministic Policy Gradient.
DifFAR	Differentiable Frequency-based Disentanglement for Aerial Video Action Recognition.
DL	Deep Learning.
DLA	Deep Learning based Optimal Auction.
DML	Distributed Machine Learning.
DNN	Deep Neural Networks.
DQN	Deep Q-Learning.
DRL	Deep Reinforcement Learning.
DT	Decision Tree.
FANET	Flying Ad-hoc Network.
FCOS	Fully Convolutional One-Stage.
FSL	Few-Shot Learning.
FTFC	Fault-Tolerant Formation Control.
GB	Gradient Boosting.
GBS	Ground Base Stations.
GSDRL	Guided Search Deep Reinforcement Learning.

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GPU	Graphics Processing Unit.
GUs	Ground Users.
ICIs	Inter-Cell Interferences.
IoT	Internet of Things.
IoTDs	Internet-of-Things Devices.
IoV	Internet of Vehicles.
IRSs	Intelligent Reflecting Surfaces.
InSAR	Interferometric Synthetic Aperture Radar.
KNN	K-Nearest Neighbour.
LIDAR	Light Detection and Ranging.
LR	Linear Regression.
LSVM	Linear Kernel SVM.
LSTM	Long Short-Term Memory.
MAPPO	Multi-Agent Proximal Policy Optimization.
MCS	Mobile Crowd Sensing.
MDP	Markov Decision Process.
MEC	Mobile Edge Computing.
ML	Machine Learning.
MUs	Mobile Users.
NB	Naïve Bayes.
NNI	Nitrogen Nutrition Index.
PEDS-AI	Pest Early Detection and Identification System.
PLSR	Partial Least Squares Regression.
QMACN	Quantum Multi-Agent Actor-Critic Networks.
QoS	Quality of Service.
R-CNN	Recurrent Convolutional Neural Network.
RBFN	Radial Basis Function Network.
RF	Random Forest.
RGB	Reed, Blue and Green.
RIS	Reconfigurable Intelligent Surface.
RL	Reinforcement Learning.
RQs	Research Questions.
RPN	Region Proposal Network.
RSRP	Received Signal Reference Power.
RSRQ	Reference Signal Received Quality.
SAR	Safety and Rescue.
SARD	Search and Rescue Image Dataset.
SCP	Semi-Automatic Classification Plugin.
SEI	Spectral Evidence of Ice.
SVM	Support Vector Machine.
SSD	Single-Shot Detector.
TA3C	Transfer Asynchronous Advantage Actor-Critic.
TWS	Trainable Weka Segmentation.
UMA	UAV-assisted Multi-task Allocation.
UEs	User Equipments.
UxV	Unmanned any Vehicle.
UTM	Unmanned Aircraft Traffic Management.
USV	Unmanned Surface Vehicle.
UAVs	Unnamed Aerial Vehicles.
WCN	Wireless Communication Network.
YOLO	You Only Look Once.

I. INTRODUCTION

The use of drones has gained prominence in the last decade for civil and military applications. Included in this category, one can cite the Unnamed Aerial Vehicles (UAVs), which are capable of flying remotely controlled or autonomously, without any type of manual intervention by the human operator, and capable of carrying loads, whether lethal or not. In addition, these vehicles can be classified in terms of size, load capacity, flight ceiling and design [1], [2].

Countries around the world have registered an increasing number of these aircrafts, in their territories. According to Brazilian open data, the National Civil Aviation Agency (ANAC, from Portuguese, Agência Nacional de Aviação Civil)[1] recorded a total of 119,155 official drone registrations in october 2022, of which 62,272 were registered for recreational use and 56,883 for use in professional activities. The North American Federal Aviation Administration (FAA)[2] shows on its website that there are 871,984 of these vehicles in activity, and the Civil Aviation Administration of China (CAAC)[3] shows a total of 120,000 commercial drones registered in 2020.

Machine Learning (ML) techniques play an important role in solving many complex problems related to tasks that have the potential to be automated in areas such as control engineering, knowledge acquisition, decision making, and also localization [3]. Advantages associated with the use of UAVs in different scenarios have led to the emergence of several studies in recent years on the use of ML techniques to assist in solving UAV-related problems in a wide variety of applications, such as networked data transmission, mobile platform landing, precision agriculture, surveillance, network access, trajectory planning, and power optimization [4], [5], [6], [7].

Due to the rapid growth in the number of publications in scientific bases, a literature review on a particular domain of knowledge is both a necessity and a challenge. Recent studies have presented literature reviews on ML applications with UAVs focused on a specific area.

In the area of environment, Ecke et al. [8] conducted a systematic literature review on the detection of biotic and abiotic stressors in forests, including tree mortality, with UAVs. Another systematic review in the area was provided by Duarte et al. [9], addressing monitoring insect-borne pests and diseases using data collected by UAVs. Rakesh et al. [10] conducted a review on the applicability of UAVs in the field of agriculture. Other studies have addressed plant counting, crop monitoring and pesticide spraying [11], [12], [13].

Bithas et al. [14] conducted a survey on studies using ML techniques in UAV-based communication to improve functional aspects such as channel modeling, resource management, positioning, and security. In the tutorial by

[1] https://www.anac.gov.br/acesso-a-informacao/dados-abertos/areas-de-atuacao/aeronaves/drones-cadastrados/painel-de-drones-cadastrados
[2] https://www.faa.gov/uas
[3] http://www.caac.gov.cn/en/SY/

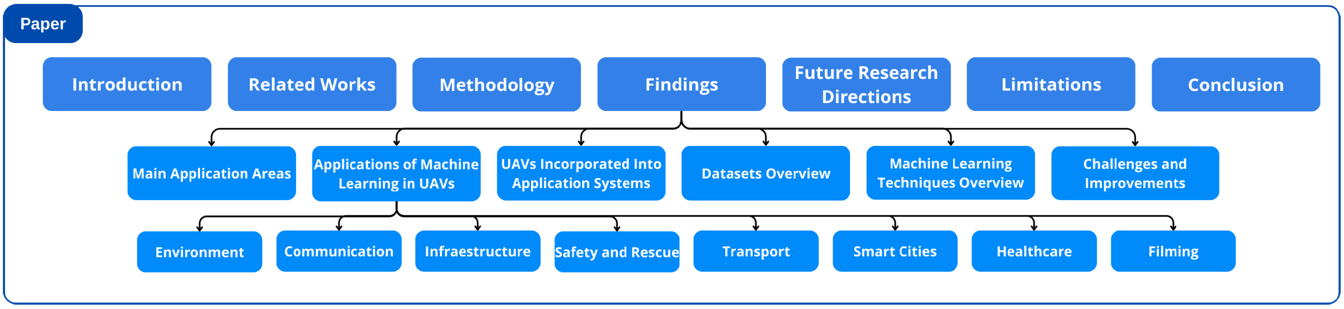

FIGURE 1. Organization of the paper.

Mozaffari et al. [15] the fundamentals, benefits and challenges of UAV-enabled wireless networks are presented. Other important topics such as 5G networks, mobile edge computing and the Internet of Things (IoT) have also been the focus in some reviews [16], [17].

In the literature, we find reviews covering more than one specific topic. Mukhamediev et al. [18] conducted a review of UAV applications and benefits in countries that have an abundance of natural resources, such as, for example, Kazakhstan. The authors have divided the selected studies into seven fields, namely: precision agriculture, monitoring hazardous geophysical processes, environmental pollution monitoring, mineral exploration, wildlife monitoring, monitoring technical and engineering structures, and traffic monitoring.

Sharma [1] presented a comparative analysis of studies, published between 2019 and 2020, on the use of ML techniques with UAVs. Research from different application domains of UAVs were presented, such as routing method for Flying Ad-hoc Network (FANET), precision agriculture, disaster response operations, crop production forecasting, tree species identification, and power allocation in drones.

Our study provides a comprehensive review of the literature on the use of ML techniques in UAVs applications to solving real-world problems. Research Questions were defined to guide the current review, and inclusion and exclusion criteria were established for the articles to be considered in the study. Steps of the review process were performed in an automated way (e.g. the selection of primary studies with FAST^2, by Yu and Menzies [19]), using tools to reduce time and manual work. In addition, a prospection of areas in which UAVs are used, a prospection is presented of subareas and applications of ML in UAVs for each area under consideration, a prospection of databases used, a prospection is presented of the most commonly used ML algorithms and techniques in UAVs, existing gaps and promising future research directions are cited.

The remainder of this article is organized as shown in Figure 1: Related works are presented in Section II. The methodology is presented in Section III. The findings are presented in Section IV. Future research directions and limitations are presented in Sections V and VI, respectively. Section VII is dedicated to the conclusions.

II. RELATED WORKS

Many reviews provide valuable insights into the current state of research and developments in the application of UAVs and Deep Learning (DL) algorithms for various aspects of agriculture, precision farming, and forestry management.

Zhou et al. [20] discuss the use of infrared thermal sensors and UAVs for assessing crop water stress in precision agriculture. The work addresses technological aspects such as thermal imaging acquisition, canopy segmentation, and crop water stress index calculation, and explores the potential of DL applications for future advancements. Morais et al. [21] present a review focused on the use of DL techniques with UAV-acquired Reed, Blue and Green (RGB) data in forestry research. The paper covers applications such as individual tree detection, tree species classification, and forest anomaly detection, and provides a critical assessment of the strengths and methodological challenges in the field.

Advances on UAV and DL for crop diseases are discussed per Bouguettaya et al. [22]. Their review paper emphasizes the importance of effective monitoring techniques to ensure stable and reliable crop productivity and food security. Rakesh et al. [10] explore the effective applicability of various types of UAVs in agriculture, their classification, and diverse applications. The authors discuss the potential for future advancements and improvements in UAV technology for different agricultural purposes.

Bouguettaya et al. [23] review the use of UAVs equipped with DL-based computer vision algorithms for early wildfire detection in forest and wildland areas. The focus is on preventing and reducing disastrous losses in terms of human lives and forest resources caused by wildfires. Amarasingam et al. [12] summarize the use of UAVs and various advanced sensors, including RGB, multispectral, hyperspectral, Light Detection and Ranging (LIDAR), and thermal cameras, for monitoring sugarcane crops. They discuss the benefits and limitations of UAV-based crop remote sensing applications in sugarcane cultivation.

Duarte et al. [9] focused on the use of UAVs and DL-based computer vision algorithms for monitoring forest insect pests and diseases. The authors identified research gaps and challenges in UAV-based monitoring of forests threatened by biotic and abiotic stressors. Ecke et al. [8] provide a systematic analysis of the use of UAVs for forest health monitoring and discuss advances in drone technology, sensors, and data processing methods for forest monitoring, also addressing limitations and research gaps in the field.

Hussain et al. [24] analyze various research studies on UAV-based imagery and ML techniques for crop yield forecasting. Hafeez et al. [13] present an analysis of drone technologies and their applications in the agricultural sector, particularly in crop monitoring and pesticide spraying for precision agriculture.

Many studies provide an overview of the field of UAV-based communications and ML-oriented applications. These studies explore the potential of UAVs, with the use of ML techniques, for improving Wireless Communication Network (WCN), IoT applications and other areas.

Bithas et al. [14] present a detailed survey of research works that utilize ML techniques for UAV-based communications. The review covers various aspects such as channel modeling, resource management, positioning and security, and challenges are presented in using UAVs for communication purposes. Kim et al. [25] focus on the application of Artificial Intelligence (AI)-driven systems in Fifth Generation (5G) networks, particularly in smart cities, discussing their potential applications in autonomous vehicles and UAVs, as well as security threats and challenges in 5G-enabled environments. Cheng et al. [26] present a comprehensive review of AI for UAV-assisted IoT applications. They explore how AI-based methods can optimize and orchestrate UAV-assisted IoT networks, enabling the provision of high-quality services to a large number of IoT devices.

For the infrastructure area, some studies have focused on issues such as analysis of power lines and damage to civil structures. Kerle et al. [27] perform a review on the evolution of how UAV-based structural disaster damage mapping is done. In their work, they analyze both simpler and DL-based approaches, and review improvements related to drones and ML on the topic at hand. Liu et al. [28] present a review focused on DL techniques for power line inspection data analysis. The authors categorize works into component detection and fault diagnosis and identify challenges for future research.

In the Transport area, reviews address DL techniques for vehicle detection from UAV imagery, showing their potential in various surveillance applications.

Srivastava et al. [29] explore DL techniques for on-ground vehicle detection from UAV images, addressing applications such as traffic management and rescue operations in disaster zones. Their review focuses on accuracy improvements, computation overhead reduction, and optimization objectives, offering valuable insights for AI researchers and traffic surveillance experts. Bouguettaya et al. [30] provide a detailed review on vehicle detection from UAV imagery using DL. The authors report the challenges related to aerial images and hardware. The paper highlights the effectiveness of DL algorithms over traditional methods and summarizes various vehicle detection approaches and datasets, aiding researchers and developers in selecting suitable methods for their needs.

Bisio et al. [41] present a systematic review on drone-based traffic monitoring systems, particularly in the context of DL. The papers addresses vehicle detection, tracking, and counting. The authors highlight the challenges faced due to object scales, angles, and occlusion. The paper by Iftikhar et al. [34] focuses on target detection in traffic congestion using UAVs and DL. The review analyzes the challenges posed by small objects in UAV images.

Shakhatreh et al. [43] explores a wide range of civil applications of UAVs, including real-time monitoring, remote sensing, precision agriculture, and security. The paper highlights key research challenges, such as charging, collision avoidance, networking, and security, providing valuable insights into future UAV uses and approaches to tackle these challenges. Osco et al. [32] address UAV remote sensing applications with DL. They present a comprehensive overview of classification and regression techniques.

Sharma [1] presents a survey and comparative analysis of works on UAV development with ML techniques. The survey highlights the importance of ML for developing solutions based on real-time data and covers various domains of UAV systems, reflecting the diversity of the topic. Mukhamediev et al. [18] discuss the potential of UAVs in resource-rich countries, focusing on various applications, such as precision agriculture, wildlife monitoring, and traffic monitoring. The authors analyze the technical, legal, and software challenges of UAV use and estimate the economic potential for Kazakhstan.

Gohari et al. [40] address surveillance drones in smart cities. Their systematic review examines application status, areas, models, and drone characteristics. Frattolillo et al. [35] present a systematic review on the use of Deep Reinforcement Learning (DRL) in cooperative and scalable multi-UAV systems. The paper categorizes multi-UAV applications into distinct classes and discusses works employing DRL techniques, providing valuable insights and future research directions to enhance UAV systems' safety and responsiveness.

Another important area is related to Distributed Machine Learning (DML). The topic was addressed by Ding et al. [48] in their review on UAV swarms. The authors report the importance of using DML for drone swarms and present and discuss the advantages and disadvantages of four of these state-of-the-art methods. In addition, they discuss several optimization problems in UAV swarms using DML algorithms.

Swarms of drones have a wide Variety of civil and military application areas, such as [49]: surveillance, leisure pursuit, search and rescue, disaster management and

TABLE 1. Surveys covering ML applications in UAV.

Study	Bases	Duration	Domain	AO	DO	ALO	CI	FD
[28]	Google Scholar	2009-2020	Power Line Inspection	√	√	√	√	√
[31]	NR	2014-2020	Smart Cities	√		√	√	√
[32]	Web of Science and Google Scholar	2016-2021	Remote Sensing (Environment, Urban and Agriculture)	√	√	√	√	√
[20]	NR	NR-2021	Crop Water Stress	√		√	√	√
[29]	NR	NR-2021	Vehicle detection		√	√	√	√
[23]	Scopus and Google Scholar	2013-2021	Wildfire Detection		√	√	√	
[33]	Scopus	2000-2021	Agriculture	√			√	√
[12]	Google Scholar, Scopus and Web of Science	2016-2021	Monitoring of Sugarcane Crops			√	√	√
[13]	NR	2010-2020	Farm Monitoring and Pesticide Spraying			√	√	√
[11]	Scopus	2018-2021	Data collection for WSN and IoT applications	√		√	√	√
[1]	NR	NR-2021	Agriculture, Communication and Disaster	√		√		√
[21]	IEEE Xplore, MDPI and Science Direct	2018-2021	Forestry	√	√	√		
[34]	NR	NR-2023	Traffic Congestion	√		√	√	
[35]	IEEE Xplore and Science Direct	2013-2022	Coverage, Adversarial Search and Game, Computational Offloading, Communication and Target-Driven Navigation	√		√		√
[9]	Google Scholar	2017-2021	Forest Insect Pests and Diseases Monitoring	√		√	√	√
[8]	Web of Science	2010-2021	Forest Health Monitoring	√		√		√
[36]	NR	NR-2022	Mobile Edge-Computing for IoT	√			√	√
[14]	NR	NR-2019	Wireless Communication Networks	√		√	√	√
[25]	NR	NR-2020	5G Networks	√		√	√	√
[37]	NR	NR-2020	Object Detection		√	√	√	√
[38]	NR	NR-2020	Inspection of Power Lines			√		√
[22]	NR	NR-2021	Crop Diseases Identification			√		
[39]	NR	NR-2022	Livestock Management	√		√	√	√
[24]	ACM, IEEE Xplore, MDPI, Science Direct and Springer	2018-2022	Predict the Crop-Yield			√		
[40]	Web of Science and Scopus	2017-2022	Surveillance (Transportation, Environment, Infrastructure, Object or People Detection, Disaster Management, Data Collection, and Other Applications)	√		√	√	
[30]	NR	NR-2022	Vehicle Detection		√	√	√	√
[41]	IEEE Xplore, Scopus, Google Scholar	2015-2021	Traffic Monitoring and Surveillance System	√	√	√	√	√
[26]	NR	NR-2023	IoT Applications	√		√	√	√
[10]	NR	NR-2021	Agriculture	√				√
[42]	NR	NR-2021	COVID-19 Pandemic	√			√	√
[43]	NR	NR-2019	Civil Applications (Real-time Monitoring of Road Traffic, Providing Wireless Coverage, Remote Sensing, Search and Rescue, Delivery of Goods, Security and Surveillance, Precision Agriculture, and Civil Infrastructure Inspection)	√		√	√	√
[27]	NR	NR-2019	Structural Damage Mapping			√	√	
[18]	NR	NR-2021	Precision Agriculture, Monitoring Hazardous Geophysical Processes, Environmental Pollution Monitoring, Exploration of Minerals, Monitoring of Wild Animal Life, Monitoring of Technical and Engineering Structures, Traffic Monitoring	√		√		√
[44]	NR	NR-2021	Reconnaissance and Surveillance, Combat, Humanitarian Demining, Public Safety, Construction, Planetary Exploration, Search and Rescue, Search and Rescue, Wireless Communication, Delivery and Precision Agriculture	√			√	√
[45]	NR	NR-2022	Communication	√		√	√	√
[46]	NR	NR-2022	Mars Exploration	√			√	√
[47]	NR	NR-2022	Disaster management, Remote sensing, Search and Rescue, Infrastructure and Construction Inspection, Precision agriculture, Real-time monitoring of road traffic, Automated Forest Restoration, Monitoring of Overhead Power Lines, Monitoring and Assessing Plant Stress, Space Exploration, Aquaculture Farm Monitoring and Management, Emergency Medical Services, Maritime Communication and Surveillance and Flying Cars and eVTOLs	√			√	√
[48]	NR	NR-2023	Forest Fire Monitoring, Smart Home, Smart City, Remote Area, Disaster Relief and V2V Network	√		√	√	√
This work	ACM, IEEE Xplore, MDPI and Science Direct	2010-2023	Environment, Communication, Safety and Rescue, Infrastructure, Transport, Smart Cities, Healthcare and Filming	√	√	√	√	√

NR = Not Reported.
AO = Applications Overview
DO = Datasets Overview
ALO = Algorithms Overview
CI = Challenges and Improvements
FD = Future Directions

environmental mapping. Important aspects must be taken into consideration in the scenario of swarms of drones: battery swapping/recharging, collision avoidance, robustness against Collisions, hovering performance and Communication reliability. Paper in the literature have been devoted do one of many of the aforementioned aspects. The paper by Yasin et al. [50] addresses collision avoidance in swarms of drones. The work of [51] presents a channel model for the air-to-air links between pairs of drones.

Despite being a topic widely explored in the literature, a comprehensive review of the applications arising from the use of ML in UAVs has not yet been fully developed. So far, no studies have been found that present in a complete and detailed way the different areas and their applications, the datasets used, the algorithms employed, the challenges faced, as well as the improvements achieved and future directions for the use of ML in UAVs.

This paper provides a comprehensive and up-to-date review of ML applications in UAVs, highlighting the main contributions and advances in the field, as well as possible limitations and opportunities for future improvements.

III. METHODOLOGY

The present review is based on a systematic processes that assist in identifying, evaluating, and synthesizing relevant information on a particular topic of interest [52], [53]. As this is a laborious task, the use of techniques and tools that facilitate this process is recommended. Recent studies have proposed automated solutions to collect data and even synthesize information from the articles found [19], [53], [54], [55], [56], [57].

Electronic databases are the main source of scientific publications and are usually the first alternative for searching scientific articles. ACM Digital Library, IEEE Xplore, Science Direct and MDPI are the databases chosen for this study. As for the publication period, articles from January 2010 to July 2023 were included. In addition, literature reviews have an investigative bias and, as such, can be guided by Research Questions (RQs) [58]. The RQs addressed in this study are:

- RQ1 - What are the main application areas of UAVs?
- RQ2 - What are the most recurrent applications of ML in UAVs?
- RQ3 - How drones are incorporated into the systems of these applications?
- RQ4 - What are the most used datasets for ML in UAVs?
- RQ5 - What are the most used ML algorithms and techniques applied to UAVs in the selected studies?
- RQ6 - What are the challenges to be overcome and improvements to be achieved in the ML applied to UAVs scenario?

Several pilot tests for the purpose of optimizing search results were conducted, resulting in the search string: (UAV OR "unmanned aerial vehicle") AND ("machine learning" OR "deep learning" OR "neural networks" OR "reinforcement learning"). The search method used was based on conducting an automated search in each of the databases using the available tools and filters. The applied filters took into consideration the publication period mentioned, from January 2010 to July 2023, as well as led to selection of journal and conference publications.

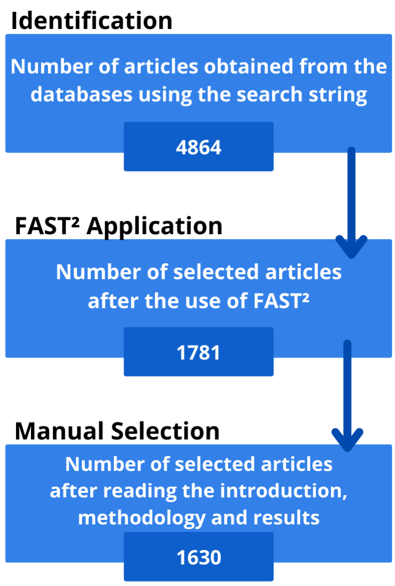

FIGURE 2. The flowchart process of the review.

TABLE 2. Inclusion and exclusion criteria.

Type	Criteria
Inclusion	Primary studies that present the topic of ML techniques and UAVs in their title, abstract and/or keywords. Studies on ML techniques in the scenario of using UAVs to solve real-world problems. Studies published in the interval January 2010 to July 2023.
Exclusion	Studies that do not present any real-world application of UAVs. Studies that focus on presenting improvements of UAVs without highlighting and/or presenting results of their usefulness in real-world applications. Studies that are solely dedicated to building and presenting datasets constructed from UAVs. Studies not written in English.

Figure 2 presents the number of studies obtained in each step of the selection of works. First, 4,864 articles were returned as a result of applying the search string to the scientific databases. To select the studies in the second step, the inclusion and exclusion criteria described in Table 2 were applied by reading the titles, abstracts, and keywords. To this step, FAST^2 [19] was used. FAST^2 is an active learning-based tool that assists researchers in the process of selecting relevant articles. At the end of the selection process there were 1,781 studies left. Subsequently, another manual selection was performed on the relevant studies resulting from the FAST^2. This selection was made by reading the full text of the selected articles, which resulted in 1,630 studies at the end.

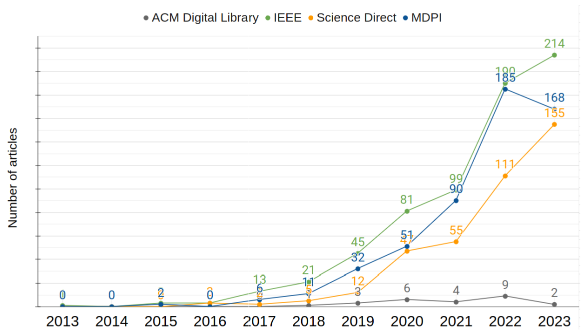

FIGURE 3. Number of published articles by database and year.

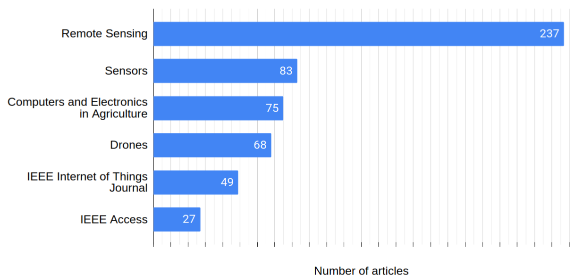

FIGURE 4. Journals and conferences that published the most articles concerning ML techniques in UAVs.

IV. FINDINGS

Figure 3 presents the number of articles published by each database over the years. Regarding the MDPI, Science Direct and IEEE databases, an upward trend is observed over the years, reaching a peak in 2023, with 214 articles published in the IEEE and 155 in Science Direct. On the other hand, ACM has the lowest number of articles published over the years, when compared to the other databases, reaching its highest number of publications in 2022, with nine studies.

In addition to collecting data regarding the number of works published per year, data were also collected about the journals that published the most. These results are shown in Figure 4, where the journal with the largest number of publications is Remote Sensing, an MDPI's open access journal, with 237 publications, followed by Sensors, also from MDPI, with 83 articles.

A. MAIN APPLICATION AREAS

Regarding RQ1, Figure 5 presents the main areas and applications of UAVs in the selected studies. Environment is the area with most publications, 746 in total, and within this area, Agriculture is the most common subarea, with 490 articles, followed by Forest Ecosystem, with 118 studies, and Environmental Preservation, with 44.

The second largest number of publications is in Communication area, with 421 studies, which have as main topics: Mobile Edge Computing (MEC), IoT and WCN. Focusing on Electrical and Civil Construction, Infrastructure is the third largest area, with 177 articles.

With 155 studies, the Safety and Rescue (SAR) area has the following main themes: Disaster and Search and Rescue Operations. The area with the lowest number of publications is Filming, with eigth studies covering applications in Sports, Exploration, Journalism and Photogrammetry.

B. APPLICATIONS OF MACHINE LEARNING IN UAVs

To answer RQ2, applications are presented from the eight subareas shown in Figure 5 - Environment, Communication, SAR, Infrastructure, Smart Cities, Transport, Healthcare, and Filming - which together sum up to 1630 studies.

1) ENVIRONMENT

Figure 6 shows the main UAV aplications in the Environment area.

- **Agriculture**
  Disease and weed detection is one of the most common applications in the subarea of Agriculture. Beeharry and Bassoo [59] performed a comparison between an Artificial Neural Network (ANN) and the AlexNet Convolutional Neural Network (CNN) for detecting weeds in crops. Tetila et al. [60], also applying CNNs, used UAVs for the automatic recognition of soybean leaf diseases from images.
  Crop yield estimation is another important application of UAVs in Agriculture. Maimaitijiang et al. [61] used RGB colors, multi-spectral and thermal sensors on a drone to estimate soybean grain productivity. In the context of plant phenotyping, Wang et al. [62] used Partial Least Squares Regression (PLSR), ANN, Random Forest (RF) and Support Vector Machine (SVM) techniques to estimate different rice characteristics through hyperspectral images collected by a UAV. Osco et al. [63] proposed a method based on a CNN to simultaneously detect and geo-locate crop rows while also performing a plant count.
  Sankararao et al. [64] proposed an early water stress identification method in groundnut canopy using UAV-based hyperspectral imaging and ML techniques, achieving 96.46% accuracy in stress detection. Gano et al. [65] developed ML-based prediction models for sorghum biomass using UAV multispectral imagery. Zhang [66] presented Pest Early Detection and Identification System (PEDS-AI), an innovative UAV-based visual-acoustic pest detection system using DL, enabling species identification in the field. Sugumar and Suganya [67] explored multi-spectral image-based high-level crop classification using a modified SVM with enhanced PCA and a hybrid metaheuristic algorithm, comparing it to methods like Naïve Bayes (NB), K-Nearest Neighbour (KNN), K-Means, and RF.
  Bergamo et al. [68] combined RGB images from a UAV with multispectral PlanetScope images to accurately map the extent of the invasive species Rosa rugosa along the Estonian coastline, enabling effective monitoring

FIGURE 5. **Main areas and applications of UAVs.**

and eradication programs. Pei et al. [69] evaluated ML models for predicting canopy nitrogen weight and Nitrogen Nutrition Index (NNI) of cotton using UAV multispectral images.

- **Forest Ecosystem**
  In the Forest Ecosystem subarea, Xia et al. [70] used fixed-wing UAV to recognize diseases in pine trees, such as pine wilt. High resolution drone images combined with DL approaches also offer significant advantages in accurately measuring forest ecosystems. Zhang et al. [71] proposed a method for tree segmentation and identification in forests based on Recurrent Convolutional Neural Network (R-CNN).
  Mangrove forests are critical to coastal ecosystems. It helps protect against changes in water temperature and salinity. Jiang et al. [72] use, firstly, an approach based on ML with the RF algorithm to select the spectral features and vegetation texture variables. Then, they implemented theRF and SVM algorithms to classify the different mangrove species.
  In the study presented by Sarkar and Kelley [73], UAV and Deep Transfer Learning were utilized for

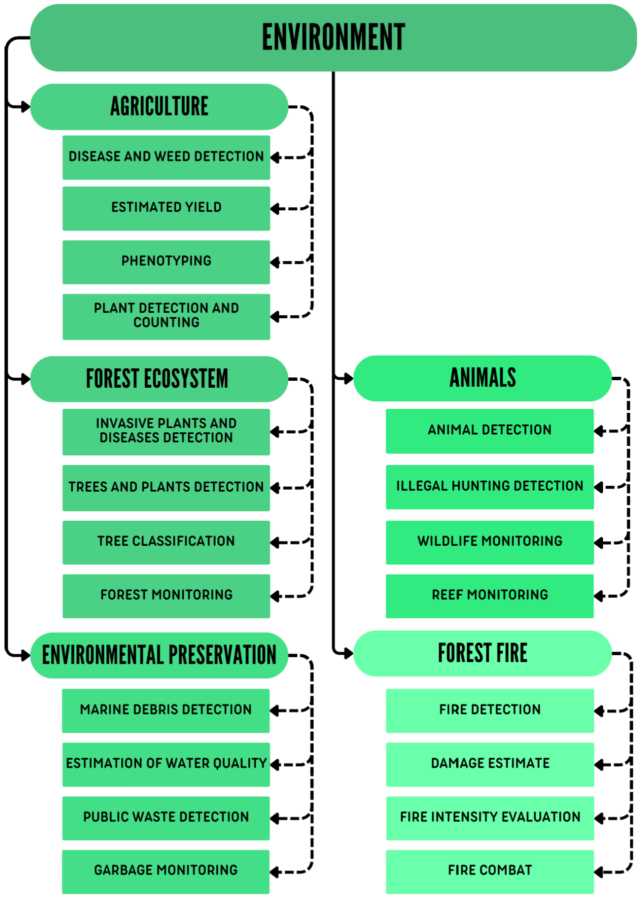

FIGURE 6. Main UAV applications in the environment area.

environmental monitoring in horticultural research. They focused on classifying invasive and native plant species in the southern regions of the USA. The MobileNetV2-Deep Convolutional Neural Network (DCNN) model with data augmentation and hyper-parameter optimization achieved a high accuracy of 94%. Pinto et al. [74] proposed an exploratory approach for Acacia dealbata classification from aerial imagery using UAV-based RGB and multispectral sensors. They trained four ML algorithms (KNN, RF, AdaBoost, and Linear Kernel SVM (LSVM)) on different datasets, with RF showing the best performance.
In the work conducted by La Salandra et al. [75], an effective approach for automatic river features extraction was presented. They combined UAV imagery with photogrammetric techniques and used Trainable Weka Segmentation (TWS) for feature extraction, achieving accuracy close to human interpretation. Mouta et al. [76] proposed a novel approach for mapping the invasive water-hyacinth (Eichhornia crassipes) in the Cávado River, Portugal. They used UAV imagery synchronized with Sentinel-2 data and classifier fusion techniques, resulting in high accuracy for mapping invaded areas throughout different seasons.

- **Preservation**
UAVs can provide great value in maritime operations that require aerial surveillance, such as the detection of objects on the water surface. In the study presented by Arnegaard et al. [77], aerial surveillance was explored for detection of marine debris. They evaluated different CNN-based architectures, more specifically variations of You Only Look Once (YOLO). Kraft et al. [78] proposed a low-cost solution to locate discarded waste in low-altitude images collected by UAVs during autonomous patrol missions.
Hyper-spectral data collected by UAVs can help identify features of water bodies, which can be used to monitor water quality. Examples of this use can be seen in the studies by Lu et al. [79], Zhang et al. [80] and Sharma et al. [81], which applied ML techniques to obtain water quality estimates based on hyper-spectral data collected by UAVs.
In the study presented by Saad et al. [82], carbon emissions after selective logging in Ulu Jelai, Malaysia, were modeled. They employed remote sensing and ML (SVM and Linear Regression (LR)) to accurately quantify emissions, assisting in optimizing forest carbon sequestration for climate change mitigation.
- **Animals**
UAVs can be used in biological research, such as animal detection, for collecting information from hard-to-reach areas, such as oceans, jungles, and remote islands. Hong et al. [83] built models to detect wild birds using Faster R-CNN, YOLO and other CNN-based approaches. Kellenberger et al. [84], [85] and Lee et al. [86] used CNN-based approaches to detect terrestrial wildlife.
Poaching can be defined as the illegal capture of wild animals for commercial purposes. It is a serious problem that threatens the survival of animals of any species. One possibility to combat this problem is the use of drones to monitor protected forest areas. Paul et al. [87] aimed to detect animal poaching in environmental preservation areas using images collected by UAVs on patrol and the YOLO method.
- **Forest Fire**
Forest fires are one of the main natural disasters in the world, causing environmentals and economic damage and even loss of life. Early detection and prediction of fire spread can help reduce affected areas and fight fires. Due to their high flexibility, low cost and great capacity to cover an area, UAVs are candidates to help solve this problem. Ghali et al. [88] adopted and optimized DL methods, more specifically a combination of EfficientNet-B5 and DenseNet-201, for early detection of forest fires.
Another important issue is fire severity and compromised area. Carvajal-Ramírez et al. [89] developed some indices for estimating fire severity. They employed a drone carrying a high-resolution multi-spectral sensor

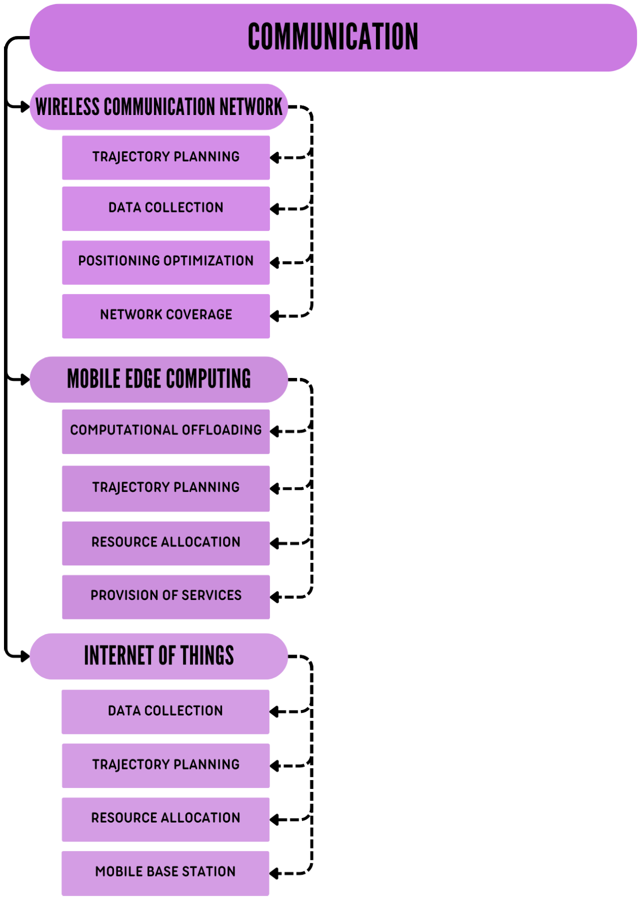

FIGURE 7. Main applications of UAVs in the Communications area.

that performed pre- and post-fire controlled flights in a Mediterranean forest. Aiming at fighting fires, Haksar and Schwager [90] proposed a strategy based on Reinforcement Learning (RL) with a team of UAVs to fight wildfires autonomously.

In the study presented by Xie and Huang [91], a transfer learning and improved Faster RCNN-based method achieved 93.7% accuracy for aerial forest fire detection using UAV imagery, outperforming traditional approaches. Namburu et al. [92] proposed the use of X-MobileNet on a UAV for timely forest fire classification and location sharing with state forest departments. Shahid et al. [93] developed FFS-UNet, a spatio-temporal architecture combining a temporal vision transformer and UNet, achieving enhanced forest fire segmentation performance in UAV-collected video datasets.

2) COMMUNICATION

Figure 7 presents the main UAV applications in the Communications area.

- **Wireless Communication Network**

  The use of UAVs as air base stations is a way to assist in the infrastructure and coverage extension of wireless networks. This application represents a flexible and cost-effective approach that has great potential to support new generations of wireless networks. Chaalal et al. [94] proposed a framework for Three Dimensional (3D) positioning of a swarm of UAVs that operate as air base stations to extend the coverage of Ground Base Stations (GBS).

  Susarla et al. [95] presented a path planning for UAVs based on connectivity restrictions. The goal of the study was to use a UAV to learn a trajectory, starting from a random location, to a destination within the GBS coverage area, considering network connectivity. To do this, they used Deep Q-Learning (DQN), wich is a DRL method.

  UAVs, due to their high mobility, can also be used as mobile relays to assist in wireless communications. Zhang et al. [96] considered drone-assisted data collection in wireless sensor networks using the Asynchronous Advantage Actor Critic (A3C) algorithm. UAV networks can also reinforce cellular networks when necessary, redirecting traffic to available GBSs. Oliveira et al. [97] used RF, Gradient Boosting (GB) and ANN algorithms to predict overloaded traffic areas. Ozer et al. [98] explored offloading computationally heavy DL tasks from UAVs to a 5G edge server to improve battery life and reduce resource requirements. However, they also analyzed the negative effects of noise introduced by the 5G wireless communication system on the DL algorithms and proposed denoising solutions to mitigate the impact. Wang and Zhang [99] proposed a novel scheme using active Intelligent Reflecting Surfaces (IRSs) to optimize energy consumption in UAV-based Sixth Generation (6G) mobile wireless networks. They employed multi-objective hierarchical DRL to minimize both UAV and ground users' energy consumption by dynamically coordinating UAV trajectory and Ground Users (GUs) scheduling strategies, as well as optimizing IRSs phase shifts and amplification factors.

  Li and Aghvami [100] focused on the cellular-connected UAV network, managing Inter-Cell Interferences (ICIs) between UAVs and User Equipments (UEs). They proposed a DRL-aided solution to jointly optimize dynamic RB coordination and time-varying beamforming design for UAVs' wireless transmission quality while protecting terrestrial UEs from interference. Yu et al. [101] tackled the Fault-Tolerant Formation Control (FTFC) problem for networked fixed-wing UAVs. They developed a RL-based approach with Actor-Critic Reinforcement Learning (ACRL) to learn the unknown nonlinear terms and compensate for RL errors, achieving finite-time convergent tracking of leader UAV with predesigned offsets.

  Park et al. [102] proposed the Quantum Multi-Agent Actor-Critic Networks (QMACN) algorithm for robust mobile access systems employing multiple

UAVs. Leveraging quantum computing principles, their approach aimed to boost the training and inference capabilities of UAV systems, enhancing the overall wireless service quality. Hu et al. [103] addressed energy efficiency improvement in UAV-Base Station (BS) access networks with renewable energy sources. They employed ACRL with a Transfer Asynchronous Advantage Actor-Critic (TA3C) algorithm, which facilitated knowledge transfer and enhanced the learning process, reducing energy consumption of UAV-BSs.
Eskandari and Savkin [104] introduced a DRL-based joint 3D navigation and phase shift control for mobile Internet of Vehicles (IoV) assisted by Reconfigurable Intelligent Surface (RIS)-equipped UAVs. They employed the RIS to enhance UAV-assisted communication in 5G and 6G networks, and intelligently automated UAV navigation using DRL for efficient communication in obstructed urban areas.

- **Mobile Edge Computing**
Users on wireless networks can generate large amount of data that can be latency sensitive and computationally intensive. Due to computational and energy limitations, these users' devices may not be able to process the data in a timely manner. MEC is one of the options to solve this problem. Specifically, user-generated data can be transferred to MEC servers, which have greater computing power, for processing. This process is called computational offloading. Wang et al. [105] presented a study on this topic, in which a UAV-assisted computational offloading scheme in a MEC structure is proposed. Li et al. [106] focused on the application of UAVs as mobile edge servers providing computational offloading services to users of a wireless network.
A UAV-assisted MEC structure was proposed by Wang et al. [107], in which several UAVs with different trajectories fly over the target area. This structure aimed to optimize the geographic fairness among the UEs, among the UAVs, and to optimize the energy consumption of all the UEs. Due to relatively small hardware and limited payload capacity, drones have limitations in providing computing and energy resources. Thus, instead of using all resources for each task, Wang et al. [108] proposed a resource allocation algorithm based on RL that allows drones to make task allocation decisions taking into account their energy and computational issues.
In the study presented by Liu et al. [109], they proposed an UAV-assisted MEC network with multiple movable UAVs and a digital twin-empowered GBS. They formulated a resource scheduling problem as a Markov Decision Process (MDP) with multiple types of agents and employed DRL based on Multi-Agent Proximal Policy Optimization (MAPPO) to minimize energy consumption for Mobile Users (MUs) and UAVs, achieving efficient computation offloading.
Hoa et al. [110] proposed a UAV-assisted multi-hop edge computing system where a UEs can offload tasks to multiple UAVs in a multi-hop fashion. They formulated a stochastic optimization problem considering dynamics and uncertainty and introduced a DRL algorithm to optimize task size for offloading, minimizing cumulative energy consumption and latency across nodes.
- **Internet of Things**
UAVs can be effectively used to perform data collection tasks in IoT networks. In the study of Khodaparast et al. [111], an IoT network assisted by several UAVs is proposed. In this network, UAVs fly towards terrestrial sensors and control the transmission power of the sensors during the data collection stage. The main objective of the study was to minimize the total energy consumption of UAVs and sensors during data collection missions. For this, the authors used the DQN and Deep Deterministic Policy Gradient (DDPG) methods.
One of the challenges faced by UAVs is energy consumption. Since drones are typically powered by batteries, their energy capacity is limited, which makes it difficult in scenarios where they are used as aerial base stations in WCN. In order to minimize the total energy consumption of a UAV-IoT system, Zhu et al. [112] formulated a combinatorial optimization problem. For this, the authors relied on DL and DRL approaches, Deep Neural Networks (DNN) and DDPG. Another study that addresses a drone-assisted IoT network is presented by Yu et al. [113], in which the fly-hover-communicate protocol [114] is deployed on a rotary-wing drone responsible for making visits to IoT devices on demand.
Li et al. [115] proposed a learning-based approach using RL to optimize UAV flight trajectories for data collection in IoT networks and minimize information age under energy constraints. Hu et al. [116] presented the Guided Search Deep Reinforcement Learning (GSDRL) algorithm for UAVs to autonomously perform data collection and forwarding tasks with different priorities. Liang et al. [117] focused on multi-UAV-assisted maritime IoT systems, optimizing UAV trajectories, mission modes, transmit power, and association relationships to minimize mission completion time for data collection and offloading.

3) INFRASTRUCTURE

Figure 8 presents the main UAV applications in the Infrastructure area.

- **Civil Construction**
Civil infrastructure projects include building roads, bridges, and other transportation infrastructure, as well as providing clean water and sanitation for cities, towns, and villages. These projects require periodic inspection to ensure the safety of users using the infrastructure. To help overcome the challenges and

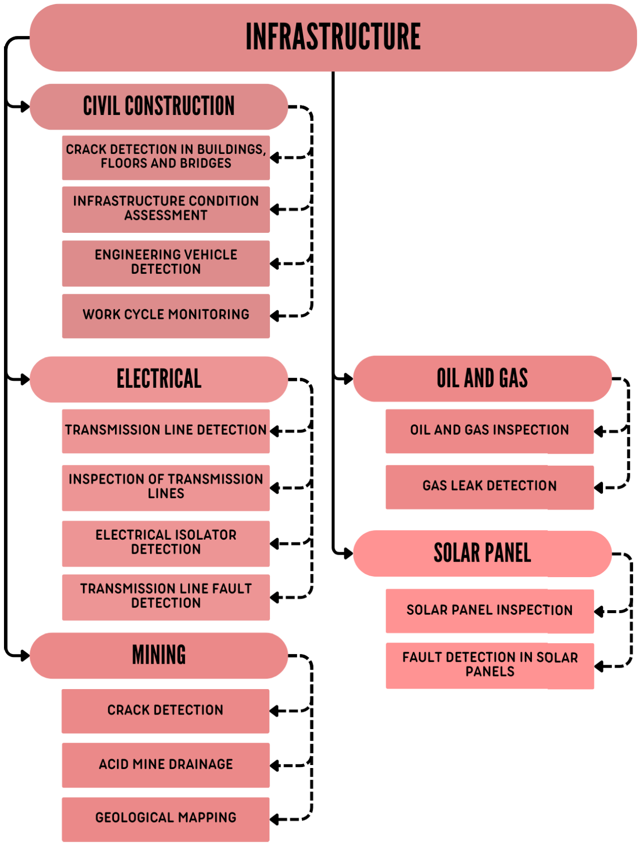

FIGURE 8. Main applications of UAVs in the Infrastructure area.

deficiencies associated with manual inspection of these infrastructures, UAVs can be used.

Some examples of this application can be seen in the studies by Silva and Lucena [118], who developed a ML-based model to detect cracks on concrete surfaces; Pan et al. [119], who made use of multi-spectral images collected by UAVs to distinguish between normal and damaged sidewalks using ML algorithms such as SVM, ANN and RF; Bae et al. [120], who presented an approach based on aerial images to inspect cracks and deformations in buildings; and Yu et al. [121], who proposed a DL-based model on the YOLOv4 method to perform real-time detection of cracks in bridges.

Recognition of engineering vehicles in aerial images is one of the significant tasks that can be assigned to UAVs. They can serve as alerts for reducing accidents involving those vehicles. Zheng et al. [122] proposed a Capsule Networks-based [123] method to recognize engineering vehicles in aerial images collected by UAVs. In order to mitigate the low efficiency and high risks arising from manual inspection of optical cables, Xian et al. [124] proposed an engineering vehicle identification and positioning method.

Another aspect of importance in this area is the monitoring of work cycles of engineering vehicles. UAVs, being flexible and mobile, stands out as a potential tool to collect information. Wu et al. [125] used UAVs and remote sensing to monitor earth-moving excavators at construction sites where monitoring cameras are not available for installation.

Gwon et al. [126] propose an image quality assessment method using a CNN for UAV-based bridge inspection considering various degradation factors. Xing et al. [127] improve the YOLOv5 DL model for UAV pavement crack detection, achieving real-time pixel-level detection with higher accuracy and faster speed. Tavasoli et al. [128] present an autonomous indoor navigation and vision-based damage assessment framework for low-cost nano aerial vehicles, achieving accurate localization of damaged structural components. Choi et al. [129] study the utilization and verification of imaging technology in a smart bridge inspection system, establishing a preliminary framework and applying it to actual bridges.

- **Electrical**

Regular inspection of power grids is essential to ensure both the efficiency and safety. This activity can be considered a major challenge due to the extensive geographical coverage of the grid. Wang et al. [130] explored the automatic detection of transmission line faults from images captured by drones. Their research was divided into two parts, first collected a dataset consisting of images of transmission lines that was labeled manually. Then, they applied the DL, Faster R-CNN, YOLOv4 and Fully Convolutional One-Stage (FCOS) algorithms for transmission line fault detection. Liu et al. [131], also focused on transmission line fault detection, proposed a detection algorithm based on RetinaNet. Yao et al. [132] were based on YOLOv4 for inspection of transmission lines with UAVs. In the scenario of autonomous patrolling, Wu et al. [133] used magnetic sensors on drones and the collected magnetic field data were used to find the relative position between the drone and the transmission lines.

Another component of the power grid that needs regular inspection is the high-voltage insulator. Chen et al. [134] proposed a modified Faster R-CNN model to improve the precision of fault detection in insulators. Based on the traditional Faster R-CNN detection framework, the authors replaced VGGNet-16 with ResNet-50.

In the paper of Alexiou et al. [135] a visual guided navigation method was proposed for UAVs during power line inspections using DL-based image segmentation to extract semantic masks of power lines and generate velocity commands for navigation. Tang et al. [136] present an Internet of Things-based cloud-edge computing infrastructure for defect detection in photovoltaic plants using UAVs with sensors and real-time detection algorithms.

Kuo et al. [137] develop a system using UAVs with thermal and RGB imaging for automatic detection, classification, and localization of defects in large photovoltaic plants. Zou et al. [138] propose an improved lightweight asymmetric CNN for surface damage identification of wind turbine blades using UAVs.

- **Oil and Gas**
  An important application of UAVs in the Infrastructure area is certainly the active monitoring, which can be considered a key point to mitigate risks. Sonkar et al. [139] presented an approach for modeling natural gas pipeline leaks using ML algorithms, such as SVM and ANN, and a drone with a gas sensor and LIDAR sensors.
- **Mining**
  Zhang et al. [140] propose a new method for identifying surface cracks in coal mining areas using ML with UAV images. The method achieves high precision crack extraction with an overall accuracy of 88.99%.
  Kou et al. [141] use UAV technology equipped with an RGB camera to collect very high-resolution images of a stone coal mining area and classify the images using SVM, RF, and U-Net methods to detect Acid Mine Drainage (AMD) distribution. The U-Net method shows significantly better recognition accuracy for AMD compared to traditional ML methods.
  Yang et al. [142] conduct a case study using drone-acquired RGB images for pit wall geological mapping in surface mining operations. They use unsupervised learning algorithms, including convolutional autoencoders, to create cluster maps for geological mapping. The results are promising for simple geological settings, but further optimization is needed for more complex geological conditions.
- **Solar Panel**
  Sustainable practices are important goals for many countries. Solar power generation is an example of such practices and the maintenance of solar panels is an essential task due to natural and mechanical circumstances. Han et al. [143] proposed a DL approach for fault detection in solar panels with YOLOv3-tiny and Long Short-Term Memory (LSTM). For the task of solar panel detection, Díaz et al. [144] compared two methods: one based on classical techniques, such as SVM, and another based on DL, with Mask R-CNN, Fast R-CNN and YOLO, both with a common post-processing step. They concluded that both methods are effective.
  Prakash and Vyas [145] use drone images and ML to calculate rooftop solar energy potential. Through automated ML approaches, they identify suitable rooftops for solar panel installation in a village setting. The models created are compared with manually created ground truth maps to assess their accuracy.

4) SAFETY AND RESCUE

Figure 9 shows the applications of UAVs in SAR.

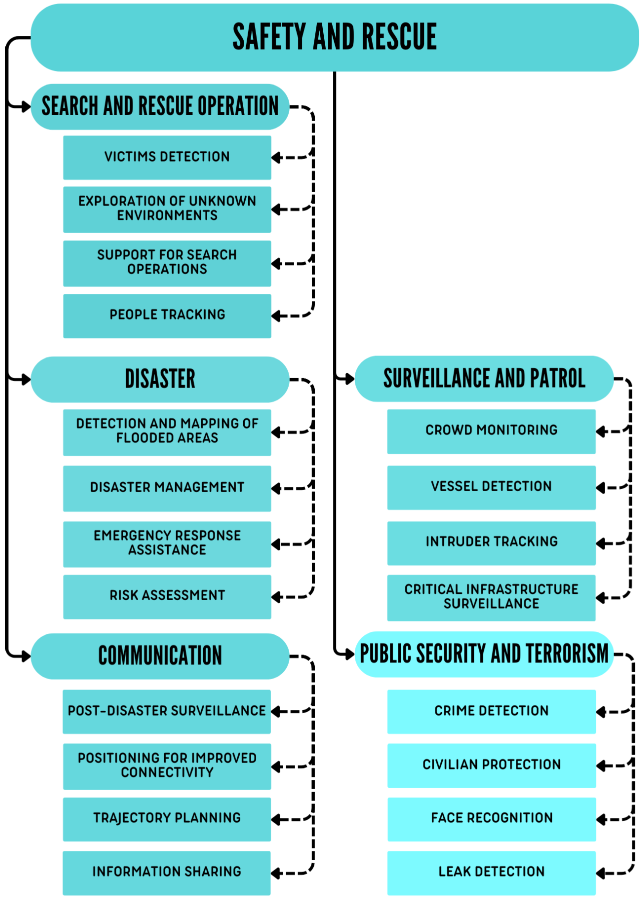

FIGURE 9. Main applications of UAVs in the SAR area.

- **Search and Rescue Operations**
  After a disaster, the first thing a Search and Rescue team does is quickly locate victims in order to minimize the number of lives lost. In these scenarios, UAVs can be used to cover large affected and difficult-to-reach areas to detect victims and assist in their rescue. Sambolek and Ivasic-Kos [146] presented investigations in this area. They compared the performance of DL detectors, such as Faster R-CNN, YOLOv4, RetinaNet, and Cascade R-CNN, on a benchmark called VisDrone and on a custom dataset they created to simulate rescue scenes, named Search and Rescue Image Dataset (SARD).
  Notably, aerial videos hold promise for various applications. However, in a SAR operation, the task of correctly identifying the points of interest, that is, points where there are possibly victims, requires a high attention of the individuals who are carrying out the aerial video monitoring. Kashihara et al. [147] proposed a system to provide a report which presents useful information, that is, the amount of people at the scene, the elapsed time, and the location of the victims. For this purpose, they used a DL approach, YOLO.
  The chance of survival of avalanche victims depends on the time in which they are located and unearthed. With

the advances in drone technology, especially cameras and optical sensors, the location of these victims can be accomplished more quickly and efficiently. A solution to assist in such avalanche search operations was proposed by Bejiga et al. [148], where UAVs equipped with high-precision cameras would fly over the avalanche-hit sites and, by using ML approaches, specifically CNN and SVM, locate the buried victims.

Wang et al. [149] presents a study on visual navigation and control of a cooperative Unmanned Surface Vehicle (USV)-UAV system for marine search and rescue. They develop a deep learning-based visual detection architecture that enhances the accuracy and efficiency of positional information extraction from UAV images.

- **Disaster**

A flood is a natural disaster that causes extensive loss of property, life and income. It is the result of sudden heavy rains causing severe overflowing of rivers and lakes. It can be caused by natural disasters and by man, through hurricanes and landslides. Munawar et al. [150] employed drones in an automated system that identifies flooded areas from aerial images. In a case study, the authors used the Haar Cascade [151] and CNN classifiers to detect landmarks, such as roads and buildings, and also identify flooded areas. One of the challenges that still persist in the use of UAVs in disaster scenarios are adverse weather conditions that negatively influence trajectories and data acquisition from the environment.

A nuclear disaster is a very serious problem for a country. Radioactive contamination can spread over large areas if a malfunction occurs while the system is in operation. This contamination can put both humans and animals living nearby at risk - especially if they eat contaminated food. An example is what happened at the Chernobyl nuclear power plant in 1986, which resulted in contamination of the surrounding territory. Briechle et al. [152] presented a method to detect, using an RF classifier, radioactive waste sites based on a set of features generated from high-resolution remote sensing data collected from drones.

Landslides are geological phenomena with destructive and catastrophic consequences. Recent advances in the field of geographic information allow for the registration and inventory of landslides to be performed through automated workflows using aerial platforms such as UAVs. Karantanellis et al. [153] compared different segmentation and classification approaches for landslide mapping and presented an image analysis workflow that incorporates ortho-photomosaics and digital surface models. The KNN, Decision Tree (DT) and RF algorithms were used to classification task.

Lee et al. [154] introduce WATT-EffNet, a lightweight and accurate model for classifying aerial disaster images using deep learning. The method outperforms the baseline EfficientNet in terms of both accuracy and computational efficiency, making it suitable for resource-constrained UAVs in disaster management scenarios.

Xie [155] explores the application of AI and DL algorithms for target extraction in UAV remote sensing images and compare the performance of Faster R-CNN and YOLOv3 algorithms. Shi et al. [156] proposes a UAV cluster-assisted task offloading model for emergent disaster scenarios. By employing a DRL-based algorithm, they optimize the energy efficiency of UAVs and improve their performance in disaster rescue missions.

- **Surveillance and Patrol**

One objective of autonomous surveillance systems is the detection of anomalies, which alert to unusual situations that may represent some danger. Bozcan and Kayacan [157] presented, using DNNs, an anomaly detection system for surveillance of critical infrastructure (i.e. airports, ports and warehouses) using UAVs.

One sector in which security is paramount is the maritime, where the safe navigation of ships is of great importance, especially in congested ports and lanes. The focus of Sejersen et al. [158] was to help ships in their navigation, mainly in ports. The authors used UAVs and ML algorithms to estimate the distance between an object of interest and potential obstacles. Zhao and Li [159], aiming to improve the efficiency of sea surface supervision, proposed a ship detection algorithm based on aerial images using YOLO and R-CNN.

Another application of UAVs in the surveillance subarea is crowd monitoring, which plays an important role in ensuring security in public areas. Bisagno et al. [160] presented a decentralized approach for reconfiguring a network of cameras, where each camera dynamically adapts its parameters and position based on UAVs and DL. The purpose of this approach is to increase and optimize the coverage of a scene where there is a crowd of people.

In the paper of Kothandaraman et al. [161] a learning algorithm called Differentiable Frequency-based Disentanglement for Aerial Video Action Recognition (DifFAR) is presented for human activity recognition in UAV videos. DifFAR simultaneously combines frequency domain representations with data-driven neural networks to model salient static and dynamic pixels in the video, crucial for action recognition.

- **Public Security and Terrorism**

Gun violence is a big problem around the world. Gun deaths are strongly present in most major cities. This led Salla et al. [162] to develop an UAV piloting system and bullet-stopping called EDNA, which is a drone that features automated real-time analytics that help teams make the right decisions in situations where gun violence may occur.

Video surveillance is an essential tool for keeping people safe in public places. UAVs have advantages in monitoring large areas and especially areas that are difficult to access. In this context, Bouhlel et al. [163] presented a DL based approach for identification of suspicious persons using data collected by sensors attached to a UAV.

Nguyen et al. [164] propose a novel real-time violence detection system for drone surveillance in their paper. They use DL techniques and achieve high accuracy with fast processing speed, making it suitable for monitoring systems that require rapid deployment and object tracking. The paper by Wagner et al. [165] introduces a data-driven ML algorithm for small target detection in a radar surveillance system. The approach shows better detection rates with low false alarm rates compared to traditional background subtraction methods, especially when applied to real data from drones and persons.

Huang et al. [166] present a railway intrusion detection method for UAV surveillance scenes. Their proposed network employs a Fused-ConvLSTM module, attention modules, and lightweight strategies to accurately detect railway intrusion events in aerial videos without pre-setting the intruding object type. In the paper by Othman and Aydin [167], a novel lightweight CNN model called HarNet is developed for human action recognition in UAV-captured videos. The model achieves a high success rate of 96.15% in classification on the UCF-ARG dataset, outperforming other DL models such as MobileNet, Xception, and VGG-19.

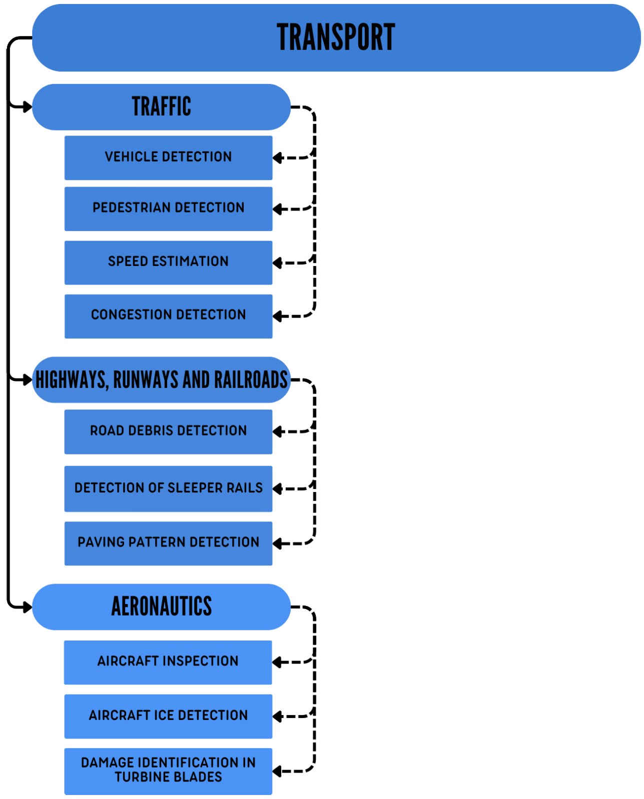

FIGURE 10. Main UAV applications in the transport area.

5) TRANSPORT

Figure 10 contains the main UAV applications in the Transport area.

- **Traffic**

  With the increasing traffic flow on highways, there is a great need for traffic monitoring. The use of drones for traffic monitoring has many advantages, such as a wider field of view, greater mobility capability, and no impact on the detected traffic. Akshatha et al. [168] proposed a car detection system in aerial images collected from UAVs based on DL techniques, specifically, YOLOv3 and FCOS. Benjdira et al. [169] investigated the performance of two CNN approaches, namely, Faster R-CNN and YOLOv3; Ammour et al. [170] presented an automatic solution for vehicle detection and counting using CNN and SVM. Based on YOLOv3, Luo et al. [171] focused on developing a fast method for automatic vehicle detection in UAV images. Another important issue in traffic is pedestrian detection. Oliveira and Wehrmeister [172] evaluated different implementations of pattern recognition systems whose objective was the automatic detection of pedestrians in aerial images captured with a multirotor UAV. The main objective was to evaluate the viability and suitability of different implementations running on low-cost computing platforms, for example, single board computers like Raspberry Pi or ordinary laptops without Graphics Processing Unit (GPU).

  Population growth has caused an increase in road usage, which in turn results in increased traffic congestion. In this context, Utomo et al. [173] proposed a vehicle detection and road density classification system using video streaming with fixed-wing UAVs. Jian et al. [174] examined how UAVs combined with CNNs could be used to recognize traffic congestion.

  In the study of Bala and Verma [175] a self-sufficient drone tracking and identification system is proposed using a stationary beam profile and a movable turret camera. The combined multi-frame ML detection approach allows for cost-effective identification of small-sized aerial invaders in both the main picture plane and the magnified image plane. Li et al. [176] introduce a Cognitive UAV (CUAV) assisted network for offloading traffic under uncertain spectrum environments via DRL. They jointly design the trajectory, time allocation, band selection, and transmission power control to maximize energy efficiency and propose a model-free DRL solution to achieve the best decision autonomously.

  Alharbi et al. [177] present a DL architecture for UAV traffic-density prediction, specifically for Unmanned Aircraft Traffic Management (UTM). Their approach utilizes a one-dimensional CNN and encoder-decoder LSTM framework with an adapted complexity metric to account for dynamic flow structures and airspace density in UTM operations. Naranjo et al. [178] develop an object detection-based system for traffic signs on drone-captured images to improve road element inventories in civil infrastructures. They use DL methods, specifically Faster R-CNN, to accurately detect and geo-reference different traffic signs from RGB images captured by a drone's onboard camera.

- **Highways, Runways and Railroads**
  The condition of road pavement is an important factor in reducing road accidents. Road monitoring, often done through visual and instrumental inspections, must occur on a recurring basis to mitigate risks. Garilli et al. [179] analyzed two supervised classification approaches, Semi-Automatic Classification Plugin (SCP) and a CNN, based on images collected by UAVs, to detect the pavement pattern. Papadopoulos and Gonzalez [180] presented a detection method to locate road debris using a UAV flying at low altitude.
  Railway track sleepers are the components responsible for maintaining the distance between the rails, as well as holding them together and serving as support. Frequent monitoring of the ties ensures better condition of the railroad, which in turn ensures the safety of cargo and passengers. Singh et al. [181] explored a YOLOv4-based object detection model for railroad ties detection in low altitude images captured by UAVs. Mammeri et al. [182] investigated the effectiveness of a fully convolutional encoder-decoder type segmentation network, U-Net, for the task of segmenting railroad track regions.
- **Aeronautics**
  Inspection of aircraft surfaces is critical for safe flight. In order to improve the efficiency of inspections, He et al. [183] designed a UAV system to collect aircraft surface images and used DL based object detection algorithms, RetinaNet and R-CNN, for aircraft surface inspection. Another critical issue for aircraft flight safety is ground deicing operations. In this context, Musci et al. [184] proposed a project called Spectral Evidence of Ice (SEI), whose goal was to provide tools for identifying ice on aircraft surfaces to ensure faster deicing fluid application operation.

6) HEALTHCARE

Figure 11 presents the main applications of UAVs in Healthcare.

- **Pandemic**
  Coronavirus 2019 (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus that can spread by the mouth or nose of an infected person. Since it is a disease with a high degree of spread, rapid testing is important to support the assessment of the immune

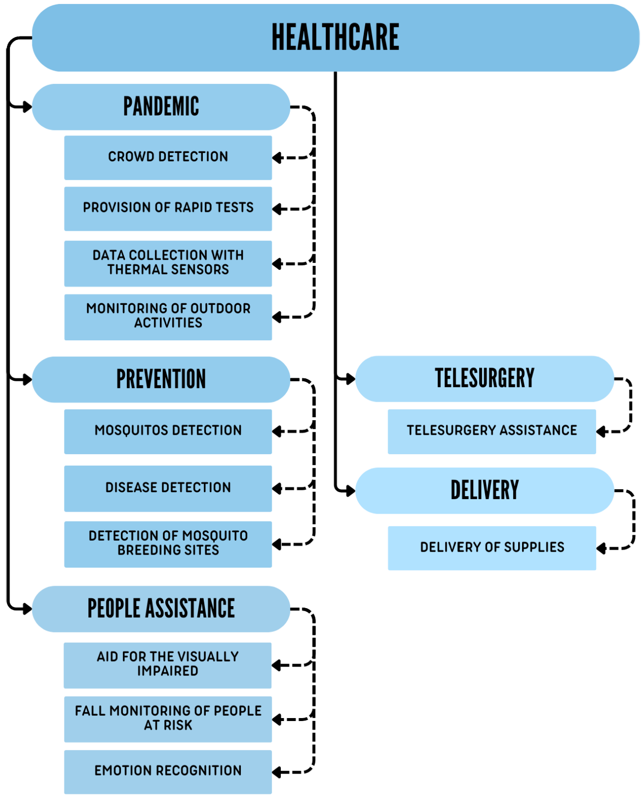

FIGURE 11. Main applications of UAVs in Healthcare.

  status of patients with symptoms and to prevent further contagion. Naren et al. [185] presented a prototype that integrates DNNs and UAVs to assist in the provision of rapid tests and medical assistance. Barnawi et al. [186] proposed a scheme based on IoT and UAVs to collect data from thermal sensors. The captured thermal images were used to determine people with high potential to be contaminated with COVID-19.
  UAVs can also be used to monitor public events to ensure compliance with health policy and trigger alerts when they notice anomalies. Masmoudi et al. [187] presented a framework for monitoring outdoor activities. They proposed a three-step approach: (1) analyzing the images collected by the UAVs using ML to locate and detect individuals; (2) mapping coordinates to assess the distances between individuals and group them; and (3) providing a trajectory for the UAV considering energy efficiency to enable inspection of more areas for health policy violations.
- **Prevention**
  Mosquitos are one of the main vectors of virus transmission in developing and underdeveloped countries. UAVs can be used as a technological tool by health surveillance teams to combat mosquito breeding grounds where vector-borne diseases such as dengue, zika, chikungunya or malaria are endemic. Britez et al. [188] presented the use of a UAV for image collection in

an urban environment and a CNN (more specifically, Single-Shot Detector (SSD) Mobile Network V2) for tire image detection. Bravo et al. [189] also proposed computational approaches for detecting objects and scenarios suspected to be potential mosquito breeding grounds from aerial images acquired by drones.

- **People Assistance**
  The Seeing Eye Drone by Grewe and Stevenson [190] is a drone whose goal is to assist people with low vision in perceiving the environment by performing exploration and obstacle detection. Iuga et al. [191] presented an app that uses a UAV for monitoring and detecting falls of people at risk. In it, the position and state of the person are determined with computer vision based on DL techniques.
  For monitoring people with specific needs in their own homes, Martínez et al. [192] presented a system capable of detecting the current emotional state of the person and triggering assistance if necessary. They presented a virtual reality platform where an avatar (i.e. the virtual representation of the individual) is monitored by an autonomous rotary-wing UAV.
- **Telesurgery**
  UAVs can provide flexible and mobile communication networks, which can be considered a great potential for telesurgery or robotic surgery applications. However, some challenges are still present in these systems, such as security and transparency. Motivated by these challenges, Gupta et al. [193] proposed a telesurgery system called Blockchain and AI-empowered Drone-assisted Telesurgery System (BATS), which is a self-managed, secure, transparent and reliable blockchain and ML enabled system with 6G UAV-assisted networks.
- **Delivery**
  The delivery of small loads via UAVs can be used for social distancing maintenance, one of the preventive actions against the dissemination of transmissible disease, such as COVID-19. Cheema et al. [194] explored the delivery of medical products via drones. They used SVM as a ML approach to detect intrusions and blockchain-based authentication aiming to increase the security of the proposed system.

7) SMART CITIES

Figure 12 presents the main UAV applications in the Smart Cities area.

- **Delivery**
  Delivery increased in recent years, especially with the COVID-19 pandemic, in which face-to-face social interaction had to be reduced. UAVs, as aerial vehicles, can deliver small cargo, such as food, medicine and other supplies. For tasks where the delivery time is short, UAVs need to have the ability to quickly navigate between environments and keep the cargo intact. Faust et al. [195] presented a RL approach for air cargo delivery tasks in environments with static obstacles. While the use of UAVs for deliveries can help the increase of the speed and accuracy of this activity, UAVs still suffer from capacity scaling issues and limitations of their loads.
  Yadav and Narasimhamurthy [196], on the other hand, addressed the problem of computing an optimal delivery schedule in a drone delivery system. The problem consisted of a set of orders, composed of a list of items, with the quantity to be delivered to customers with known locations. Bacanli et al. [197] generated a synthetic dataset for the scenario where drones are used to send packages between two neighborhoods.
  In the paper of Luo et al. [198], a framework called KeepEdge is presented for visual information-assisted positioning in UAV delivery services. They integrate DNN into an edge computing framework to enable edge intelligence and use knowledge distillation to produce a lightweight model with high accuracy for onboard UAV positioning.
- **Data gathering**
  Data produced by aerial surveillance systems, such as UAV networks, need to be transferred to ground stations so that reliable analysis can be performed. Based on this need, Lee et al. [199] proposed a Deep Learning based Optimal Auction (DLA) algorithm to collect aerial surveillance data considering the high mobility and flexibility existing in UAV networks.
  Focusing on the UAV assisted Mobile Crowd Sensing (MCS) scenario, Gao et al. [200] proposed a task

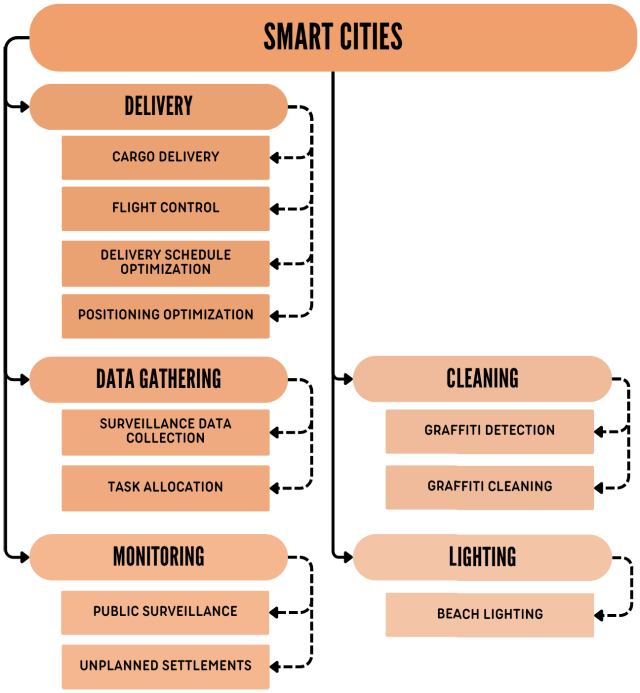

FIGURE 12. Main UAV applications in the Smart Cities area.

allocation method called UAV-assisted Multi-task Allocation (UMA). The goal was to jointly optimize sensing coverage and data quality.

Fan et al. [201] propose an RIS-Assisted UAV system for fresh data collection in 3D urban environments. They utilize a RIS to mitigate signal propagation impairments caused by building blockages and minimize the Age of Information (AoI) of Internet-of-Things Devices (IoTDs) collected by the UAV using a DRL approach called "SAC-AO-RIS."

In the study by Mondal et al. [202], the energy efficiency maximization problem is addressed for UAV-assisted wireless communications. DRL based on a DDPG algorithm is used to optimize user associations, transmit power allocations, and UAV trajectories, achieving a 15.63% improvement in total energy efficiency compared to the benchmark approach.

- **Monitoring**
  Closed Circuit Television (CCTV) is an image capture and retention system consisting of digital or analog cameras that enables video surveillance. Drones can be considered as one of the key technologies to increase the capacity of these systems in a smart city environment. Yun et al. [203] analyzed a scenario in which UAVs, with CCTV cameras attached, flew over a city area collecting images to assist surveillance services. Gevaert et al. [204] described a framework that takes advantage of high-resolution images and UAVs to detect changes in unplanned settlements.
- **Cleaning**
  Graffiti makes up the urban landscape of contemporary cities and can be considered as a pervasive problem in many cities. Wang et al. [205] surveyed a ML approach, with SSD and MobileNet, for graffiti detection and removal with UAVs. Nahar et al. [206] presented an intelligent graffiti cleaning system based on edge detection and ML algorithms to perform real-time detection of graffiti in images.
  Masuduzzaman et al. [207] propose an automated and secure garbage management scheme using Unmanned any Vehicle (UxV) integrated with DL models for garbage detection. They develop a lightweight DL model using MISH and rectified linear unit activation functions for garbage detection. Additionally, they incorporate multiaccess edge computing for improved Quality of Service (QoS) and a blockchain-based technique for secure hazardous garbage tracking.
- **Lighting**
  The beach is one of the most visited tourist attractions. Most beaches are less crowded at night due to lack of lighting. With the help of DL and wireless communication, UAVs can be used to overcome this problem. Shirbhate and Das [208] present a proposal that uses CNNs for obstacle detection with OpenCV, a library for developing applications in the field of computer vision. Thus, UAVs can be used for both static lighting, where they remain stationary, and dynamic lighting, where they can move by dodging obstacles.

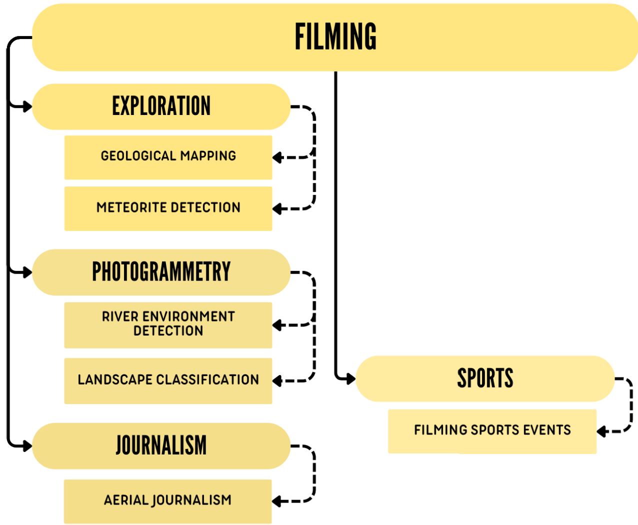

FIGURE 13. Main UAV applications in the Filming area.

8) FILMING

Figure 13 presents the main UAV applications in the Filming area.

- **Exploration**
  Geological mapping is a type of investigation whose purpose is to identify rocks, deformations, faults, fractures, and other information about the surface of the explored area. Geological mapping is an important support for exploration missions. In this context, Sang et al. [209] proposed a method for high-resolution geological mapping using UAVs and DL algorithms. AlOwais et al. [210] presented an automated meteorite detection system that employs an autonomous UAV programmed to recognize and locate meteorites using CNN.
- **Photogrammetry**
  Photogrammetry can be defined as the science of extracting from photographs the shape, features, dimensions, and position of objects contained therein. Photogrammetric technologies in conjunction with ML techniques can enable a better understanding of environmental and atropic issues. Meng et al. [211] presented an object-oriented classification ensemble algorithm to extract information from aerial imagery, such as height and texture, to improve landscape classification and terrain estimation.
  Zefri et al. [212] present a two-layer solution for inspecting large-scale photovoltaic arrays using aerial LWIR multiview photogrammetry and DL. Layer 1 generates a georeferenced orthomosaic, and Layer 2 performs tile-based deep semantic segmentation to detect overheated regions on PV arrays. The

FPN-DenseNet121 model achieves the best performance with a mean mIoU of 93.44% and F1-score of 96.39%.

Fiorillo et al. [57] propose a fast UAV photogrammetry-based methodology to quantify roof damage in historic buildings after a light seismic event. The automated mapping using supervised machine learning image classification and a combination of 3D survey techniques provides comprehensive documentation and quantitative data on historical buildings.

- **Journalism**
  In the recent digital age, information and communication technologies are rapidly changing the media and journalism industry. The media industry can use many techniques to capture news or events, produce breaking news clips and photos. Thus, the term aerojournalism was born, which refers to the ability to create and deliver media content in a timely and efficient manner through aerial devices. Almalki et al. [213] integrated a drone with ML to enable aerojournalism by training a neural network using the Radial Basis Function Network (RBFN) approach.
- **Sports**
  An important problem in ML is training good quality models using small datasets. One approach that can be used in such cases is few-shot image learning, whose goal is to use a small amount of training examples to train a model capable of recognizing a certain number of classes. In this context, Patsiouras et al. [214] investigated the behavior of Few-Shot Learning (FSL) methods in the cinematic scenario for filming sports events with UAVs. More specifically, they applied FSL methods to recognize the leader of a cycling race using only a few images of him.

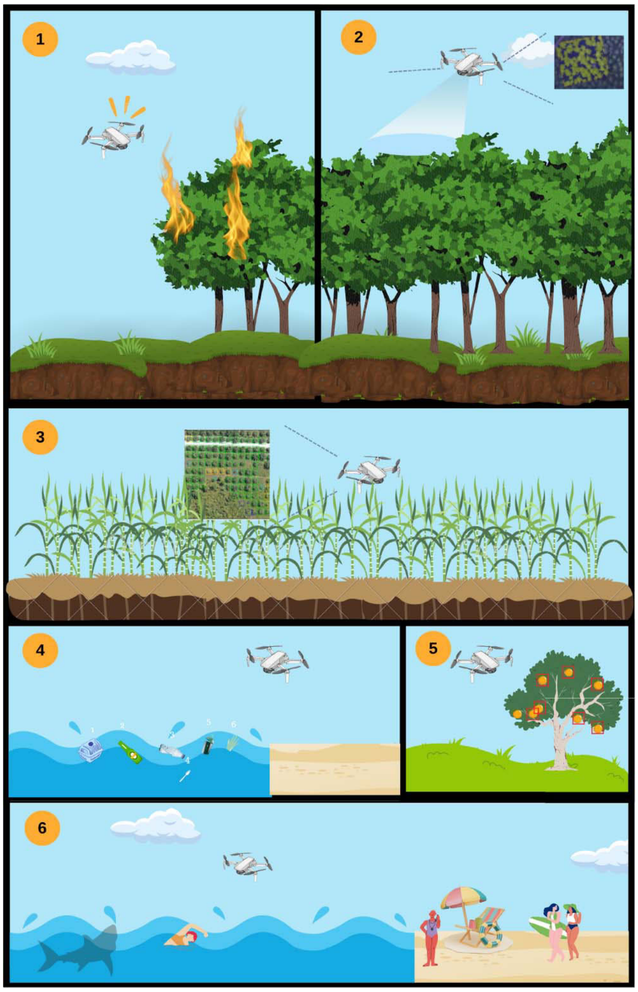

FIGURE 14. UAVs incorporated into systems of environment applications.

C. UAV-BASED APPLICATIONS

To answer RQ3, this section presents how UAVs are incorporated into systems for real-world applications. Contextualized figures are provided for each of the seven areas: Environment, Communication, Infrastructure, SAR, Transport, Smart Cities, Healthcare and Filming. Each figure presents a list of drone's primary function within that specific context.

Figure 14 presents examples of how UAVs are used within environment applications.

Functions of UAVs in applications:

- Context 1: A human-operated drone is utilized to fly over forested areas, capturing images that serve multiple purposes. The captured images aid in fire detection, helping firefighters to identify potential fire outbreaks promptly.
- Context 2: UAVs are utilized for forest mapping, providing valuable data that aids in the management and control of forest ecosystems.
- Context 3: Monitoring the status of large plantations can be efficiently conducted using UAVs, which can fly over vast areas swiftly and without causing any damage.
- Context 4: A remotely controlled drone is deployed for sea missions, conducting searches and counting of marine debris. These operations are efficiently performed using ML algorithms, which enable the drone to autonomously identify and quantify the presence of marine debris in the sea.
- Context 5: The UAV is remotely controlled to fly over target agricultural areas. Equipped with high-resolution sensors, it captures detailed images, which are processed using DL algorithms. These algorithms analyze the images to estimate crop yield, measure the size of plants or fruits, and perform accurate counting.
- Context 6: The UAV conducts sea surveillance to detect potential threats to bathers, specifically focusing on sharks [215]. Upon identifying a potential threat, it promptly alerts the bathers to ensure their safety.

Figure 15 presents examples of how UAVs are used within communication applications.

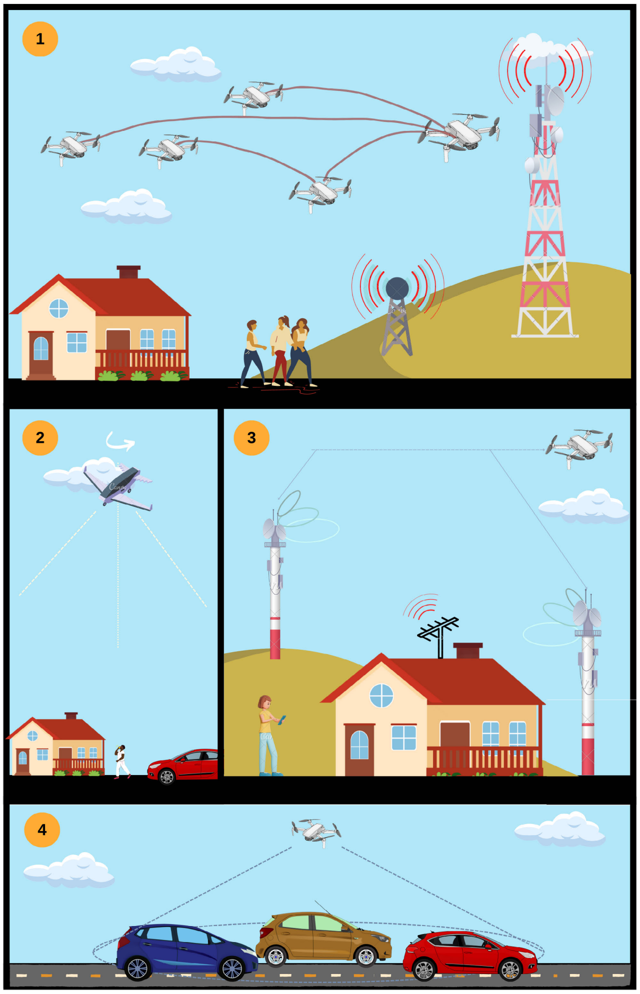

FIGURE 15. UAVs incorporated into systems of communication applications.

Functions of UAVs in applications:

- Context 1: In the context of this application, the UAV functions as a mobile access point, acting as a base station to provide wireless network connectivity in remote areas or emergency situations. Its ability to fly and be easily relocated allows for more flexible and adaptable coverage, particularly in regions where terrestrial infrastructure is limited or non-existent.
- Context 2: The UAV is equipped with cellular communication technology and acts as an airborne base station, providing network connectivity to mobile devices such as smartphones and tablets in a specific geographic area. Its strategic flight at selected altitudes and locations expands network coverage and improves service quality in hard-to-reach or dynamically changing areas. The UAVs main function in this application is to optimize the energy efficiency of cellular access points.
- Context 3: UAV serves as an aerial access point, facilitating communication between mobile devices and the Internet, particularly in environments with terrestrial obstacles or limited communication infrastructure. Its main function in this application is to enhance the reliability of aerial mobile communications. Using prediction models of Received Signal Reference Power (RSRP) and Reference Signal Received Quality (RSRQ), the UAV can anticipate and optimize signal conditions for connected devices, ensuring a stable and high-quality connection.
- Context 4: The UAV acts as a flying access point equipped with mmWave technology, providing high-frequency communication to support high data transfer rates. Using computer vision, the UAV detects and tracks moving ground vehicles, allowing for the adjustment of mmWave beamforming to direct the communication signal straight to the vehicles.

Figure 16 presents examples of how UAVs are used within infrastructure applications.

Functions of UAVs in applications:

- Context 1: The main function of the UAV in this application is to provide an aerial platform for inspecting power transmission lines. Flying close to the structures, the UAV captures images that are analyzed by the enhanced DL models, accurately detecting faults in the insulators, such as cracks or wear. This application is valuable for preventive maintenance and energy efficiency.
- Context 2: The main function of the UAV in this application is to provide a mobile platform for efficient and accurate detection of dense construction vehicles. By flying over urban areas, the UAV collects visual data that are processed by DL algorithms, enabling the identification of dense construction vehicles even in complex and densely populated environments.
- Context 3: The function of the UAV in this application is to provide an efficient aerial platform for the early detection of faults in solar panels. Flying over solar installations, the UAV can conduct comprehensive and fast inspections, enabling maintenance teams to identify and address issues such as hot spots, micro-cracks and oxidation.
- Context 4: The UAV serves as an aerial platform capable of conducting detailed inspections on different types of infrastructure. It flies over the structures and collects visual data to be processed by DL algorithms.
- Context 5: The UAV is equipped with cameras and sensors that capture high-resolution images of the transmission lines and surrounding areas. Through the use of deep learning algorithms, the UAV can analyze the images and identify patterns that indicate the presence of bird nests on the transmission line structures.
- Context 6: The UAV provides a privileged aerial view and secure access to hard-to-reach areas for humans. This aerial inspection enables the early detection of damages and corrosion, allowing infrastructure authorities and maintenance teams to take corrective measures

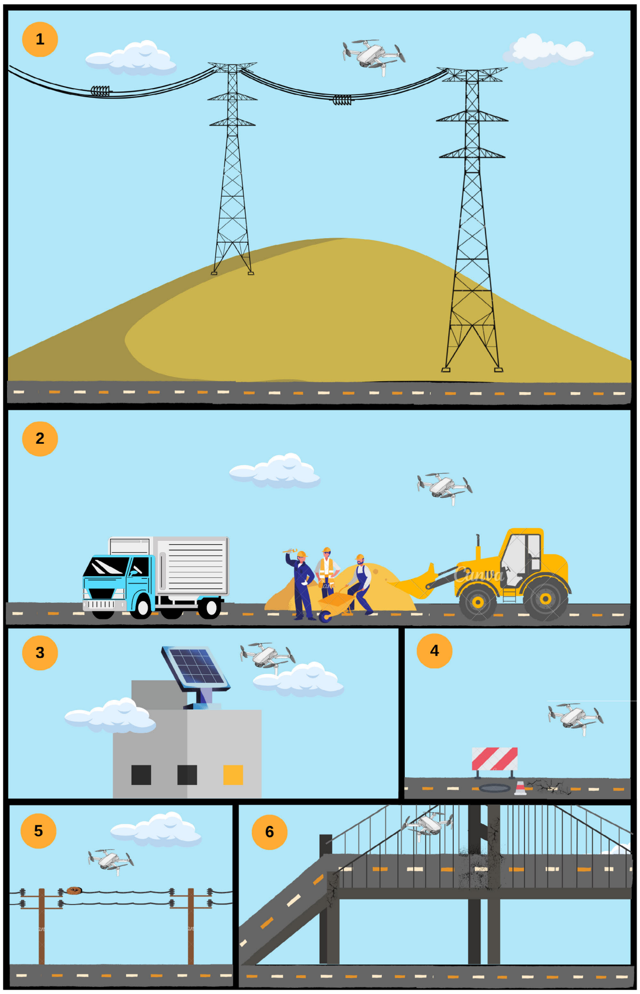

FIGURE 16. UAVs incorporated into systems of Infrastructure applications.

FIGURE 17. UAVs incorporated into systems of SAR applications.

before problems worsen and compromise the safety and functionality of the structures.

Figure 17 presents examples of how UAVs are used within SAR applications.

Functions of UAVs in applications:

- Context 1: In this application, the refined analysis of landslide susceptibility is carried out based on Interferometric Synthetic Aperture Radar (InSAR) technology and data from multiple UAV sources. The UAVs act as aerial platforms to collect detailed images and geospatial data from different perspectives, enabling a comprehensive view of the areas of interest.
- Context 2: The UAV, aided by the DL method, can fly over urban areas and capture images that will be analyzed to warn of possible anomalous situations, such as suspicious activity, strange objects or unusual behavior.
- Context 3: The drones perform quick and detailed assessments of areas affected by climate change, using AI to identify patterns and issues related to climate change. This application is extremely valuable in climate crisis situations, such as natural disasters, droughts, floods, and forest fires.
- Context 4: The main function of the UAV in this application is to provide a privileged aerial view, enabling early and rapid detection of individuals in emergency or disaster situations. Through the use of AI techniques, such as DL, the UAV processes the collected images and identifies patterns that may indicate the presence of human beings.

Figure 18 presents examples of how UAVs are used within Transport applications.

Functions of UAVs in applications:

- Context 1: In this application, the function of the UAV is to provide an aerial platform for capturing images at low altitudes, enabling precise segmentation of instances of railway track sleepers.
- Context 2: The UAV flies over the area of interest and captures high-resolution images to enable the pedestrian detection model to locate potential pedestrians. The images are later stored and transmitted for processing on the ground, where the model is executed. Compression

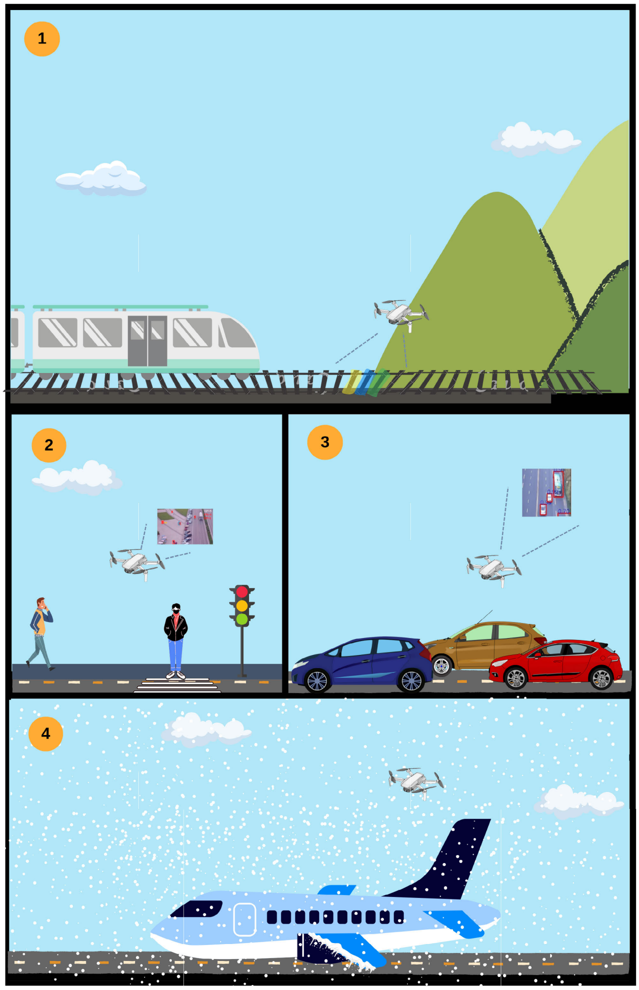

FIGURE 18. UAVs incorporated into systems of Transport applications.

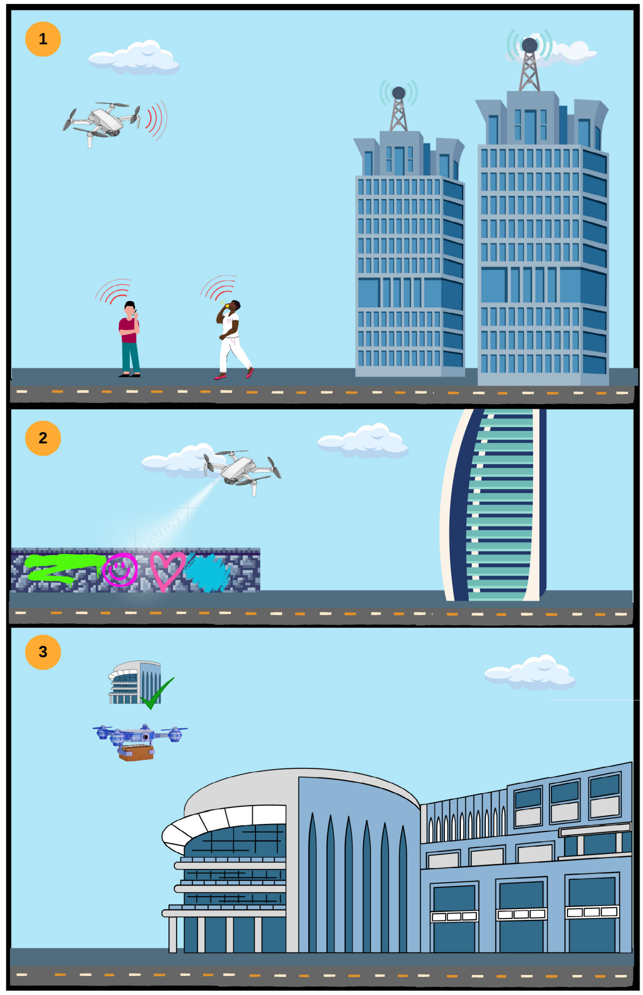

FIGURE 19. UAVs incorporated into systems of Smart Cities applications.

technology is used to reduce the size of image data, facilitating efficient storage and transmission.

- Context 3: The UAV captures images that are processed by a CNN specialized in detecting vehicles. As the UAV flies, the images are transmitted in real-time to a computer on the ground, where the CNN analyzes and identifies the presence of vehicles, marking their positions in the images.
- Context 4: In this application, the UAV has the function of collecting hyperspectral and multispectral images of the surface of aircraft. The images are processed using ML techniques to detect the presence of ice on the aircraft's surface.

Figure 19 presents examples of how UAVs are used within Smart Cities applications.

Functions of UAVs in applications:

- Context 1: With the assistance of the UAV, it is possible to obtain a privileged and comprehensive aerial view of the area, allowing for more efficient and accurate detection of moving crowds. Multitask allocation refers to the UAV's ability to perform multiple detection tasks simultaneously, enabling broader coverage and a rapid response to events or situations involving mobile crowds.
- Context 2: In this application, the UAV acts as an autonomous system to detect and remove graffiti in hard-to-reach areas. The UAV flies over the affected surfaces, such as walls and facades, and captures images of these areas.
- Context 3: In this application, the UAV is used in conjunction with an edge intelligence framework to perform visual-assisted positioning in item delivery. The UAV is responsible for flying to the delivery locations, while the edge intelligence framework provides support for real-time data processing and analysis.

Figure 20 presents examples of how UAVs are used within Healthcare applications.

Functions of UAVs in applications:

- Context 1: In this application, the function of the UAV is to act as a means of communication and transportation to enable remote-assisted tele-surgery. The UAV is used to transmit data, such as images and medical information,

FIGURE 20. UAVs incorporated into systems of Healthcare applications.

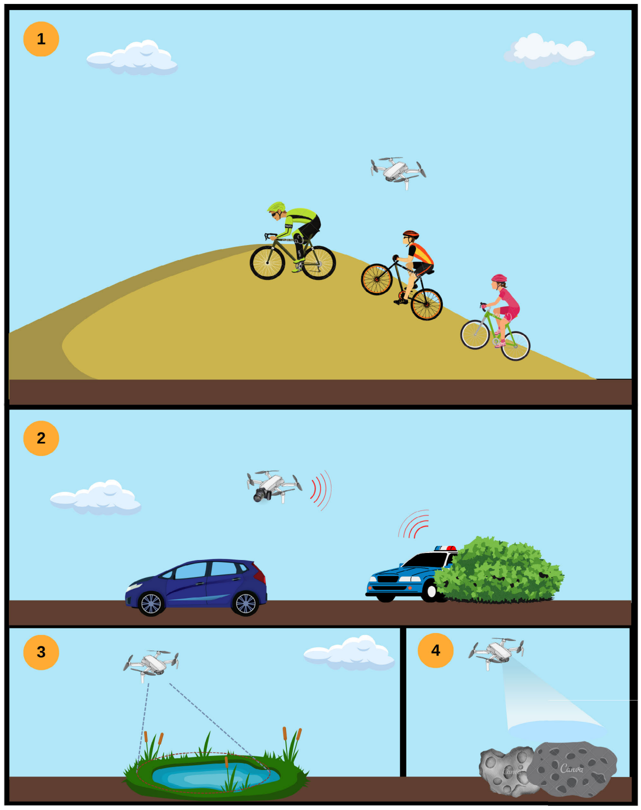

FIGURE 21. UAVs incorporated into systems of Filming applications.

between the medical team and the patient during the surgical procedure.

- Context 2: In this application, the function of the UAV is to provide an aerial platform for acquiring aerial thermal images. The UAV is used to fly over areas and collect thermal images of people and environments. These images are subsequently processed by an IoT and AI based system to perform COVID-19 screening.
- Context 3: The UAV flies over crowded areas and collects images to detect and count crowds of people. Through the use of DL algorithms, the UAV is capable of recognizing and distinguishing people at different distances, enabling accurate crowd detection in various scenarios, such as public events, protests, or emergency situations.
- Context 4: In this application, the function of the UAV is to perform the secure delivery of medical supplies. The UAV is used to transport medicines, medical equipment, and other essential items quickly and efficiently to hard-to-reach areas or during emergency situations.
- Context 5: The UAV flies over rural areas and collects health data, such as thermal images and vital signs of people. These data are transmitted to a medical center where they are analyzed by the DNN-based system to identify potential cases of Covid-19. This approach allows for fast and remote screening in hard-to-reach areas, contributing to early detection and control of the virus spread in rural communities.
- Context 6: In this application, the function of the UAV is to act as an assistant to visually impaired individuals with mobility. The UAV is equipped with vision-based technology and DL, enabling it to detect obstacles and provide real-time information to help visually impaired individuals navigate safely in outdoor environments.

Figure 21 presents examples of how UAVs are used within Filming applications.

Functions of UAVs in applications:

- Context 1: In this application, few-shot image recognition is used to enhance sports cinematography performed by UAVs. The system can identify and track athletes and moving objects, enabling more dynamic and immersive cinematography during sports events.
- Context 2: In this application, the use of UAV in conjunction with AI aims to empower smart journalism through the optimization of an information dissemination model. The UAV is deployed to gather data from hard-to-reach or journalistically significant locations.

With the aid of AI, this data is processed and analyzed to provide relevant and accurate information to journalists, enabling more comprehensive and up-to-date news coverage. This combination of technologies enhances the capacity for news production, offering the public more comprehensive and contextualized information.
- Context 3: In this application, the use of UAVs in conjunction with ML systems aims to perform bathymetric detection in river environments. The UAVs fly over the river areas and collect remote sensing data, such as images and depth data of the water bodies.
- Context 4: In this application, UAVs are used in conjunction with DL to carry out meteorite hunting. The UAVs fly over specific areas and capture detailed images, which are analyzed by DL algorithms to identify potential meteorites. This approach enables a more efficient and accurate search for meteorites in remote and hard-to-reach areas.

D. DATASETS OVERVIEW
To answer RQ4, a search was carried out among the selected studies for dataset used and available. For some areas and applications addressed in this paper, no avaliable datasets was observed in our research. The most used datasets for ML applications in Environment, Communication, Infrastructure, SAR, Transport and Helthcare are presented in Table 3.

E. MACHINE LEARNING TECHNIQUES OVERVIEW
To answer RQ5, Figure 22 presents the five most commonly used ML techniques in the selected studies. Other applications have used CNN-based techniques, but the authors have not provided information on the specific approach used, and for this reason they are not shown in 22. In general, CNN-based ML techniques are the most widely used in the aforementioned scenario. Some of these CNN-based applications are: Classification of Agricultural Crops [276], Classification of Constructions [277], [278], Tree Count [279], Trees Detection [280], [281], [282], [283], Victim Detection [284], [285], [286], [287], Cattle Detection [288], [289], Plant Disease Detection [290], [291], [292], Fault Detection [293], [294], [295], [296], Weed Detection [297], [298], [299], Bridge Inspection [300], [301], [302], [303], [304], Maturity Estimate of Plantations [305], Vegetation Coverage Mapping [306], Vegetation Cover Monitoring [307], Electrical Insulator Monitoring [308] and Trajectory Planning [309].

1) YOU ONLY LOOK ONCE (YOLO)
YOLO is a single pass method that uses a CNN as a feature extractor. Instead of selecting the interesting part of an image, it predicts classes and bounding boxes for the entire image in just one run of the algorithm. Due to this feature, YOLO is able to achieve a higher detection speed than techniques such as R-CNN or Faster R-CNN [310]. As shown in Figure 22, Classification of Maturity of Plantations [311], Fruit Count [312], [313], Tree Counting [279], Land Vehicle Count [314], Aquatic Animal Detection [215], Garbage Detection [315], [316], [317], Plant Detection [318], [319], [320], Plant Disease Detection [321], Vehicle Detection [322], [323], Victim Detection [253], Yield Estimate [324], Inspection of Transmission Lines [325], Traffic Monitoring [326], Recognition Electrical Equipment Recognition [327] and Engineering Vehicle Recognition [328] are some of the applications related to the Detection, Recognition or Counting tasks.

2) FASTER R-CNN
Faster R-CNN is one of the methods that can be used for object detection. It consists of two components: a fully convolutional Region Proposal Network (RPN) to propose candidate regions, followed by a Fast R-CNN classifier [329]. Some applications of Faster R-CNN, are shown in Table 22: Classification of Maturity of Plantations [330], Bird Counting [331], Plant Count [63], Plant Detection [332], [333], Victim Detection [334], Plant Disease Detection [335], [336], [337], Fire Detection [91], Weed Detection [337], Marine Debris Detection [316], Vehicle Detection [169], Landslide Detection [338], Estimated Amount of Woody Debris [339], Road Traffic Monitoring [340], Estimated Number of Trees [341] and Person Re-identification [342].

3) SUPPORT VECTOR MACHINE (SVM)
SVM was developed based on the idea of a hyperplane that best separates two classes, dot-product convolution operations to handle non-linear problems, and the notion of soft margins to find the hyperplane with the fewest possible errors in the training set. The data points of the classes nearest to the hyperplane are called support vectors [343]. Some applications related to this technique can be seen in Table 22, such as: Crack Detection [140], [344], Weed Detection [345], Monitoring of Plantations [346], [347], [348], Pest Monitoring [349], [350], Vegetation Classification [351], [352], [353], Water Quality Classification [354], Plantation Yield Estimation [355], [356], [357], [358] and Estimation of Chlorophyll Content [359], [360], [361]. Detection, Monitoring, Classification and Estimate are the main tasks related to this technique.

4) RANDOM FOREST (RF)
RF is one of the DT based ML techniques. It uses an ensemble learning strategy called bagging, which allows each DT to be able to handle different random samples of the input data, resulting in a set of distinct trees. Furthermore, RF is able to achieve better generalization of the model by compensating the errors of the different elements of the forest [362]. Table 22 shows applications found in the selected studies for RF technique. Fruit Detection [363], Garbage Detection [364], Plant Diseases Detection [365], [366], Plant Detection [367], [368], [369], Tree Trunk Detection [370], Monitoring of Plantations [371], [372],

TABLE 3. Datasets overview in Environment, Communication, Infrastructure, SAR, Transport and Helthcare areas.

SA	Name	Description	Name	Description
Environment	GWHD [216]	Global Wheat Head Detection Dataset	Farm Map [217]	Mapping of cultivation areas
	RCGC [218]	Red Clover Ground Cover	Salinas AVIRIS [219]	Hyperspectral imagery of Salina Valley
	UAVWeedSegmentation [220]	Weed Segmentation of Sorghum Fields	Agriculture-Vision [221]	Aerial farmland images
	Heracleum [222]	Aerial images of hogweed	Miscanthus trials [223]	Phenotype Key Traits in Miscanthus
	Melons Plantation [224]	Yield estimation of melons	Rice Seedling [225]	Open Rice Seedling Dataset
	PLD-M [226]	Data set of Kiwi vine	Grassland field [227]	Grassland with Broad-leaved Dock
	DALES [228]	LiDAR Data Set for Point Cloud Segmentation	Pistachio Trees [229]	Imagery dataset captured at nadir and oblique angles over pistachio trees
	SAVMAP [230]	Management and biodiversity conservation in semi-arid savanna	Crocodiles [231]	Free-ranging mugger crocodiles
	iHabiMap [232]	Habitat Mapping, Monitoring and Assessment	FLAME [233]	Aerial imagery pile burn detection
	FLAME2 [234]	Fire detection and modeling		
Communication	RadioML [235]	Synthetic simulated channel effects and over-the-air recordings	CRAWDAD [236]	Real-time position data reported by buses
	SNDZoo [237]	Virtualised Network Functions	MDC [238]	Continuous data pertaining to the behaviour of individuals and social networks
	QOS-FOG [239]	QOS Requirements for FOG Computing Applications	TOPO4MEC [240]	Network Topologies description
Infrastructure	VEDAI [241]	Detection of engineering vehicles	CrackTree [242]	Road pavement images
	CRKWH100 [243]	Road pavement images	CrackLS315 [243]	Road pavement images
	Stone331 [243]	Images of stone surface	ZJU SYG crack [244]	Crack data set for object detection
	Surface Crack Detection [245]	Images of concrete surfaces with and without crack	Concrete Crack [246]	Concrete images having cracks
	PLD-UAV [247]	Power line detection	PV Plants [248]	Boundaries of Photovoltaic plants
SAR	SARD [249]	Detecting casualties and persons in search and rescue scenarios	Thermal image dataset [250]	Thermal image for survivor detection
	HERIDAL [251]	Aerial Imagery in Supporting Land Search and Rescue	SeaDronesSee [252]	Vision benchmark for maritime search and rescue
	VictimDet [253]	Disaster Victim Detection	Swimmers [254]	Images for detecting open water swimmers
	Hand gesture [255]	Real-Time human detection and Gesture recognition		
	AIDER [256]	Image Dataset for Emergency Response Applications	FloodNet [257]	Dataset for Post Flood Scene Understanding
	DED-1 [258]	Collapsed Building Detection in Post-Earthquake	PRAI-1581 [259]	Person Re-identification
	Crime [260]	Reported incidents of crime	UCF-ARG [261]	Multiview Human Action
Transport	P-DESTRE [262]	Pedestrian detection, tracking, and re-identification	CUHK-SYSU [263]	Large scale benchmark for person search
	DRHIT01 [264]	Person re-identification	Stanford Drone Dataset [265]	Human Trajectory Prediction
	Aerial Cars [266]	Aerial car detection	INRIA Pedestrian [267]	Pedestrian detection
	UAVDT [268]	Benchmark object detection and tracking	FLIR Thermal [269]	Fully annotated thermal and visible spectrum frames
	OTCBVS [270]	Thermal pedestrian database	VEDAI [271]	Vehicle detection in aerial imagery
	VRAI [272]	Vehicle re-identification for aerial image		
Healthcare	Face Mask [273]	Face Mask detection	Oxford Town Centre [274]	Video of pedestrians in a busy downtown area
	MBG [275]	Potential Aedes aegypti breeding grounds		

SA = Subarea.

Trees Classification [373], [374], [375], Geographic Classification [376], Plantation Yield Estimation [377], [378], [379], [380] and Estimation of Foliar Water Indicators [381] are some of these applications.

	YOLO	Faster RCNN	SVM	RF	KNN
Task	Applications	Applications	Applications	Applications	Applications
Classification	• Classification of Maturity of Plantations	• Classification of Maturity of Plantations	• Plant Classification • Tree Classification • Vegetation Classification • Water Quality Classification	• Trees Classification • Plant Classification • Geographic Classification	• Vegetation Classification • Tree Classification
Counting	• Tree Counting • Land Vehicle Count • Fruit Count	• Bird Counting • Plant Count • Fire Detection	• Plant Count		• Plant Count
Detection	• Aquatic Animal Detection • Garbage Detection • Plant Detection • Plant Disease Detection • Victim Detection • Vehicle Detection • Crack Detection • Pest Detection • Livestock Detection	• Plant Detection • Victim Detection • Plant Disease Detection • Bird's Nest Detection • Weed Detection • Marine Debris Detection • Vehicle Detection • Transmission Tower Detection • Threat Detection • Landslide Detection	• Crack Detection • Weed Detection • Plant Disease Detection • Coastal Trash Detection	• Fruit Detection • Garbage Detection • Plant Detection • Tree Trunk Detection • Detection of Dead Woody Components	• Detection of Disease in Plants • Detection of Invasive Plants • Detection of Planting Lines • Coastal Trash Detection • Late Burn Detection
Estimation	• Yield Estimate	• Estimated Amount of Woody Debris • Estimated Number of Trees	• Plantation Yield Estimation • Estimation of Chlorophyll Content • Nitrogen Level Estimation	• Plantation Yield Estimation • Estimation of Foliar Water Indicators • Leaf Coverage Estimate • Estimation of Soil Salt Content	• Estimation of Chlorophyll Content • Estimation of Changes in Vegetation Cover • Plantation Yield Estimate
Inspection	• Inspection of Transmission Lines • Solar Plant Inspection		• Solar Panel Inspection		
Mapping			• Digital Mapping of Soil Organic Carbon • Mapping of Plantations • Mapping of Plantation Coverage • Flood Mapping	• Flood Mapping • Weed Mapping • Mapping of Riverside Habitats • Land Cover Mapping	• Monitoring of Invasive Plants
Monitoring	• Traffic Monitoring • River Garbage Monitoring	• Road Traffic Monitoring	• Monitoring of Plantations • Pest Monitoring • Soil Salinity Monitoring	• Monitoring of Plantations • Pasture Monitoring	
Re-identification		• Person Re-identification			
Recognition	• Electrical Equipment Recognition • Engineering Vehicle Recognition • Crocodiles Recognition	• Person Re-identification			

FIGURE 22. Machine Learning techniques in the scenario of UAV applications.

5) K-NEAREST NEIGHBORS (KNN)

The KNN algorithm is a supervised ML algorithm used for classification and regression tasks. In classification, the KNN determines the class of a new example based on the classes of the "k" nearest examples to it in a feature space. The value of "k" is a hyperparameter defined by the user. The algorithm calculates the distances between the new example and the known examples in the training set, selects the "k" closest neighbors, and then assigns the most common class among these neighbors to the new example [382]. Some applications related to KNN can be seen in Table 22, such as: Vegetation Classification [375], [383], Plant Count [384], Detection of Disease in Plants [385], Detection of Invasive Plants [386], Coastal Trash Detection [364], Estimation of Chlorophyll Content [387], [388], Plantation Yield Estimate [378], Monitoring of Invasive Plants [389].

F. CHALLENGES AND IMPROVEMENTS

To answer RQ6, this section presents the main challenges to be overcome and improvements to be achieved in the use of UAVs for real-world applications.

- **Regulation**
  The use of UAVs in agriculture crops, in pandemics scenarios or even on farms or for communication purposes, in many countries, is limited by too few or

too many government regulatory policies on UAVs. Because regulations on UAVs are continuously created and updated, these aspects must be considered [33].

- **Security**
Vulnerabilities in the operation of drones, such as GPS jamming and hacking, make them attractive for malicious users to have the possibility to carry out cyber-terrorism and other illegal activities, which is worrying when dealing with systems directly linked to health, for example. Despite the promising applications of UAVs in wireless networks, there are several concerns regarding public safety, crash prevention, data protection, and especially privacy, due to the possibility of attaching a camera or information-capturing device to the UAV, which can occasionally violate people's privacy [115], [390], [391], [392].
- **Energy Restrictions**
UAVs face several battery life restrictions, which inhibit, for example, their ability to cover large distances, make multiple deliveries of medicines or vaccines, and serve as a mobile base station for a long time [194], [393], [394].
- **Autonomous Navigation**
One of the main uses of UAVs in Smart Cities is for data collection and surveillance. In many cases, an autonomous control capability of the drone is needed so that it can maneuver in and out of enclosed locations and avoid obstacles [395], [396], [397], [398], [399].
- **Real-time Problems**
For road traffic management or parking lot management, UAVs must detect and/or classify vehicles in real-time in usually disordered environments. This becomes a complex task as UAV platforms have limited hardware resources [400], [401], [402].
- **Datasets**
One challenge for object detection, classification or segmentation in aerial imagery is the availability of pre-classified datasets. There are few labeled publicly available datasets that contain large amounts of instances representing different climate scenarios, which makes detectors less accurate, especially DL-based detectors, which rely on large amounts of images for their training [403], [404], [405].
- **Digital Image Processing**
Computer vision-based approaches are susceptible to visibility-related problems, such as the presence of fog, rain, shadow and interference. Some of these are amenable to normalization using digital image processing techniques [406], [407], [408].
- **Climate**
UAVs are significantly affected by adverse climatic conditions. Rainy, stormy and cloudy climate situations can hinder their use in rescue operations. Such situations can be present in emergencies with floods, storms, and earthquakes, which are among the most frequent natural disasters, with a high mortality rate [409], [410], [411].
- **Drone Swarms**
Drone swarms can cover larger areas in a shorter time which is a positive point for their use in search and rescue operations, whose main goal is to find missing people in the shortest possible time to ensure better assistance. However, the control and communication of UAV swarms is still a challenge to be faced [412], [413], [414].
- **Communication Management**
Adventure tourism, such as rafting, mountain biking, paragliding, and hiking, are popular with diverse audiences. These activities are often carried out in regions far away from capital cities, in places where wireless communication (e. g. Fourth Generation (4G) and 5G) is scarce. This affects UAVs in their communication with systems and/or other drones [415], [416], [417].
- **Scalable Communication Network Designs**
As the number of users of wireless communication networks increases, the use of UAVs to support these networks seems promising. However, scalable network designs that meet current and future network demands are still a challenge [418], [419], [420].
- **Energy Management**
The use of UAVs for communication demands that these vehicles have a long operation time. This requires good resource management that is mainly affected by the interaction between flight time, power, and trajectory planning of the UAVs. One issue to be explored is the recharging of the UAVs battery through wireless power transfer while they are still flying [421], [422], [423].
- **Trajectory Planning**
Planning an optimal path for UAVs is an important challenge in UAV-based communication systems. The trajectory of a UAV is significantly affected by several factors, among them: flight time, power constraints, end-user demands, and collision avoidance [424], [425], [426], [427].
- **Technology Integration**
Depending on the problem the integration of various technologies, such as UAVs, Wireless Sensor Networks, IoT, is necessary. But this integration increases the level of complexity of the system.
- **Load Limitation**
UAVs have limitations regarding the size and weight of the cargo carried. This can be a challenge when using them for transporting relatively heavy objects and performing activities such as spraying crops or using water to fight fires [185], [195], [428].
- **Selection of Hyperparameters** Hyperparameter selection plays a fundamental role in machine learning algorithms. A variety of methods can be applied, such as grid search and computational intelligence optimization algorithms, such as PSO and genetic algorithms. Hyperparameter optimization has been addressed in the literature, e.g., [429] and [430].

V. FUTURE RESEARCH DIRECTIONS

The field of ML applied to UAVs has grown exponentially over the years. Recently, researchers have investigated the use of drones in new and important applications. In this context, some open research topics in order to stimulate further investigation in ML applied to drones in different scenarios are presented below.

- **UAV Swarms**: UAV swarms constitutes a hot topic in the literature, mainly in the context of ML algorithms adopted for optimizations problems such as trajectory, resource allocation and sensing. Researchers are also focused on used UAV swarms in emerging applications, such as virtual reality in metaverse and UAV swarm-enabled reconfigurable intelligent surfaces, that are uses cases in the new wireless systems generations.
- **Autonomous Drones:** Autonomy is a relevant aspect regarding individual drone or swarms of drones. In this scenario, autonomous recharging is a relevant issue [431]. Autonomy also concerns decisions, at the light of legal and ethical issues. The paper of Konert and Balcerzak [432] analyzes those issues on using drones as weapons.
- **Security of UAVs:** Considering the presence of eavesdroppers in UAV scenarios, AI algorithms have been considered in order to enhance the secrecy performance. Thus, the study of new algorithms that are robust to eavesdroppers and capable of increasing the data security constitutes a relevant research topic and are of interest to researchers.
- **Energy Harvesting Technologies:** In the literature, energy harvesting technologies applied to UAV has been considered a relevant topic and has been researched extensively in recent years. The aforementioned technology is proposed in different contexts, such as to charge UAVs since the limited flight time is due to its insufficient battery capacity; and in UAV-enabled wireless communication system with energy harvesting. The future research directions about energy harvesting for UAVs mainly focuses on power allocation, path planning and transmission ways, which are open issues related to ML that need further investigation. UAV aided wireless power transfer is also a promising future direction.
- **UAV Autopilot System:** The trajectory of autonomous UAVs is a very complex task. Thus, AI algorithms can be used by drones to plan their flights autonomously. Currently, related research aims the use of ML to perform UAV autopilot system. In such studies, new learning techniques have been proposed for this task. However, studies have to be carried out in order to investigate the learning of the UAV in other environments and scenarios with multi UAVs.
- **Blockchain-Assisted UAV:** Several papers have pointed blockchain-assisted UAV network as a relevant topic to be studied. This occur since the blockchain properties have several benefits for UAVs, including better privacy as it enables data security; and improving the quality of services in terms of delay, throughput and reliability. The existing literature suggests that there are critical challenges in this topic concerning architectures able to reduce computing and storage requirements while dealing with security and privacy issues. In UAVs, ML and blockchain are jointly combined to facilitate their application in different fields.
- **UAVs to Space Missions:** The use of ML in drones for space exploration is a new topic. The advantages provided by UAVs have the potential to support space missions, but still with several challenges to be solved, mainly those related to efficiency, cost, design and flight trajectories optimization issues. Thus, it is expected that ML techniques applied to the mentioned aspects for the UAVs can enable improvements in terms of efficiency and robustness.
- **Distributed Machine Learning (DML):** DML may be used for a variety of purposes, such as to optimize communication, computation and resource distribution. For this reason, DML may be seen as an interesting research direction in the scenario of UAVs. Information security plays an importante role in the framework of DML.
- **Multi-modal Sensor Data Fusion:** The use of a combination of sensors - such as visual cameras, infrared sensors, radar, and sonar - can provide a more complete perception of the environment for a UAV. Sensor data fusion techniques can be employed to improve object detection, navigation and other critical tasks.
- **Ethical ML for UAVs:** This area addresses the ethical challenges associated with the use of ML in UAVs. This can include issues such as algorithmic bias, autonomous decision-making in complex ethical scenarios (such as the use of drones in military operations), and the protection of personal data collected by drones.

VI. LIMITATIONS

While this study is a comprehensive review of the literature on the use of ML techniques in UAVs, it is important to recognize some potential limitations that could affect the findings and interpretations:

- **Publication Bias**: Can occur when certain studies or findings are more likely to be published due to factors like positive results or significance. This bias may lead to an over-representation of certain applications of ML in UAVs, while potentially neglecting less favorable or non-significant findings. As a result, the review's conclusions may not fully reflect the entire landscape of ML applications in UAVs, and important insights could be missed.
- **Data Source Selection**: The selection of databases or sources used to gather articles can influence the comprehensiveness of the review. If certain relevant

databases or gray literature are excluded, it could lead to a limited scope of the study and potentially miss out on valuable studies that are not indexed in major databases. This limitation may result in an incomplete picture of the state of research in the field.
- **Limitations in Subarea Prospections**: The identification of subareas and applications of ML in UAVs is dependent on the scope and categorization criteria set for the review. If the categorization is too broad or predefined subareas do not adequately capture the diversity of applications, the review may overlook emerging or niche use cases of ML in UAVs. This could result in an incomplete representation of the potential applications and benefits of ML techniques in specific UAV domains.
- **Generalization of Findings**: The macro-level understanding provided by the review may lack detailed insights into specific contexts or implementations. ML applications in UAVs can vary significantly depending on factors like industry, geographical location, or specific use cases. By aiming for a broader overview, the review might not address the nuances and challenges faced by researchers and practitioners in different domains. Consequently, the practical implications of the review's findings might be limited for those seeking specific guidance or detailed understanding.

VII. CONCLUSION

Unmanned Aerial Vehicles (UAVs), combined with intelligent data processing methods, have been widely used in civil and military applications. From service delivery to victim detection in environmental disasters, UAVs are useful in a variety of tasks. In this paper, a review of the literature on ML applications in UAVs is presented. The main areas and subareas are listed, as well as the most recurrent ML techniques in the selected studies.

Some recurring challenges have also been identified regarding the use of drones in civil applications, such as weather conditions that directly influence their trajectories and acquisition of environmental data; power constraints, as many UAV models are typically powered by batteries, which makes it difficult to use them for missions with long periods of time; limited cargo capacity due to the small size of the UAV; and the risk of information security attacks, where there is the possibility of UAVs being controlled for illegal purposes such as invasion of privacy and smuggling.

Throughout this review, emphasis is also given to the most commonly used ML techniques in the selected studies, such as Support Vector Machine, Random Forest and Artificial Neural Network and Deep Learning approaches, namely You Only Look Once, Faster R-CNN and Convolutional Neural Network based algorithms. The main applications of each aforementioned technique were also identified.

It must be considered as a possible limitation of this study the task of gathering the largest amount of relevant articles related to the use of UAVs and ML in the real-world problems, especially considering works not indexed in the databases used. Therefore, future research must be conducted considering a larger number of academic databases. Also, other fields of computing, such as swarm intelligence, can be explored in the future.

The increasing number of existing studies in academic databases for a large variety of different tasks and applications shows the potential of UAVs. These existing scientific contributions will make possible the massive and common use of these vehicles in both domestic and industrial contexts in the future.

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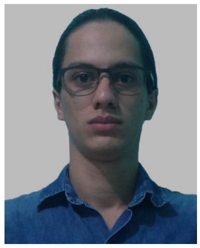

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