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A Scoping Review on Unmanned Aerial Vehicles in Disaster Management: Challenges and Opportunities

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Abstract—**Unmanned Aerial Vehicles (UAVs), or drones, have recently become transformative tools in disaster management. This paper provides an overview of the role of drones in dis- aster response and recovery, covering natural disasters such as earthquakes, floods, and wildfires, as well as man-made incidents like industrial accidents and humanitarian crises. UAVs offer advantages including rapid data collection, real-time situational awareness, and improved communication capabilities. Notable examples include the use of drones in the 2015 Nepal earthquake for mapping and search operations, and during the 2017 Hurricane Harvey for flood assessment and resource distribution. Advanced technologies further enhance drone capabilities; AI algorithms were used in the 2019 Mozambique cyclone to prioritize rescue operations, while thermal sensors located survivors in the 2018 Mexico earthquake. Despite these benefits, challenges such as privacy concerns, regulatory issues, and community acceptance remain. For instance, privacy issues arose during Hurricane Harvey due to aerial surveillance, and regulatory barriers delayed responses in the 2018 Indonesia earthquake. Ethical dilemmas also surface, such as balancing response urgency with privacy rights and ensuring equitable access to UAV services. The paper discusses potential solutions, including establishing privacy protocols, engaging communities, and streamlining regulations. Collaboration between government agencies, NGOs, and the private sector is essential to develop standardized protocols and enhance community acceptance. By integrating AI, machine learning, and advanced sensors, drones can significantly improve disaster response efficiency. In conclusion, drones play a pivotal role in revolutionizing disaster management strategies. Ongoing advancements in drone technology offer unprecedented opportunities to enhance disaster response, ultimately mitigating human suffering and preserving critical infrastructure. This paper reviews the role of drones in disaster response and recovery efforts, covering various disaster types including natural and man-made incidents.**

Keywords—Unmanned Aerial Vehicles (UAVs); Disaster Management Real-time; Situational Awareness; Search and Rescue Operations; Advanced Technologies Integration.

I. INTRODUCTION

The advancement of technology has revolutionized problem- solving approaches across various sectors, including business and defense. One significant contributor to this transformation is the emergence of drone technology. Unmanned Aerial Vehicles (UAVs) represent a category of aircraft that can operate autonomously without a pilot on board or under remote control [1][2]. Initially developed for military purposes, drones are extensively researched for their potential applications across numerous industries. Drones have diversified applications, ranging from remote sensing and photogrammetry to cinematography, disaster response, military reconnaissance, and logistical support. Particularly in disaster management, the utilization of drones has witnessed exponential growth in recent years. Their adoption by disaster management organizations has spurred further research, driven by the recognition of their advantages over traditional technologies in this domain. The application of drones in disaster management can be categorized based on the stages of the disaster event or the specific tasks performed by these devices. This categorization facilitates a more systematic exploration of their potential roles in mitigating the impact of disasters and improving response effectiveness. Complex operations demanding advanced capabilities have nurtured the development of drones through the years. Their operational capabilities have made them grow into different classes, with differentiation mainly in power, size, and application conditions [3]. Disasters in all possible forms have been observed to be detrimental to the masses, wildlife, nature, and thus the economies of regions and nations worldwide, with their scale primarily determining the size of the loss. Being a common concern in different areas of the world, they are not looked upon differently from nation to nation. Instead, countries, especially those more prone to such disasters, have made joint decisions every day in the hope of predicting or mitigating the possibility of the occurrence of such events or reducing the impact of such disasters. Furthermore, due to many authorities' lack of coordinated operations during a crisis, proper data gathering can be challenging in an emergency [4][5]. Such large-scale, sophisticated activities necessitate ongoing technological advancements. As a result, it was suggested that new approaches and technologies incorporating tools enabling telecommunication and remote sensing, along with spatial and temporal oriented databases, would be necessary to increase disaster management efficiency [5][6]. Therefore, the application of drones in disaster management was studied and has been proven to have numerous benefits, including reduced time required to locate victims and subsequent intervention in a larger area, providing critical information to first responders during and before various operations, and an ever-increasing capability to perform more and more complex tasks due to the increasing development of drone technology. A conflict of study patterns and different classification schemes of various entities was observed in most of the reviews concerning the application of UAVs in disaster management. The focus of this paper lies in combining and unifying various studies, reviews, and demonstrations carried out in the context of the application of UAVs in disaster management-related use cases, thus providing details from multiple studies that differ from each other in many ways.

High-frequency communication, particularly in the millimeter-wave (mm-wave) range, addresses congestion and achieves high data transmission speeds, making it highly advantageous for UAV applications. These frequencies offer large bandwidths, enabling the transmission of high-resolution data and supporting real-time video streaming and advanced sensing capabilities. However, several technical challenges accompany these benefits. Propagation characteristics at high frequencies include higher free-space path loss and susceptibility to atmospheric absorption, rain, and foliage, which can significantly attenuate signals. Designing efficient antennas at mm-wave frequencies requires advanced materials and precise manufacturing techniques to achieve desired performance characteristics, such as gain and beamwidth. Signal attenuation and the need for line-of-sight communication necessitate innovative solutions, such as beamforming and multi-hop networks, to maintain reliable connections in dynamic disaster environments. Regulatory aspects are also crucial in the deployment of mm-wave communication systems. While the 57-66 GHz range is license-free, it is subject to power limits and other regulations to minimize interference and ensure fair usage. These regulations vary by country, influencing how UAV communication systems are designed and implemented. Specific applications of this spectrum in disaster management include establishing temporary high-speed communication networks, providing real-time video feeds to emergency responders, and enabling rapid data transfer between UAVs and command centers. While the 60 GHz band offers significant advantages for high-speed wireless communication, it also presents several technical challenges that impact the design and performance of wireless systems operating in this frequency range. The propagation characteristics at 60 GHz include higher free-space path loss, which increases the attenuation of signals over distance compared to lower frequency bands, making long-range communication more difficult and necessitating the use of higher power or more sensitive receivers. Diffraction is less effective at higher frequencies, meaning that signals are more likely to be blocked by physical obstructions such as buildings, trees, and even human bodies. This limitation requires careful planning of antenna placement and the use of line-of-sight communication paths to ensure reliable connections. Blockage by obstacles is a significant concern, as 60 GHz signals cannot easily penetrate walls or other solid materials. This necessitates innovative solutions like beamforming, which focuses the signal in a specific direction to improve coverage and reduce the likelihood of blockage. Atmospheric absorption, particularly by oxygen molecules, is also more pronounced at 60 GHz, leading to further signal attenuation. This absorption effect must be accounted for in the design of wireless systems, particularly for outdoor applications where weather conditions can further exacerbate signal degradation. The design of efficient antennas for the 60 GHz band requires advanced materials and precise manufacturing techniques to achieve desired performance characteristics such as gain and beamwidth. High-frequency antennas must be small yet capable of handling high power levels and maintaining efficiency. These challenges highlight the need for innovative solutions to optimize the performance of wireless systems operating at 60 GHz. Techniques such as multi-hop networks, where data is relayed through multiple intermediate nodes, can help extend coverage and mitigate signal attenuation. Advanced signal processing algorithms and adaptive communication protocols are also essential to dynamically adjust to changing environmental conditions and maintain robust communication links. Despite these advancements, significant challenges and gaps remain in the current research. One major challenge is the integration of drones with existing disaster response frameworks, particularly regarding data interoperability and communication protocols. Additionally, while drones offer high-frequency communication and wireless instrumentation benefits, further investigation is needed to optimize these technologies for real-time data analysis and decision-making in dynamic disaster scenarios. This paper aims to address these research gaps by unifying various studies, reviews, and demonstrations of UAV applications in disaster management-related use cases. By doing so, it provides comprehensive insights and identifies areas for future research to enhance the effectiveness of UAVs in disaster management.

The research contribution of this paper is significant in its consolidation and synthesis of various studies, reviews, and demonstrations of UAV applications in disaster management. It addresses critical gaps in current research by examining high-frequency communication technologies, particularly in the millimeter-wave range, and their application in optimizing UAV operations during disaster response. By exploring the benefits, technical challenges, and regulatory considerations associated with these frequencies, the paper offers insights into enhancing communication networks for real-time data transmission and situational awareness in dynamic disaster environments. Additionally, it emphasizes the integration of drones into existing disaster response frameworks, highlighting issues of data interoperability, communication protocols, and the adaptation of UAV technologies to improve operational efficiency and effectiveness. This comprehensive approach not only provides a unified perspective on UAV utilization but also sets the stage for future research aimed at advancing disaster management strategies through innovative UAV applications.

II. DRONES IN DISASTER MANAGEMENT

A disaster is a risk that results in a large-scale occurrence that causes severe physical damage or destruction, loss of life, or significant environmental change [7]. They substantially interrupt a community's ability to cope with its resources. It has been discovered that they can endanger people's lives, harming their economic, social, and cultural existence. Natural, man- made, and technical risks, as well as various elements that influence a community's exposure and vulnerability, can all contribute to disasters. They can range from earthquakes to floods to hurricanes to wars to reactor meltdowns to terrorist acts like bombing, kidnapping, and murder to much more. They can differ by region, vastness, scale of loss, and many more parameters. Disasters can either be predicted ahead of time or they can be sudden. Earthquakes are sudden disasters, while floods can be predicted by measuring the rainfall, the structural integrity of dams, and the status of rivers. Climate change and global warming have been detrimental to the earth in the context of significant causes of the increase in disasters all around the world. According to the 2020 Ecological Threat Register (ETR), there has been a tenfold increase in natural disasters, from 39 incidents in 1936 to 396 incidents in 2019. The International Disaster Database also observed that the cases have been rising more rapidly in the last two decades and predicted that this trend is expected to continue.

Disasters are classified as natural, man-made, and simulated. Natural and man-made catastrophes are then divided into four categories based on whether they are caused by an environ- mental, medical, industrial, or terrorist incident [5]. Disaster management is a general term that refers to the process that includes mitigation, preparedness, response, and recovery [4]. According to the director of the Centre for Robot-Assisted Search and Rescue (CRASAR) at Texas AM University, autonomous robot assistance was first deployed in genuine SAR efforts after the 9/11 disaster, and the development of these systems has been progressing at a pace ever since, leading the path to the emergent use of drones in such applications. Drones were initially designed as aircraft that could fly autonomously or semi-autonomously while being piloted only by specially trained personnel, but with advancements, they have developed into complex devices that could be used by anyone with substantial training. Drones are mobile [8][9][10], and airborne [11] and hence offer numerous advantages over their alternatives. Some areas where drones have been extensively used are crime scene inspection [2][5], marine fauna detection [5][12], habitat destruction estimation [5][13], crop monitoring [5][14], and vegetation mapping [5][15]. Moreover, drone mapping has proven to be the most prominent advantage of this technology. It has been applied in various industries such as construction, agriculture, mining, and infrastructure inspection [5][16]. Furthermore, the recent advent of drones due to better perception, commercialization, reduced costs, and advancements has led to an increase in drone applications in disaster management and humanitarian relief, even expanding to include search and rescue operations [5][17][18], disaster prevention [3][5], and disaster management [5][19][20].

Several studies have focused on the reasons for the usage of drones in disaster management [21], and a comprehensive list, as observed from the findings of most of the studies, is as follows:

- They reduce the risk of human exposure to danger
- They increase the effectiveness of responders and their operations
- They provide unique capabilities that cannot be envisioned using other conventional technologies
- They are highly deployable
- They are cost-efficient
- They can be augmented according to mission-specific requirements
- They are easily upgradeable.

Furthermore, the use of drones appears to have significant potential in a wide range of industries, including civil (photography, construction, mining, delivery, agriculture, logistic disaster management), environmental (air quality monitoring, soil monitoring, crop monitoring, water, underwater, mountain inspection), and defense (combat aircraft, warzone medical supply, spying, reconnaissance, surveillance at the border, bomb-dropping, and missile launching).

Disasters of all forms lead to a deterioration in the health and welfare of the masses, and mass disasters [5], in particular, are the cause of widespread loss. Thus, the need for a rapid and effective response at the time when a disaster strike is critical. Moreover, the accuracy of critical data collection and its verification is also difficult during such emergencies due to the lack of coordination between local communities and agencies during a disaster [6]. After thorough research and years of experimentation, it was concluded that the solution to overcome such problems is an optimal technological integration of telecommunication and remote sensing tools with spatial and temporal-oriented databases [5][22]. Thus, drone technology, thanks to the technological advancements brought through years of rigorous research and experimentation, has been advanced to a powerful level of integration of the aforementioned technologies and has proved to be the best in the context of assistance in many disaster management operations.

Moreover, the contribution to the advancements in this technology varies by country, and it has been observed that the majority of studies on the technology have been carried out in the United States. This could be reasoned since the United States has observed the most weather-related disasters over the last two decades [23]. Hurricane Harvey, which struck in 2017, is considered by far the most destructive and expensive calamity in U.S. history. It caused damages in excess of 100 billion dollars, resulting in the largest mass migration due to a natural disaster since the U.S. Civil War [24]. The economic impact associated with such large-scale disasters, both natural and man-made, urges governments and international institutions to acknowledge the threat of such occurrences and make subsequent preparations. It was observed that the occurrence of such disasters is more frequent than anyone could realize, and as per the United Nations Office for Disaster Risk Reduction, around 3500 flood disasters were observed globally in just three decades between 1980 and 2011. They significantly shorten the time duration required to locate victims of disaster and subsequent intervention by searching larger areas in much shorter periods of time. They assist first responders in decision- making by providing crucial information about the optimal route during the operation. They can search for living victims buried beneath surfaces such as rubble, snow, debris, etc., with the help of state-of-the-art sensor technologies. They have also assisted humans physically in many operations [17]. They have been applied during SAR missions [25], for data acquisition [26], triage [27], and rapid assessment [28]. Some studied use- cases of drone applications include border surveillance [9], water rescue [29], and monitoring of aquatic terrains [30; 31]. Moreover, they have been used for the transportation of supplies [32], recovering hazardous materials [33], or autonomously manipulating objects [34]. One more prominent application of UAVs in this context is the exploitation of their capability to act as enablers of wireless communication in critically affected areas where the communication infrastructure has been demolished due to disaster [8]. An example of this where drones have been used as mobile nodes in communication networks is demonstrated in [35]. Another example demonstrated the usage of UAVs in their ideal weather conditions in the aftermath of a disaster such as an earthquake or flood. Communication access to wide areas was established using an aerial cell network [36]. Studies reveal that research and development in drone technology was primarily focused on the context of natural disasters, with search and rescue, emergency, simulated, and man-made disasters attracting lesser attention. The use of drones in natural disasters was sought after in landslides, hurricanes, earthquakes, floods, forest fires, and volcanic eruptions. Simulated disasters included a variety of hazards involving crashed aircraft, destroyed cars, and floods. Studies on applications of drones in man-made disasters involved a single scenario where the technology was applied during the radiation mapping process after the catastrophe struck at the Chernobyl Nuclear reactor when drones flew outside contaminated areas to reduce operator risk.

The four primary areas of application of drones, as noted from the different studies, are (1) monitoring, (2) mapping or damage assessment, (3) search and rescue, and (4) transportation. There are also some other applications of drones, namely, training, relief, and autonomous manipulation, which we found to be an integral part of the aforementioned classified phases and, thus, have not been formed into separate sections in the paper. Moreover, different studies have considered different schemes for classifications, one of which is by the American Red Cross [37]. It classifies operations into 4 categories: (1) search and rescue (SAR); (2) reconnaissance and mapping (RM); (3) structural inspection (SI); and (4) debris estimation (DE). Despite being highly correlated, we found that the former classification scheme has been more widely used in studies. Thus, we have chosen the former scheme for the scope of this paper. Also, drones are mostly used for search and rescue whereas usage for transportation of emergency aid was comparatively less. Based on a broader understanding, the operations of UAVs in disaster management can be classified into stages according to two architectures (Fig. 1). The first architecture is the one that classifies operations into three phases relative to the occurrence of the actual disaster.

- Pre-disaster
- Intervention (activity immediately after the occurrence of a disaster) and
- Post-disaster (activity after the primary disaster elimination)

Meanwhile, the second scheme’s classification results in

- Preparedness
- Assessment and
- Response and recovery

The operations of the first phases of both schemes align with each other, while the second phase of the former scheme is inclusive of the second and third phases of the latter scheme, and the third phase of the former scheme is included in the third phase of the latter scheme [27]. Disaster management operations in the context of a chemical accident during illegal transport can be studied as an example to understand the different phases, where road transport surveillance and following the spread of toxic smoke relate to prevention and early detection, real-time monitoring after the onset and information supply are related to intervention and mitigation, and lastly, post-disaster activity after the intervention is related to damage assessment [7]. Going by the results of most of the work in this area, we have chosen the second scheme for the scope of our study.

Evaluation of areas impacted by a disaster, assessment of the extent of damage caused by it, and combination of information into reports for various further uses. This is an operation that is carried out before intervention, that is, before the response and recovery phase, to get a better understanding of the affected areas, during the response and recovery phase, for updating information, as well as in the post-disaster phase, to assess the overall damage it has caused eventually contributing to quick assessment and recovery. Like monitoring, the evaluation also supports first responders in decision-making. Drone Mapping is the most well-known use of technology, with applications in building, agriculture, mining, and inspection of infrastructure [5]. Drones have been shown to be incredibly effective in monitoring, mapping, and damage assessment. Information is a more pressing necessity that may be less obvious to individuals outside the civil, government, or military response entities. The developments in technology have been fully utilized in this sector. Furthermore, compared to fixed-wing and helicopter counterparts, they have proven more economical, rapid, and suited for usage in more adverse weather conditions and more widespread scenarios. Drone mapping has already been employed in the aftermath of floods [38]-[39], landslides [40]-[41], rockfall [42], forest fire [43], storms [44][45], tsunami [46], volcano [47], earthquake [48], and even the Chornobyl Nuclear Power Plant Accident [5][49]. UAV-based gas monitoring has been proposed in studies to support evacuation measures [50]. Swarm-based radiation detection systems have also been shown [51], which could prove valuable and successful in appraising large-scale man-made disasters. Furthermore, technology has shown that it may be used to provide information inaccessible by ground vehicles, especially in highly hostile situations such as glaciers and volcanos [26][28][52]-[53]. They have proven to be more efficient than first responder information [41] in terms of supplying high-resolution imagery in less time than satellite images [47][54] and GPS Survey [44]. They have demonstrated their usefulness in assessing erosion and flooding by providing 2D and 3D data in a shorter amount of time [44]. A web system to share aerial images captured by drones was developed, allowing for more efficient information sharing [55]. Drones have proven helpful in assessing building damage in hard-to- reach places and terrains [54][56][57]. UAVs were successfully employed in firefighting, where they were successfully used for heat source detection [58; 59] and victim location [60]. They have been employed to aid personnel on the ground in various cases [58][59][61].

Drone images were used to construct 3D models of the catastrophe site using appropriate software [62]. Flight planning, GNSS-RTK surveying, aerial photo capture, key point extraction, 3D point cloud extraction, image matching [5], DEM synthesis and ortho-image generation are some of the drone mapping methods used. A DEM, or Digital Elevation Model, is a 3D model built by drone-based photogrammetry that has proven to be the most effective for evacuation planning [47]. LIDAR, or Light Detection and Ranging, is yet another conventional sensory technique for drone sensing. DEM, being more advantageous than LIDAR, still has some limitations regarding low-altitude flight. Thus, the latter has been con- strained for high-altitude applications such as creating models and subsequent mapping in the aftermath of floods. Perception in the current level of advancements, subsequent familiarization, awareness, and governmental regulations have been a hindrance in the exploitation of the technology in disaster management, as helicopters have received faster approval and with fewer permission requirements, despite the advantages drones boast over the use of their helicopter counterparts [63]. The lack of a centrally accepted system for coordination, deployment of drones, and sharing of subsequent information across agencies and governmental organizations is a significant setback to the technological advancements carried out in the drone industry so far [64]. They provide great flexibility and are best suited to scanning smaller regions or isolated buildings with limited space. In contrast, fixed-wing drones are better suited to mapping broad areas like floods, wildfires [5][38] and earthquakes. They are significantly more advantageous than fixed-wing rotors and helicopters since they can hover and inspect damage while gaining less airspace.

Furthermore, advances in drone photogrammetry have elevated the technology, allowing them to record high-resolution photographs while maneuvering at rapid speeds over the assessment region. Drone photographs are used to make orthophotos. These are then utilized for 3D reconstruction and mapping tasks, such as identifying critically afflicted areas. VirtualDub, PhotoScan, and Pix4Dmapper are the programmed used in the process. Lue et al. advocated that numerous remote sensing platforms, such as satellite pictures, drone photogrammetry, and ground-based radar, be utilized to research landslides before and after disasters to prevent them in the future [40]. Advanced sensing techniques have brought about numerous solutions to the dependency of drones on GNSS data, with camera-based navigation and laser-based depth-sensing being derived as the conventional alternatives to purely depending on GPS data for navigation. Additionally, camera-based navigation plays a crucial role in visualizing the environment apart from being purely used for navigation, as in the case where GPS-based systems are used. NASA’s Jet Propulsion Laboratory (JPL) team has developed a tracking system called POINTER (Precision Outdoor and Indoor Navigation and Tracking for Emergency Responders) that could help firefighters navigate indoor environments where GPS tracking and communications are limited. Orolia and Satelles Inc. have formed a strategic alliance to develop a unique space-based PNT technology that provides location and timing data independent from traditional GPS and GNSS satellite signals to reduce the vulnerabilities of spoofing, interference, and jamming associated with GPS/GNSS and is said to be ‘fail-safe’.

The efficiency of drones can be significantly increased by using a multi-functional drone that can outperform a single-purpose drone but with application-specific programming chosen from the available software in the context of the specific environment, operation and climatic condition [65]. Deep learning algorithms aiding the photogrammetry techniques helped achieve better results rapidly with a precise map of infrastructure damage, subsequently helping the first responders in their rescue efforts [56]. In the context of 3D reconstruction, drone SFM technology has proven to be very effective in creating high-quality digital surface models of landforms [66]. Additionally, image segmentation methods based on deep learning can be used to identify hotspots such as forest fires from orthophotos [43]. As the capability of drones increases, so does their use in search and rescue operations. Studies reveal that disaster response has to be implemented within 72 hours of the event to avoid larger scales of loss in life and economy [27][67][68]. Considering the study, speed and mobility are noted to be the two most essential factors in SAR operations. Their assistance significantly speeds up the process and results in a more effective search of the affected area without endangering the lives of rescuers. Drones assist in ground search through the acquisition of aerial images of places that were difficult or impossible to reach [18]. Commercial drones have also been used at high altitudes to locate a missing climber [69]. UAVs and UGVs can also be used to traverse complex terrains such as caves and underground mines, while land-based robots can destroy blockage and clear paths [70]. The authors of a study that compared the performance of drones with rescuers for locating victims in a snow-covered environment concluded that the drones could search and locate victims over much larger areas in even less time than rescuers [5][71]. Additionally, their applications in response [37] and recovery [33] have been studied well in the context of firefighting [72], oil spills or floods [73], and the location of victims [10][60][61][74]. They have been used for the protection of human resources and personal property, assistance in evacuation efforts [50][51], and humanitarian localization [75].

Search and Rescue teams are crucial when recovering from a disaster (natural or man-made). These personnel risk their lives to traverse through dangerous/hostile terrains to rescue people stuck there and offer aid. They help distribute food and water, medicines and vaccines, temporary shelters, etc. [76]. To streamline and reduce the threat to life for both the rescue teams and the civilians, governments all over the world have invested heavily in research on the use of drones to make the search and rescue work safer and less time-consuming. This would also allow the personnel to traverse through terrains that were previously difficult to navigate and get real-time updates on the status of their surroundings, allowing them to find and save civilians with much greater ease and lesser risk [70][76][77][78]. Drones also will enable the rescue personnel to provide relief aid with ease as they can simply be loaded with payload in the form of emergency supplies and sent to victims stuck whilst simultaneously not being in any immediate danger of working in such sensitive cases [79]. UAVs overcome the limitations of the terrestrial system in terms of accessibility, speed, and reliability [80]. The technology emerged in defense for surveillance and combat purposes and has since observed exponential growth in many industries. The development of the first-ever semi-automatic aero plane can be traced back to 1916 as an aerial torpedo. The operation of completely autonomous UAVs, however, dates as far back as the Vietnam War [81]. Further advancements by integrating advanced navigation sensors into UAVs made them an integral part of the armed forces. Furthermore, the emergence of technology has eliminated constraints of UAV exercises in the military and also expanded its usage in commercial applications such as agriculture, scientific activities, recreation, commerce, photogrammetry, disaster management, civil operations, and many more [82] with agriculture and infrastructure attracting most of the applications.

Drones were initially created as primary machines, but as technological needs coming from complex missions have increased, their capability and complexity have also increased. Using unmanned aerial vehicles in public airspace raises several technical and societal problems [83]. Some concerns and obstacles regarding safety and security have surfaced due to the increased use of drones. The most pressing safety concerns are airworthiness, malevolent behavior, and interference with public property. Modern efforts to resolve these concerns have not been deemed enough, and hence, drone safety cannot be guaranteed. Concerns about cybersecurity, privacy, and public safety must be prioritized in this setting [83]. Moreover, various studies have examined security, privacy, and safety issues, with one focusing on the deployment of civil drones in national airspace [84]. The threat to persons, property, and privacy rights grows as civilian UAVs become more accessible and thus used [33][83][84]. Secure communication methods must also be used to protect data communication [85][86]. Despite their widespread use, drone technology is regarded as revolutionary, as its use and accessibility are growing faster than public knowledge of possible concerns or legislations to address these concerns [33]. Drones' rapid adaptation and growth in commercial applications necessitate rules that ensure their safe, secure, and certified use [87]. International organizations such as the International Civil Aviation Organization (ICAO) and the European Aviation Safety Agency (EASA) urge governments to develop regulations and standards for civil aviation [88]. Different governments are expected to continue implementing laws on using unmanned aerial vehicles (UAVs) [27][89][90], which may face frequent change. Soon, uniformity and long- term effectiveness in rules, regardless of region or application, may contribute to a better understanding and acceptance of drone technology.

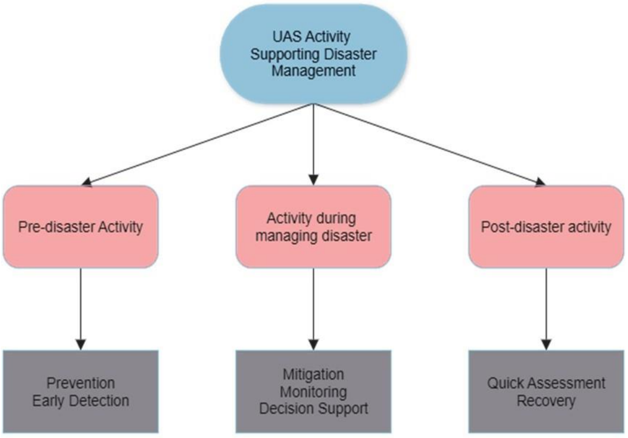

Fig. 1. Three stages of disaster management

A. Technological Gaps and Future Scope

The most significant trade-off to be made in drone technology is the one between payload capacity and endurance. Lithium- ion batteries are conventionally used onboard UAVs, supplying them with power. Still, the power backup of these batteries is not as large as that of the other batteries. As payload increases, flight time decreases as the discharge from the cells must be increased, thus draining the same amount of power in less time. Moreover, fixed-wing drones are more efficient in power usage, but they cannot hover and maintain speed at a place. Most papers demonstrated the usage of drones in typical weather conditions, so there may be a delay in the response of flight operations in the event of an absolute disaster. This has introduced a bias into the performance of drones due to the lack of real-world disasters in studies [5]. To overcome this issue, researchers have been suggested to conduct their research with adverse weather conditions and proper augmentation of hardware and software specific to the condition in which the experiment is conducted. Moreover, lack of cooperation and response delays among local communities and agencies have been detrimental to the negative perception and awareness of the inclusion of drones in disaster response.

Studies reveal that the technical capabilities of drone technology are determined mainly by the level of application and advancements of computer science in the technology. Single drones can always fail during flight due to various climatic and technological reasons. Research of drone application in swarms and heterogeneous collaboration with other cyber- physical security systems is being invested in by numerous research projects [91][92] and studies [93][94]. Swarms of drones can execute multiple tasks in a single iteration, reduce time, and also solve the problem that if one drone fails, others complete the mission. The development of robot swarms is currently under heavy research and development, with significant contributions from algorithms developed by computer science teams worldwide. Another significant contribution by computer science to making drones smarter is their increasing capability to think like humans, which is possible through integrating artificial intelligence algorithms such as deep learning techniques into the operating firmware. The technology is limited by human control through human operators, where the power of artificial intelligence could be leveraged to its full potential, allowing such devices to make smarter decisions and operate autonomously. A comprehensive analysis of the ones and zeros between autonomous and human-operated control has been discussed [21][95]. Another fallback to using drones can be adverse climatic conditions, where they become less efficient, increasing operation costs.

The authors of [96] identified that three types of applications that are currently attracting a lot of attention in the context of research and development in drone technology are (1) formation control and self-assembly methods [94][97], [98][99], (2) localization and search methods [100]-[101], and (3) techniques for solving optimization problems [102][103]. Moreover, the ability of drones to play an active role in the physical rescue effort is the next step to extending the capability of drones. In this context, Griff Aviation developed the Griff series of drones that could lift enormous amounts of weight to ten times more than most of the other UAS systems while carrying the payload longer. The Griff 300, also called the “megadrone” with 8 propellers and weighing 165 lbs. boasts a lifting capability of 300kg. As mentioned earlier, massive dependence on conventional navigation units such as GPS mounted on drones to measure position, velocity, and elevation is a significant setback to the advancements in sensing and perception capabilities. Since these GPS signals are very insensitive to noise and interference, there is always a possibility of losing contact. Here, initiating an emergency landing routine is necessary, where the inertial navigation system plays a significant role. Moreover, algorithms are still being developed that could increase the estimation of elevation and position by the Inertial Navigation Unit (INU). Other sensing units, such as cameras, also pose limitations in accurately using drones for specialized applications. An example of this setback is multispectral imaging in agricultural applications, where the data collection is prone to total irradiation, sun angle, and adverse weather conditions such as rain and heavy winds.

The MOBNET system, jointly developed by Orbital (Spain), DD (Netherlands), CEIT (Spain), NAVPOS (Germany), and SGSP, aims to provide the most advanced tool for locating people in locations with widespread usage of mobile phones [76]. The system relies on devices that use Global Navigation Satellite Systems (GNSS) [104] and Digital Cellular Technologies (DCT), enabling accurate positioning of all possible kinds of terrain. Various organizations have been working towards closing the gap between manufacturers and SAR professionals. Forums conducted by such organizations elevate the level of awareness of drone use and impart knowledge to responsible communities on the planning, procurement, and budget prioritization of drone technology in SAR operations. Necessary information on how the capabilities of drones can be augmented and adapted to meet specific mission requirements and standard operating procedures to operate under legislative regulations is also given so that the technology is exploited to its full potential. These exhibitions act as an interface between the consumer and the provider, whether private, governmental, military, or industry. On the other hand, humanitarian relief organizations have applied smart systems such as artificial intelligence and machine learning to their operations. One such instance was when Rescue Global and academics from the Orchid Project collaborated after the 2015 earthquakes in Nepal when they jointly took pre- and post-disaster imagery and utilized crowd- sourced data analysis and machine learning to identify locations affected by the quakes that had not yet been assessed or received aid. The information was then integrated into ‘heat maps’ that the SAR teams could use during decision-making. International Search and Rescue Advisory Group (INSARAG), since its inception in 1991 in Europe, has made a significant contribution to coordination in humanitarian relief under the supervision of the United Nations [105].

In summary, the advancement of drone technology has significantly impacted various sectors, including disaster management. Initially developed for military purposes, drones are now extensively researched and utilized across multiple industries due to their diverse applications, ranging from remote sensing to disaster response. The utilization of drones in disaster management has witnessed exponential growth, driven by their ability to reduce risks to human responders, increase operational effectiveness, and provide unique capabilities. Disasters, whether natural, man-made, or simulated, pose significant com- munity challenges, necessitating rapid and effective responses. Drones have emerged as valuable tools in disaster management, offering benefits such as rapid assessment, search and rescue capabilities, transportation of emergency aid, and assistance in communication restoration. Research and development in drone technology have primarily focused on natural disasters, with applications ranging from monitoring and mapping to search and rescue operations. Different classification schemes exist for categorizing drone operations in disaster management, with a shared focus on preparedness, assessment, and response/recovery phases. Despite drones’ advantages, challenges remain, including perception barriers, regulatory issues, and agency coordination. However, advancements in technology, such as deep learning algorithms and multi-functionality drones, continue to enhance the efficiency and effectiveness of drone operations in disaster management. In conclusion, drones play a crucial role in disaster management, offering rapid response capabilities, precise assessment tools, and enhanced situational awareness, ultimately contributing to mitigating disaster im- pacts and protecting lives and property.

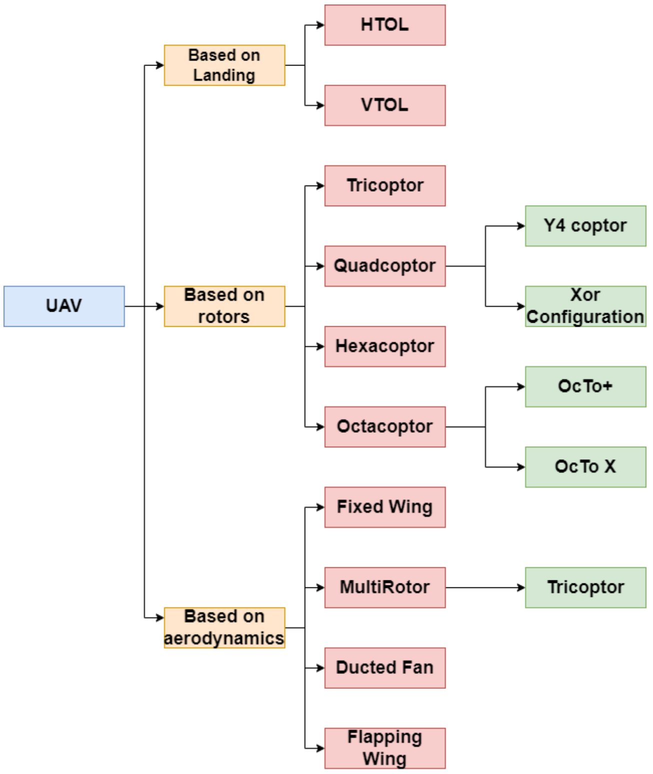

Fig. 2. UAV classification

III. UAV CLASSIFICATION

In Unmanned Aerial Systems (UAS), a diverse array of aircraft types has been developed and continues to undergo refinement. These encompass fixed-wing aircraft [106][107], helicopters [108][109], multi-copters [110], motor parachutes, gliders [111][112], and UAVs featuring Vertical Take-off and Landing (VTOL) capabilities [113][114], alongside commercially available drones. Each category of UAVs is tailored to specific mission requirements, offering distinct advantages and facing unique limitations. A very broad classification of UAVs [115] is given in Fig. 2

One pivotal criterion for classification is the landing method- ology, with two primary categories emerging: Horizontal Takeoff and Landing (HTOL) and Vertical Take-off and Landing (VTOL) aircraft. HTOLs, resembling traditional fixed-wing aircraft, boast higher cruising speeds and smoother landing operations. In contrast, VTOL aircraft are distinguished by their ability to vertically ascend, descend, and hover [116][117], with advanced designs often incorporating thrust vectoring technology [118][70]. Vertical Take-off and Landing (VTOL) UAVs are designed to ascend, descend, and hover vertically, making them versatile for missions where traditional runways are impractical. These UAVs often utilize advanced thrust vectoring technology for precise control. For instance, the DJI Matrice 300 RTK features a maximum takeoff weight of up to 9 kg, with a flight time of up to 55 minutes. It includes RTK positioning, obstacle avoidance AI, and a dual-camera system, making it suitable for complex aerial inspections and mapping tasks. Another example, the Boeing Insitu ScanEagle, boasts a maximum takeoff weight of 22 kg and can endure up to 20 hours in flight. It is equipped with reconnaissance and surveillance capabilities, employing electro-optical and infrared sensors for enhanced situational awareness. Horizontal Take- off and Landing (HTOL) UAVs resemble traditional fixed-wing aircraft, optimized for high cruising speeds and efficient long- range operations. These UAVs typically require runways or catapult systems for takeoff and landing. The General Atomics MQ-9 Reaper, for example, has a maximum takeoff weight of 4,760 kg and can stay airborne for up to 27 hours. It is extensively used for armed reconnaissance missions, carrying various sensors and weapons payloads. The Textron Systems Shadow TUAS (RQ-7Bv2) is another HTOL UAV, weighing

178 kg with an endurance of up to 9 hours. It features tactical reconnaissance capabilities, equipped with day/night surveillance cameras and a laser designator, supporting secure data links for real-time information dissemination. Multi- copters, also known as multirotor UAVs, employ multiple rotor systems (e.g., quadcopters, hexacopters) to achieve stable flight, hovering capabilities, and agile maneuverability. These UAVs are ideal for close-range inspections and real-time monitoring tasks. The DJI Phantom 4 Pro V2.0, weighing 1.4 kg, offers a flight time of up to 30 minutes and features a high-resolution camera capable of capturing 4K video and 20 MP photos. It incorporates advanced obstacle sensing technology, GPS navigation, and intelligent flight modes, making it suitable for professional aerial photography and surveying. In contrast, the Intel Aero Ready to Fly Drone weighs 1.6 kg and can fly for up to 35 minutes. Designed for developers, it integrates Intel RealSense depth and vision capabilities, supporting various operating systems and applications in research and development scenarios.

Notably, the Harrier Jump Jet is a prominent example of a successful VTOL aircraft, demonstrating the feasibility of this approach. Aerodynamics play a crucial role in another classification scheme, where fixed-wing drones represent a more straightforward design yet are saturated in terms of innovation [119]. These drones use forward acceleration to generate lift, controlled by velocity and wing angle. Conversely, flapping-wing drones draw inspiration from natural flight mechanisms observed in birds and insects [120][121]. Characterized by lightweight, flexible wings, these drones exhibit enhanced maneuverability and can operate effectively in adverse weather conditions [77]. Additionally, the combination of fixed and flapping wings in specific designs enhances overall aerodynamic efficiency [122], mirroring biological principles for optimized flight performance. Multirotor UAVs, commonly called multicopper, offer distinct capabilities, particularly hovering and vertical take-off and landing maneuvers [123][124]. Their design facilitates efficient surveillance operations due to their ability to maintain stable flight at lower speeds, making them ideal for capturing detailed imagery and conducting close-up inspections. However, their endurance is typically limited by higher power consumption, necessitating careful mission planning to optimize performance and achieve de- sired objectives. Weight and range serve as additional classification parameters, reflecting the operational capabilities and limitations of different UAV models [125]-[128]. Moreover, classifications based on size, power, and application conditions further refine categorization, encompassing a diverse range of vehicles such as fixed-wing, rotary-wing, tiltrotor, ducted fan, helicopter, ornithopter, and unconventional drones [5][16]. These classifications enable stakeholders to select the most suitable UAV platform for specific mission requirements, whether surveillance, monitoring, disaster response or beyond. Each category offers unique advantages and presents distinct challenges, underscoring the importance of strategic selection to maximize mission effectiveness and operational success in various contexts.

Hybrid UAVs represent a significant leap forward in unmanned aerial vehicle technology by combining the strengths of different aircraft types. These platforms integrate the vertical take-off and landing (VTOL) capabilities of multi rotors with the efficiency and endurance of fixed-wing aircraft. This hybrid design allows them to operate in diverse scenarios, such as rapid deployment in confined areas where traditional runways are unavailable, while also covering large distances efficiently once airborne. For example, the Hybrid Tiger developed by Quantum Systems can vertically take off like a multi rotor and then transition to fixed-wing flight for extended missions like mapping vast areas or conducting surveillance over long distances. Advancements in AI-driven autonomous navigation further enhance the capabilities of UAVs, making them smarter and more adaptive to complex environments. AI algorithms enable UAVs to autonomously plan optimal flight paths, dynamically adjust routes to avoid obstacles detected in real-time, and respond to environmental changes without human intervention. This capability is crucial in scenarios where precision and reliability are paramount, such as disaster response operations where UAVs need to navigate through debris or inspect damaged infrastructure safely. For instance, in agriculture, AI-driven UAVs can autonomously survey fields, analyze crop health using sensors and imaging systems, and even apply targeted treatments based on real-time data analysis. This not only improves efficiency but also reduces costs and environmental impact by optimizing resource use. In disaster management, AI-powered UAVs can rapidly assess disaster-stricken areas, identify survivors or hazards, and relay critical information to emergency responders in real-time, significantly improving response times and effectiveness.

Within each category of UAVs, significant variations exist that cater to specific mission requirements and operational environments. In the fixed-wing aircraft category, variations include high-altitude long-endurance (HALE) UAVs designed for extended surveillance and reconnaissance missions. These UAVs typically have large wingspans and are powered by efficient engines or solar panels to maximize endurance. In contrast, small fixed-wing UAVs are lightweight and portable, suitable for rapid deployment and shorter missions requiring maneuverability in tight spaces. In the multi rotor category, variations range from quadcopters to octocopters, with the number of rotors influencing payload capacity, stability, and flight endurance. Quadcopters are agile and commonly used for aerial photography and inspection tasks, whereas octocopters offer increased stability and payload capacity, making them suitable for heavier payloads or long-duration flights. Vertical take-off and landing (VTOL) UAVs encompass various designs, including tiltrotors and tiltwings, which combine the advantages of vertical and horizontal flight. Tiltrotors, like the Bell V-22 Osprey, can transition between vertical and horizontal flight modes, offering versatility for both military and civilian ap- plications. Tiltwings, such as the Quad TiltRotor developed by NASA, feature rotating wings that enable efficient vertical take- off and landing while maximizing efficiency in horizontal flight.

The operational landscape for unmanned aerial vehicles (UAVs), commonly known as drones, is shaped by a myriad of complex regulatory challenges and operational hurdles that UAV operators must navigate. At the forefront are stringent airspace regulations, which vary significantly across different regions and countries. These regulations dictate where drones can fly, at what altitudes, and under what conditions to ensure safety and prevent potential collisions with manned aircraft. Compliance with these regulations is essential but can be cumbersome, often requiring operators to obtain permits or licenses for specific flight operations. Privacy concerns also present significant challenges for UAV operators, especially in urban or residential areas where drones may capture sensitive personal information or intrude on private property. Regulations governing data collection, storage, and use are critical to protect individuals' privacy rights and maintain public trust in UAV technology. Adhering to these regulations often involves implementing robust data protection measures and obtaining con- sent when conducting surveillance or data-gathering activities. Technical limitations further complicate UAV operations. These include constraints such as limited battery life, which restricts flight endurance and operational range, and payload capacity, which affects the types of tasks drones can perform effectively. Overcoming these challenges requires continual advancements in battery technology, lightweight materials, and aerodynamic design to enhance flight efficiency and mission capabilities. Beyond regulatory and technical hurdles, gaining public acceptance of UAVs remains a significant challenge. Misconceptions about privacy invasion, safety risks, and noise pollution can lead to resistance from communities and stakeholders. Effective communication and transparency about the benefits of UAV technology, such as enhanced disaster response, environmental monitoring, and infrastructure inspection, are essential to foster positive attitudes and cooperation. In response to these multi- faceted challenges, collaboration between government agencies, industry stakeholders, researchers, and the public is crucial. Developing standardized regulatory frameworks, promoting technological innovation, and conducting public awareness campaigns can help address these challenges while ensuring that UAV operations are safe, responsible, and beneficial to society. One of the significant technological challenges faced by UAVs is power consumption. UAVs, especially those used

for long-duration flights or carrying heavy payloads, require sufficient power to operate efficiently. Current battery technologies often struggle to meet the demand for extended flight times, limiting the operational range and endurance of UAVs. Moreover, the weight of batteries can affect the UAV's overall performance and payload capacity.

Researchers are exploring various approaches to tackle this challenge. One direction involves advancements in battery technology, such as the development of higher energy density batteries and improved power management systems to optimize energy usage during flight. Another approach focuses on alternative power sources, including solar panels or fuel cells, to extend flight duration without significantly increasing weight. Additionally, research into energy-efficient propulsion systems and aero- dynamic designs aims to reduce overall power consumption, enhancing the UAV's endurance and operational capabilities. The limited endurance of UAVs is closely related to power consumption but encompasses broader challenges in achieving sustained flight over extended periods. Factors contributing to limited endurance include aerodynamic inefficiencies, weight constraints, and operational demands. Addressing these challenges requires innovative design solutions and operational strategies. Researchers are exploring lightweight materials and aerodynamic profiles to improve efficiency and reduce drag, thereby extending flight times. Advances in propulsion systems, such as electric motors and hybrid propulsion configurations, aim to enhance thrust-to-weight ratios and optimize energy consumption during flight. Moreover, optimizing flight planning and operational strategies through predictive analytics and real- time monitoring can maximize endurance by minimizing energy expenditure and optimizing flight paths. Ongoing research focuses on integrating these technological advancements with rigorous testing and validation to ensure reliable and extended UAV operations across various applications.

Developments have significantly changed our approach to the emergence of drone technology, making a significant contribution to complete transformation. A UAV is any non-piloted air- craft that can fly autonomously or partially remotely controlled [1][2]. They were initially developed for combat purposes but now form a significant part of research in the prospect of applications in various capacities. They are employed for multiple applications, including remote sensing, photogrammetry, film shooting, disaster management, combat, aerial reconnaissance, transport of supplies, and training personnel. The research and development of drone applications for disaster management has grown exponentially in recent years, owing to a better perception of their advantages over technologies conventionally used for the same application. Moreover, the adoption of drones by disaster management organizations has fueled research on the possibility of even better exploitation of them in light of such weighty concerns. Applications of drones in disaster management are divided according to stages relative to the actual event of the disaster or based on the type of work performed by the devices. Complex operations demanding advanced capabilities have nurtured the development of drones through the years. Their operational capabilities have made them grow into different classes, with differentiation mainly in power, size, and application conditions [3].

Future research in UAV technology is poised to explore several promising directions and emerging trends that could significantly shape the field. One key area of focus is enhancing autonomous capabilities through advanced artificial intelligence (AI) and machine learning (ML) algorithms. These technologies aim to enable UAVs to autonomously navigate complex environments, make real-time decisions, and adapt to dynamic situations without human intervention. Research in AI-driven swarm intelligence is also gaining traction, aiming to coordinate fleets of UAVs to perform collaborative tasks efficiently. Moreover, there is increasing interest in improving UAV endurance and range through innovative propulsion systems, energy harvesting techniques, and lightweight materials. This includes exploring hybrid propulsion systems combining electric and combustion engines, as well as integrating renewable energy sources such as solar and wind to extend flight durations. Efforts to minimize environmental impact and enhance sustainability are driving research into eco-friendly UAV designs and operations. Furthermore, the development of robust and secure communication networks for UAVs remains a critical research area. Future studies will likely focus on enhancing communication proto- cols, optimizing spectrum usage, and addressing cybersecurity challenges to ensure reliable and secure data transmission between UAVs and ground control stations. Additionally, advancements in sensor technologies, including high-resolution imaging, LiDAR, and hyperspectral sensors, are expected to enhance UAV capabilities in data collection and analysis. These sensors will enable more accurate environmental monitoring, disaster assessment, infrastructure inspection, and precision agriculture applications. Lastly, regulatory frameworks governing UAV operations are evolving globally, and future research will explore policy implications, safety standards, and ethical considerations associated with UAV deployment. Addressing these multifaceted challenges and opportunities will be crucial for realizing the full potential of UAV technology across various industries and societal applications in the coming years.

IV. RESEARCH AND DEVELOPMENT

A. *Challenges*

1) *Safety, Privacy, and Security Issues:*

Initially designed as simple devices, drones have evolved in capability and complexity to meet the demands of challenging missions. Their use in public airspace has given rise to numerous technical and societal issues [83]. The surge in drone usage has brought to light several safety and security concerns, including air- worthiness, malicious activities, and interference with public property. Despite contemporary efforts to address these issues, drone safety remains unassured. In this context, cybersecurity, privacy, and public safety are paramount. Various research has delved into these issues, focusing on deploying civilian drones in national airspace [84]. As civilian Unmanned Aerial Vehicles (UAVs) become increasingly accessible and more prevalent, the risk to individuals, property, and privacy rights escalates. One study suggested using a data broker to mitigate the privacy and security risks associated with information sharing among stakeholders. Additionally, secure communication methods are essential for data protection [85][86].

Safety concerns are paramount in UAV operations due to the potential for accidents that can cause damage or injury.

For example, in 2015, a drone crash-landed on the White House lawn, prompting concerns about the safety of UAVs near critical infrastructure. Another incident occurred in 2017 when a drone collided with a commercial aircraft in Canada, causing minor damage but highlighting the risks of UAVs operating in controlled airspace. These incidents underscore the importance of stringent safety protocols and technological advancements, such as geofencing and collision avoidance systems, to prevent accidents. Privacy Issues UAVs equipped with high-resolution cameras and other sensors can inadvertently or deliberately invade privacy. A notable incident occurred in 2014 when a drone hovered over a woman’s property in Seattle, leading to a lawsuit that raised awareness about privacy infringements. Additionally, in 2019, the city of San Diego faced backlash when it planned to deploy drones for surveillance during the COVID-19 pandemic, with citizens expressing concerns over potential misuse of the technology. These examples illustrate the need for clear regulations and ethical guidelines to balance the benefits of UAVs with individual privacy rights. UAVs can pose significant security risks if used maliciously. For instance, in 2018, drones were used in an attempted assassination of Venezuelan President Nicola´s Maduro, where explosive-laden UAVs targeted a public event. Another example is the use of drones by criminal organizations for smuggling contraband into prisons, bypassing traditional security measures. These incidents highlight the potential for UAVs to be used as tools for terrorism and criminal activities. To address these challenges, advanced counter-UAV technologies, such as radio frequency jammers and drone-detection radar systems, are being devel- oped to detect and neutralize rogue drones.

2) *Controlling Bodies and Regulations:*

Drone technology, despite its extensive usage, is considered revolutionary. Its adoption and accessibility are outpacing public awareness of potential issues and the development of legislation to address these concerns [33]. Drones’ rapid evolution and proliferation in commercial sectors call for regulations that ensure their safe, secure, and certified operation. Global entities like the International Civil Aviation Organization (ICAO) and the European Aviation Safety Agency (EASA) are encouraging governments to establish rules and standards for civilian aviation [88]. It is anticipated that various governments will continue to enact laws about using Unmanned Aerial Vehicles (UAVs) [27][89][90], which may be subject to frequent modifications. In the fore- seeable future, establishing consistent and enduring regulations, irrespective of geographical location or application, could foster a better comprehension and acceptance of drone technology.

The regulatory frameworks for UAV operations vary significantly across different regions, reflecting diverse approaches to safety, privacy, and airspace management. In the United States, the Federal Aviation Administration (FAA) enforces strict guidelines for UAV usage, including registration, remote identification, and operational limits, especially near airports and populated areas. The European Union, through the Euro- pean Union Aviation Safety Agency (EASA), has implemented a unified set of regulations that categorize drones based on risk and intended use, promoting harmonization across member states. Conversely, countries like India and China have rapidly evolving regulatory landscapes that balance innovation with stringent oversight due to concerns about national security and privacy. These regional disparities create complexities for international UAV operators who must navigate different rules and standards, often necessitating region-specific adaptations of their technology and practices. Current regulations, however, are often insufficient to address the rapid advancements in UAV technology and the increasing variety of applications. For instance, existing frameworks may not fully cover emerging issues like autonomous drone operations, swarm technologies, or the integration of UAVs into urban air mobility systems. Furthermore, the enforcement of privacy protections is lagging, as seen in the patchwork of state and local laws that fail to pro- vide comprehensive guidelines. To improve regulatory efficacy, there is a need for more dynamic and adaptable policies that include specific provisions for advanced technologies, enhanced coordination between national and international regulatory bodies, and the incorporation of real-time data sharing to improve situational awareness and response capabilities.

3) *Technological Gaps & Future:*

In drone technology, the primary tradeoff lies between payload capacity and endurance. UAVs typically use lithium-ion batteries for power, but these batteries don’t have as much power backup as others. As the payload increases, the flight time decreases due to the increased cell discharge, draining the same amount of power in less time. Fixed-wing drones are more power-efficient but cannot hover and maintain speed at a specific location. Most studies have demonstrated drone usage under typical weather conditions, which could cause delays in flight operations during natural disasters. This has introduced a performance bias in drones due to the absence of real-world disasters in studies [5]. To address this, researchers must conduct their studies under adverse weather conditions and augment their hardware and software accordingly. Additionally, the lack of cooperation and response delays among local communities and agencies have negatively impacted the perception and awareness of drone usage in disaster response. The application level and advancements in computer science primarily determine the technical capabilities of drone technology. Single drones can fail during flight due to various climatic and technological factors. Research into drone application in swarms and heterogeneous collaboration with other cyber-physical security systems is being pursued by numerous research works [91]-[94]. Drone swarms can execute multiple tasks in a single iteration, reduce time, and solve problems where others complete the mission if one drone fails. The development of robot swarms is currently a central area of research and development, with significant contributions from computer science teams worldwide. Another significant contribution of computer science is the increasing capability of drones to mimic human thinking, which is made possible by integrating artificial intelligence algorithms such as deep learning techniques into the operating firmware. The technology is limited by human operator control, where the full potential of artificial intelligence could be leveraged, allowing such devices to make smarter decisions and operate autonomously. A comprehensive analysis of the binary between autonomous and human-operated control has been discussed [21][95]. An- other drawback of drones is adverse climatic conditions, where they become less efficient, increasing the operation cost. The authors of [96] identified three types of applications that are currently garnering significant attention in the context of drone technology research and development: (1) formation control and self-assembly methods [94][97]-[99], (2) localization and search methods [100][101], and (3) techniques for solving optimization problems [102][103]. Furthermore, their active role in physical rescue efforts is the next step in extending drone capability. In this context, Griff Aviation developed the Griff series of drones that can lift enormous amounts of weight, up to ten times more than most other UAS systems, while carrying the payload for longer durations. The Griff 300, also known as the “megadrone” with eight propellers and weighing 165 lbs, is touted to have a lifting capability of 300kg.

As highlighted in the search and rescue section, the heavy reliance on conventional navigation units like GPS, which are mounted on drones to measure position, velocity, and elevation, poses a significant challenge to advancements in sensing and perception capabilities. Given the sensitivity of these GPS signals to noise and interference, there’s always a risk of losing contact. In such cases, initiating an emergency landing routine becomes necessary, where the inertial navigation system plays a crucial role. Furthermore, algorithms that could enhance the estimation of elevation and position by the Inertial Navigation Unit (INU) are still under development. Other sensing units, such as cameras, also present limitations in using drones accurately for specialized applications. An instance of this limitation is multispectral imaging in agricultural applications, where data collection is susceptible to total irradiation, sun angle, and adverse weather conditions like rain and strong winds. The MOBNET system, a collaborative effort by Orbital (Spain), DD (Netherlands), CEIT (Spain), NAVPOS (Germany), and SGSP, aims to provide an advanced tool for locating individuals in areas with extensive mobile phone usage [76]. This system relies on devices that utilize Global Navigation Satellite Systems (GNSS) [104] and Digital Cellular Technologies (DCT), enabling precise positioning across all types of terrain. Several organizations are working to bridge the gap between manufacturers and SAR professionals. Forums organized by these entities raise awareness about drone usage and provide responsible communities with knowledge on the planning, procurement, and budget prioritization of drone technology in SAR operations. They also provide essential information on how drone capabilities can be enhanced and adapted to meet specific mission requirements and operate under legislative regulations, thereby fully exploiting the technology’s potential. These exhibitions serve as a platform for interaction between consumers and providers, whether they are private, governmental, military, or industry entities. On the other hand, humanitarian relief organizations have also incorporated innovative systems like artificial intelligence and machine learning into their operations. A notable example is the collaboration between Rescue Global and academics from the Orchid Project following the 2015 earthquakes in Nepal. They jointly took pre- and post-disaster imagery and utilized crowdsourced data analysis and machine learning to identify quake-affected locations that had not yet been assessed or received aid. This information was then integrated into ‘heat maps’, which the SAR teams could use for decision-making. The International Search and Rescue Advisory Group (INSARAG), established in 1991 in Europe, has significantly contributed to coordinating humanitarian relief under the supervision of the United Nations [105]. Recent advancements in software aimed at reducing power consumption in UAVs include algorithms like dynamic power management (DPM) and energy-aware adaptive sampling. For instance, the implementation of the Power Efficient Mobile Communication (PEMC) algorithm in UAVs has shown a reduction in energy consumption by dynamically adjusting transmission power based on signal strength and distance to the receiver. Another example is the use of the Adaptive Data Collection (ADC) algorithm, which optimizes sensor data collection intervals based on the UAV’s current state and mission requirements, leading to significant energy savings. Case studies, such as those conducted by the University of Washington, have demonstrated that incorporating these algorithms can extend UAV flight times by up to 20pec, illustrating the practical benefits of software advancements in power efficiency.

Ongoing research efforts are focusing on mitigating battery limitations in UAVs through several innovative approaches. One key area of development is the enhancement of battery technology, including the use of solid-state batteries, which offer higher energy density and safety compared to traditional lithium-ion batteries. Researchers are also exploring alternative power sources such as hydrogen fuel cells, which can provide longer flight times and quicker refueling compared to conventional batteries. Additionally, solar-powered UAVs are being developed to harness renewable energy, potentially enabling indefinite flight durations for certain applications. Improvements in power management systems, including smart algorithms for optimizing energy use during flight, are also cru- cial in extending UAV endurance. To address payload capacity challenges, technological advancements are being pursued to increase the efficiency and strength of UAV structures. The use of lightweight, high-strength materials such as carbon fiber composites can significantly reduce the weight of the UAV, allowing for higher payload capacities without compromising performance. Modular designs that enable UAVs to switch out different payloads easily are also being developed, enhancing their versatility for various missions. Innovations in miniaturization technology are allowing for smaller, lighter payloads without sacrificing functionality, thus increasing the overall efficiency of UAV operations. Furthermore, improvements in propulsion systems, including more efficient motors and propellers, can help UAVs carry heavier loads while maintaining stability and control.

V. HARDWARE

A UAV, or Unmanned Aerial Vehicle, is a type of aircraft that operates without a pilot. It relies on an airframe and a computer system, including sensors, GPS, servos, and CPUs. These components enable the UAV to fly autonomously. The size, type, and configuration of a UAV can vary based on its intended application. Despite the lack of a common standard for transmission, connections, and components in the UAV industry, it's possible to abstract standard functionalities from individual representations. UAVs have many applications, including emergency security, communication, environment, and monitoring. Recently, their use has expanded to civil and commercial purposes. While military UAVs are explicitly designed for surveillance missions, civil UAVs can perform many tasks with minimal reconfiguration time and overhead [129][130]. A complex UAV consists of several primary submodules that work together to create a valuable observation platform as depicted in the Fig. 6. A UAV System (UAS) design includes not only the UAV itself but also subsystems such as the communication link between the UAV and the user, the ground control station, and various related accessories. The design process spans the initial frame design to controlling a 'ready to fly' vehicle. Selecting components like the airframe, controller, motor propellers, and power supply requires careful consideration and mathematical calculations by experienced personnel.

An Unmanned Aerial Vehicle (UAV) is built around a lightweight, aerodynamic, and stable airframe. It's designed to fly without a pilot on board. The specific application determines the airframe's design parameters, such as coverage area, maximum altitude, speed, climb rate, endurance, and stability [131]. A higher altitude allows for a larger coverage area and increased survivability, although aviation laws limit the maximum altitude. The climb rate and the aircraft's aerodynamic design also affect its survivability and endurance. The critical components of an aircraft include the inertial measurement unit, motors, propellers, receiver, processor, and the airframe itself [77]. The materials used in manufacturing these components can be metallic, such as alloys, aluminum, and titanium, or non-metallic, like transparent and reinforced plastic [132] and carbon-reinforced fiber. The design includes brushless motors and propellers, with electronic speed controllers adjusting the power supply to the motors based on commands from the throttle stick. If a flight controller is used, it acts as a hub, connecting the flight computer with the electronic speed controllers, inertial measurement unit, receiver, and other hardware. The onboard controller manages the operation of the sensors, including the payload. The inertial measurement unit comprises a three-axis accelerometer, a gyroscope providing 3-axis raw data, a three-axis magnetometer, and a GPS unit. The flight computer, essentially the heart of the UAV, serves as an add-on to enhance the onboard computational processing capabilities of the UAV. It runs complex software that the flight controller can- not process independently. Integrating a computer with a flight controller unlocks the full potential of autonomous drones. Flight computers and controllers also enable the streaming of real-time data, such as audio and video, to the ground control station for analysis. They can also analyze data themselves, depending on the specific operation requirements. This data is encoded according to the controller's actions and streamed back to the ground control station. A ground station is typically equipped with a wireless router and a computer, which are used to capture process, and display data [133][134]. The ideal setup would be an open-system, multi-platform architecture. This would ensure compatibility with various devices, including those that operate in the air, water, underwater, and on the ground. It would also have the capability to process information in real-time, control both homogeneous and heterogeneous swarms of UAVs and their payloads, and establish robust communication with other ground control stations [135][136]. In addition to these capabilities, the ground station must adhere to specific safety and security requirements. These include warning systems and emergency action plans to handle any failures or power outages. The communication link between the onboard sensors of a drone and the ground control station is a crucial component of a UAV system (Fig. 3). This link employs various communication protocols, including IEEE 802.11, to facilitate communication between the drone's flight computer and controller. Routers with high-gain omnidirectional antennas minimize path loss and enhance the signal-to-noise ratio. For online transmission of high-fidelity video and audio to the ground station, separate wireless links based on technologies such as Orthogonal Frequency Division Multiplexing (OFDM) and Wi-Fi are utilized. Studies have explored dual communication links, specifically Satellite and Radio frequencies. These two links operate complementarily, providing a backup option if one fails [78].

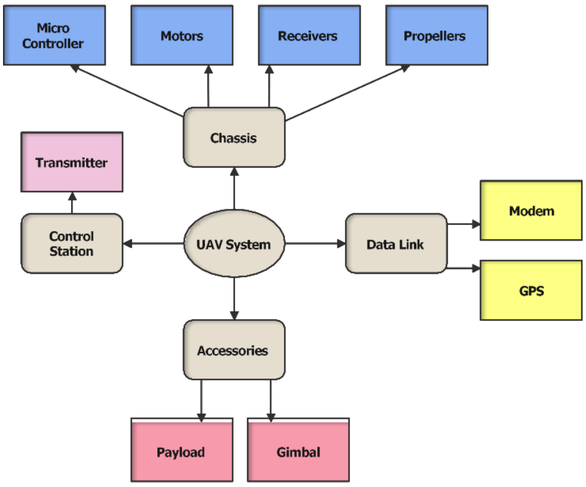

Fig. 3. UAV subsystem

A. *Accessories, Payload and Sensing Equipment*

As the demand for applications in photogrammetry, film shooting, mapping, creating digital elevation models, monitoring, and surveillance increases, Unmanned Aerial Vehicles (UAVs) are equipped with advanced imaging technologies. These include multispectral cameras [137], thermal cameras, hyper-spectral cameras [138], digital cameras [137], and film imaging units [139][140]. The payload of a UAV, which includes cameras, infrared, and thermal sensors, gathers information that is either processed onboard or transmitted to the base station for remote processing. Different applications require specific technologies, necessitating crucial decision-making from a broad spectrum of imaging technologies. For instance, thermal sensors have enabled drones in the mining, oil, and gas industries. At the same time, hyperspectral cameras that work with narrow spectral bands provide more information with ultra-high resolution than multispectral cameras. The payload capacity critical factor in selecting a UAV. Different operations re a specialized payload for each specific monitoring, assessment intervention, or transport use case. The requirement for a particular payload varies as the applications differ in size and type. For example, applications range from locating avalanche victims with signals from specialized wirelessly enabled devices to using UAV-based ground-penetrating radar for scanning large areas [141], and from carrying hardware required for data acquisition [142] to embedded video processing. Each class of UAV, however, is limited by its carrying capacity. Therefor selecting the correct device for each specific operation is a crucial decision for disaster management teams in the ‘preparedness’ stage.

In addition to the specialized sensors mounted onto drones as a payload, such as those studied for the detection of radiation [51], ground-penetrating radar [141], and infrared and ultraviolet spectrometers [52] for detecting and measuring volcanic gases, UAV technology also employs numerous o embedded sensors. These conventional sensors, developed for navigation, control, and guidance of aircraft through various terrains, are seen as necessities of technology in the current advanced era of drones. Studies report heavy use of the Global Navigation Satellite System or ‘GPS’ [75][143][144], sonar sensors, Radio Detection and Ranging (RADAR), LiDAR (Light Detection and Ranging), laser range finders [145], optical and hyperspectral cameras, and Synthetic-Aperture Radar [75]. Imaging systems or cameras, have been prominent among the sensing technologies embedded in drones. A powerful combi- nation of advanced imaging technologies and state-of-the-art sensing techniques powered by artificial intelligence, machine learning, and computer vision algorithms have increased aerial perception. Additionally, deep learning techniques with big data have enabled onboard real-time processing for sensing in robust detection and tracking in different scenarios. A study on precision agriculture [146] has classified imaging technologies into visible spectrum imaging, infrared spectrum imaging [147], and fluorescence excitation. The software components of a UAV system are displayed in Fig. 4.

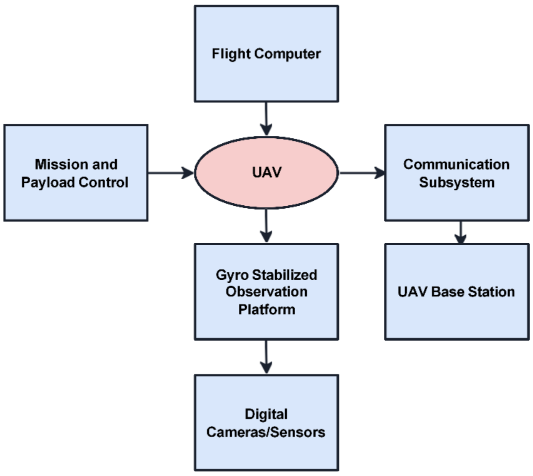

Fig. 4. UAV hardware components

VI. SOFTWARE

The onboard processing power of Unmanned Aerial Vehicles (UAVs) is limited and varies from device to device. The software components of a UAV system are depicted in Fig. 5. However, the efficiency of the algorithms and the software required to perform tasks is continually improving, becoming less power-consuming. This advancement enhances the technology’s capability to contribute to data processing and problem-solving tasks. The software used in UAVs handles flight path planning, processes collected information, and analyzes UAV data. This supports service providers and local communities by providing actionable intelligence for better decision-making. Such software is commonly used in various sectors, including agriculture, mining, construction, disaster management, and recreation. Integrating drones with existing systems and coordinating their use among different agencies and local communities present several challenges. Compatibility with current communication and data management systems is often problematic, as drones typically generate large volumes of data that require efficient processing and sharing. Different agencies may use varied platforms and software, complicating data interoperability. Additionally, there is often a lack of standardized protocols and procedures for drone operations, which can lead to inconsistencies and inefficiencies. Engaging local communities is also crucial, as their acceptance and cooperation are vital for successful drone deployment. However, privacy concerns, regulatory compliance, and ensuring equitable access to UAV-enabled services can create resistance. Addressing these challenges requires comprehensive planning, robust regulatory frameworks, and ongoing collaboration among all stakeholders. Practical UAV software features include flight plan automation, augmented view, geo-rectification of images, and generation of 2D/3D models. Furthermore, advancements in software development have enabled drones to become more autonomous. The algorithms required for flight path calculations can now be run onboard by the devices themselves. As embedded processors become smaller and more powerful, the computational power increases, substantially reducing the drone’s weight. This development has also significantly benefited the communication infrastructure by decreasing the amount of data that needs to be communicated to a centralized command.

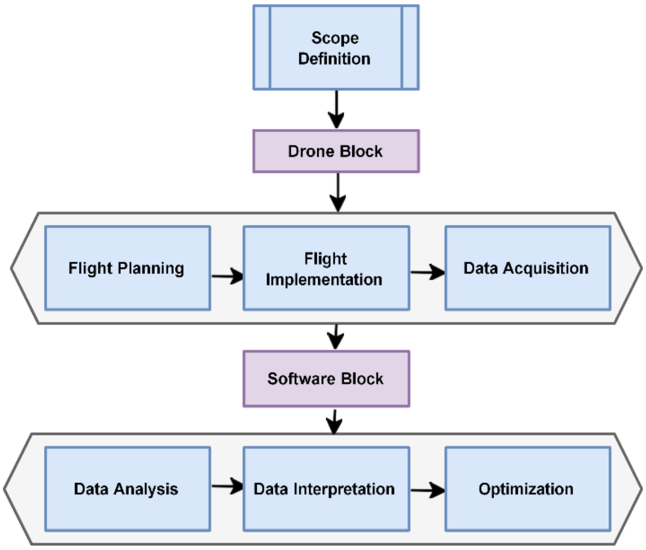

Fig. 5. UAV Software Components

A. Drone Sensors

The increasing demands for drone sensing capabilities have led to significant advancements in drone perception. How- ever, drone perception differs from robotic perception and requires specialized knowledge, research, and development. This involves intensive experimentation and substantial investment from academia, industry, and governments to achieve further progress. A general pipeline for complete perception, particularly in alarm raising, has been demonstrated in [78]. Various automatic platforms, including Unmanned Aerial Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), space exploration probes, and missiles, are equipped with cameras and other exteroceptive sensors to enhance vehicle perception. However, these are primarily used as payload and not for piloting the vehicle itself [148]. The use of computer vision for UAV perception and navigation is becoming increasingly mainstream. This is particularly necessary when UAVs operate at lower altitudes to avoid obstacles, especially in unknown or GPS-denied conditions. The data from the exteroceptive sensors can be processed to gather information about the UAV's motion or the 3D structure of the environment [149][150]. Some of the sensors that can be used are

- RGB camera – Used to detect the different objects in terrains such as plants, buildings, etc.
- Thermal camera – Used to detect heat signatures radiated from different bodies.
- LiDAR – Used to measure distance between two objects or between the UAV and different objects or obstacles.
- GPS – Used to track the drone's movement and help in navigation.
- Electro-optic sensors – They can provide the relative position of the obstacle by determining the elevation and azimuth employing a camera but do not provide distance or speed information [118][149].

Drones have many sensors, including multi-spectral cameras, hyperspectral cameras, SONAR, and Laser Range finders. Accurate data pre-processing is crucial, as inaccuracies can lead to errors in subsequent processes. This involves image selection, accurate georeferencing, ortho-rectification, and mosaicking. Studies have demonstrated the potential of using the OpenCV pipeline for the autonomous landing of UAVs with computer vision, where the OpenCV library is used for image processing tasks such as detecting a landing site. Georeferenced images are then subjected to supervised and unsupervised learning techniques for feature extraction, such as roads, tracks, humans, wildlife, forestry, agriculture, land cover, water bodies, etc. Various machine learning algorithms are used for classification, including Maximum Likelihood Classification (MLC), Random Forest methods, and Support Vector Machines (SVMs). Deep learning techniques, such as Convolutional Neural Networks (CNNs), are employed. Feature Vector classification using region size and region mean intensity has proven effective in determining fire hotspots while searching over large regions, such as in the case of forest fires [78]. The method used was 8-connected region growing, and classification was done using a fuzzy classifier. The collected data is used to visualize the surrounding environment and stored in memory for future use. Software, such as Agisoft, has facilitated the creation of visualization models, such as Digital Elevation Models (DEMs) using processed orthophotos. Open-source software like RViz, which provides easier visualization of real-time sensor data from UAVs, has enabled faster experimentation, fueling re- search and development in complex algorithms. Techniques like Drone SFM rapid georeferencing and machine vision techniques such as 3D Cloud point extraction, waypoints, Ground Control Points (GCPs), Orth mosaicking, and orthorectification have accelerated the use of drones in real-life scenarios.

RGB cameras, LiDAR, and thermal cameras are integral to UAVs for capturing visual, depth, and thermal data, respectively, yet each comes with distinct limitations in practical applications. RGB cameras, while versatile in capturing high- resolution images, struggle in low-light conditions and can produce inaccurate color representations. LiDAR, renowned for precise distance measurements, faces challenges in detecting transparent or reflective surfaces and incurs high costs, limiting its widespread deployment. Thermal cameras excel in identifying heat signatures but are constrained by lower spatial resolution and difficulty in distinguishing objects with similar temperatures. Moreover, all sensors are susceptible to environmental factors such as weather, which can compromise data quality and reliability. Addressing these limitations requires continual advancements in sensor technology to enhance accuracy across diverse operational environments. Deep Learning algorithms, including neural networks, are pivotal in UAV applications for tasks such as object detection and path planning, yet they confront significant practical limitations. While effective in recognizing patterns from large datasets, they demand substantial computational resources and extensive training data to achieve optimal performance, posing challenges in real-time applications with constrained computing capabilities onboard UAVs. Occupancy Grid Mapping (OGM) algorithms, crucial for mapping unknown environments, encounter limitations in dynamic environments with moving obstacles or changes in terrain, necessitating robust adaptation mechanisms. Similarly, Simultaneous Localization and Mapping (SLAM) techniques like SACHER face challenges in maintaining accuracy over extended periods and in environments with limited feature-rich structures. Overcoming these algorithmic limitations demands advancements in real-time processing capabilities, adaptive learning models, and robustness to dynamic environmental changes, ensuring reliable performance across varied UAV missions.

RGB (Red, Green, Blue) cameras are among the most commonly used sensors in drones. They capture high-resolution im- ages and videos, providing detailed visual information about the affected areas. In disaster scenarios, RGB cameras are used for damage assessment and search and rescue. They capture images of damaged infrastructure to assess the extent of destruction and prioritize response efforts. For example, during the 2019 Hurricane Dorian in the Bahamas, RGB cameras helped quickly assess the damage to buildings and roads [151]. Additionally, they aid in identifying and locating survivors in rubble or flood- waters, as seen in the 2018 earthquake in Sulawesi, Indonesia [152]. Thermal cameras detect heat signatures, making them invaluable in low-visibility conditions such as smoke, fog, or darkness. They are primarily used for search and rescue and fire monitoring. Thermal cameras detect the body heat of trapped or injured individuals, particularly at night or in smoky environments. During the 2017 Grenfell Tower fire in London, thermal cameras helped identify heat sources within the building [153]. They also identify hotspots and monitor fire spread to guide firefighting efforts, as extensively demonstrated during the 2020 Australian bushfires [154]. LiDAR (Light Detection and Ranging) sensors use laser pulses to create high-resolution, three-dimensional maps of the terrain. Their applications in disaster management include mapping and surveying and debris detection. LiDAR creates detailed topographic maps to identify changes in the landscape caused by events like landslides or earthquakes. For instance, it was used to map landslide-prone areas following the 2015 Nepal earthquake [155]. Addition- ally, LiDAR technology was utilized after the 2011 Japan tsunami to map debris fields [156]. Multispectral and hyper- spectral sensors capture data across multiple wavelengths of light, beyond the visible spectrum. They are used for vegetation health monitoring and environmental impact assessment. These sensors assess the health of vegetation and identify areas of stress or damage, crucial for post-disaster agricultural recovery. Multispectral sensors were used to monitor crop health after the 2018 Kerala floods in India [157]. Hyperspectral sensors also help assess environmental damage, such as after the 2010 Deepwater Horizon oil spill [158]. Gas sensors detect the presence and concentration of various gases, which is critical in hazardous environments. Their applications include hazardous material detection and volcanic activity monitoring. Gas sensors identify the release of toxic gases in industrial accidents or natural disasters, as demonstrated during the 2019 chemical plant explosion in Xiangshui, China [159]. They also measure gas emissions from active volcanoes to predict eruptions and assess volcanic activity, such as in monitoring emissions from the Kilauea volcano in Hawaii [160].

To maximize the utilization of the sensors, algorithms have been developed to allow drones to regulate the use of the sensors based on the data gathered, reducing human interference and thereby minimizing error [7]. Some examples of such algorithms are: The Occupancy Grid Map (OGM) Algorithm is a family of computer algorithms in probabilistic robotics. These algorithms, designed for mobile robots like Unmanned Aerial Vehicles (UAVs) and Automated Guided Vehicles (AGVs), generate maps from noisy and uncertain sensor measurement data, assuming the robot's pose (location/altitude) is known. First proposed by H. Moravec and A. Elfes in 1985, the principle behind these algorithms is to represent a map of the environment as an evenly spaced field of binary random variables. Each variable represents the presence of an obstacle at that location in the environment currently being traversed. These algorithms compute approximate posterior estimates for the random variables and consist of four components: interpretation, integration, position estimation, and exploration. However, the OGM algorithm has some weaknesses, such as slow update speed and inaccurate prediction of dynamic objects, because they accumulate measurements and only show the occupancy probability of the current state [118][161].

The Dynamic Occupancy Grid Map estimates the local environment around the vehicle, including each cell's occupancy probability and kinematic attributes like acceleration, velocity, and turn rate. SACHER, which stands for Soft Actor-Critic (SAC) with Hindsight Experience Relay (HER), belongs to the Deep Reinforcement Learning (DRL) algorithm family. SAC is a model-free, off-policy DRL algorithm based on the maximum entropy framework that outperforms comparable DRL algorithms like TD3 regarding resilience, learning performance, and exploration. However, maximizing the entropy-augmented aim in SAC may degrade the optimality of the learning outcomes. HER is a sample-efficient replay method that enhances the performance of off-policy DRL algorithms by allowing the agent to learn from both failures and successes [162]. Applying HER to SAC improves SAC's learning performance. Because HER increases SAC's sampling efficiency, SACHER obtains the intended ideal outcomes more accurately and quickly than SAC. SACHER's application to the perception through sensors problem of UAVs under varied impediments results in increased navigational and control capabilities. This is because SACHER calculates the best navigation path for the UAV in the face of various impediments. SACHER's effectiveness in cumulative reward and tracking error in UAV operation is compared to that of state-of-the-art DRL algorithms, DDPG, and SAC. The SACHER technique can also be used for arbitrary UAV models [148][162].

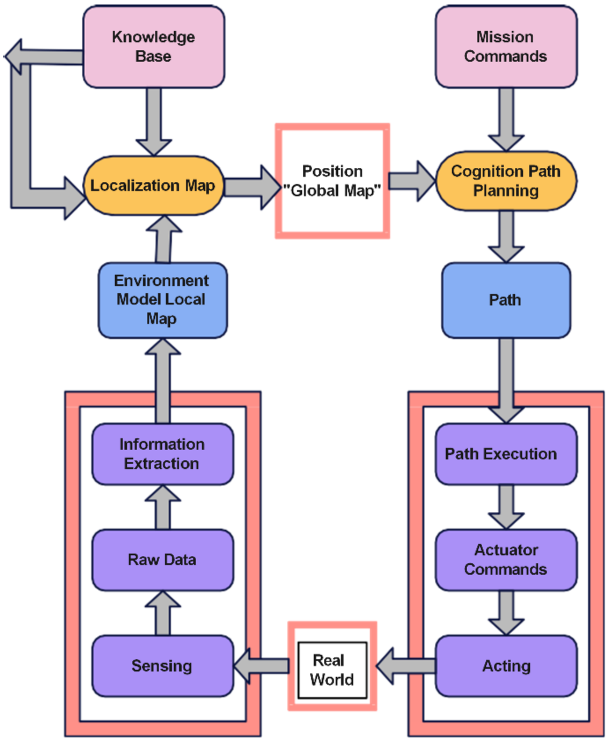

Fig. 6. Software interconnection

B. *Detection and Tracking*

Currently, computer vision is a highly sought-after field in Artificial Intelligence research. It has gained significant traction as it enables scientists and engineers to imbue drones and robots with intelligence, enabling them to tackle real-time problems. Computer vision encompasses tasks such as object tracking, object counting, and object detection, which are crucial for monitoring a specific environment. However, challenges such as motion blur, altitude, occlusion, and changes in camera angle make these tasks more complex. The methods to detect objects in UAV images can be categorized and detailed. Initially, datasets specific to object detection tasks are identified. Subsequently, existing research works across various applications are summarized. Ultimately, a robust object detection framework with a secure onboard processing system can be employed to address identified gaps in the datasets. If deployed on drones, this detection and tracking feature can be utilized for search and rescue operations in disaster zones or areas difficult for SAR teams to traverse. This feature can also track footprints to locate missing people, objects, animals, etc., using datasets like the search parameters [163][164]. The research is ongoing to optimize and streamline the detection and tracking algorithms to reduce processing time while maintaining or improving the quality of the processed images. New algorithms are continually proposed, tested, and implemented to enhance speed.

One example is the YOLO Algorithm, which offers real-time object detection using neural networks. It is widely acclaimed for its speed and accuracy. YOLO (You Only Look Once) is an algorithm that detects and recognizes various objects in an image in real-time. In YOLO, object detection is treated as a regression problem, and it provides the class probabilities of the detected images. It employs Convolutional Neural Networks (CNN) to detect objects in real-time. The algorithm necessitates only a single forward propagation through a neural network to detect objects, implying that a single algorithm run is sufficient to predict an entire image. The CNN is used to predict bounding boxes and various class probabilities simultaneously. The algorithm has several variants, including tiny YOLO and YOLO V3 [165][166]. The following reasons make YOLO a vital algorithm.

- Speed: The speed of detection improves as the prediction of objects happens in real-time.
- High Accuracy: It is a predictive technique that provides accurate results with minimal background errors.
- Learning Capabilities: It has excellent learning capabilities that allow it to learn the representation of objects and apply them in object detection [167][168].
- YOLO algorithms work using the 3 techniques mentioned below: Residual Blocks: In this, the image is divided into various grids with a dimension of S x S. Bounding Box Regression: An outline highlights a specific object in an image. Every bounding box in an image consists of the width (bw), height (bh), Class (Ex. person, car, dog, etc.) represented by "c" and a bounding box center (bx,bh) attributes. Intersection Over Union (IOU): It is a principle of object detection that describes the boxes' overlapping. YOLO uses IOU to provide an output box which surrounds the objects perfectly. The prediction of the bounding boxes and their confidence scores is the responsibility of each cell. If the predicted bounding box is the same as the actual box, then IOU is 1. This mechanism eliminates bounding boxes, which are not equal to the actual box [166][168].
- Some of the fields in which YOLO algorithms can be applied are: Autonomous Driving: It can be used in self-driving automobiles to identify pedestrians, parking signals, and other vehicles. Object detection avoids collisions because no human driver controls the car under autopilot. Wildlife: In the outdoors, YOLO can detect many species and types of animals. Wildlife rangers and journalists use this to identify animals in recorded videos and photographs. Security: YOLO is also helpful in enforcing security in an area, as YOLO can detect them if they pass through a restricted area [165][167].

Due to its resilience and speed, the Deep SORT Algorithm is a highly effective tool for detecting individuals in crowded or busy areas. Unlike systems that track based on distance and velocity alone, Deep SORT also considers a person's appearance. This feature is incorporated by computing deep features for each bounding box and then using deep feature similarity to influence the tracking logic [169][170]. For the algorithm to function optimally, it is best practice to train models on millions of human images. This training allows the extraction of a 128-dimensional vector for each bounding box to capture critical features of the box. Deep features enable the model to easily track people in a crowd or those very close in an image [171]. However, despite its strengths, the Deep SORT Algorithm has some weaknesses. If the bounding boxes are too large, too much background is captured in the features, reducing the algorithm's effectiveness. Additionally, if people are dressed similarly, as is often the case in schools and sports, it can lead to similar features being matched and IDs being switched [169].

C. *Navigation, Control and Guidance*

The rise in unmanned aerial vehicles (UAVs) operating in low-altitude airspace, such as urban environments, could potentially increase accident risks. The components of a drone control are shown in Fig. 7. There are chances of drones falling and causing harm to people or damaging vehicles. UAVs might also intrude into commercial airspace, necessitating safe airspace to mitigate these risks. One such measure is geofencing, which divides the airspace into designated safe zones. However, this may not be feasible in cities like Singapore, where available airspace is limited. An alternative approach is airspace utilization, where risk-cost and risk-cost maps are used to ensure safer and risk-free operations [172][173]. Path planning must consider numerous ground and aerial obstacles. Achieving the optimal path within a plausible time frame is challenging, and various path-planning applications have been experimented with to solve as close to optimal as possible [174][175][176]. The Anytime algorithm, for instance, demonstrates particle swarm optimization and can depict the path quality dependent on computation time. This algorithm can generate solutions within any given computational time interval, improving the solutions as computation time increases. Simulations have shown that these algorithms can compute good paths in a relatively short amount of time [177]. Each UAV computes its path, and if communication permits, these paths are shared among UAVs in a swarm to reach a specific geographical position without collision. An adaptive path planning algorithm coordinates UAVs deployed for land-based surveillance. This algorithm uses a global cost function to generate different paths for the UAVs and can adapt to exceptions and obstacles that might occur along the path [178]. In addition to the algorithms above, many others, such as A* (A Star), Djikstra, etc., have been discussed in studies and extensively used in robots and UAVs. Path planning is closely related to various navigation applications that provide directional and positional commands to UAVs. GPS satellites can provide a means to calculate the position of the signal receiver, but these calculations are not always accurate. UAVs monitor the environment and consider multiple targets, processing information and labelling images with numerous target classes. The data from various UAVs are then fused to form a comprehensive picture. Each UAV is associated with a ground station, which gathers data from the sensors and filters and fuses it either at the ground station or on the UAV processors [172][174][179].

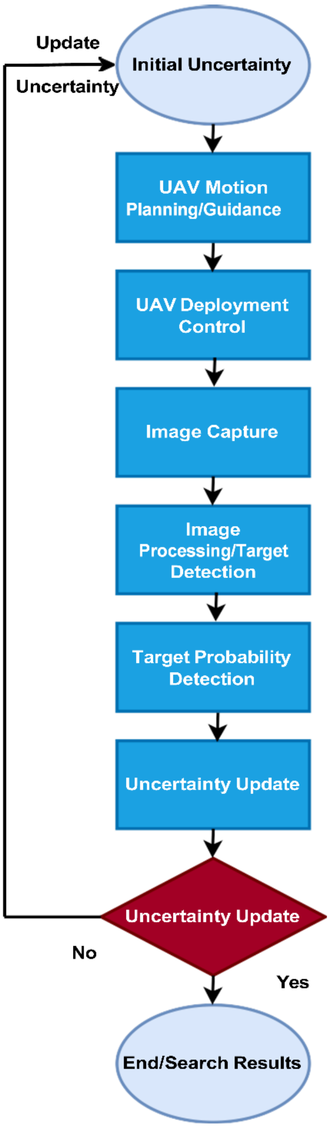

Fig. 7. Flowchart of drone control process for target detection and uncertainty management

With advancements in wireless technology, GPS-based navigation systems are increasingly used for location-based needs and traffic control. However, due to limited satellite availability, GPS-based vehicle systems face challenges monitoring objects in urban contexts, making it difficult to deploy filtering and other statistical procedures [180]-[183]. The Fuzzy Logic Algorithm, one of the most widely used computational methods, takes noisy and imprecise inputs and converts them into a crisp output. Fuzzy logic facilitates the mapping and matching of the output from the GPS receiver due to its tolerance for imprecise inputs [184]. The study [185] discusses the navigation challenges faced by Unmanned Aerial Vehicles (UAVs) flying in formation through environments laden with obstacles. When static obstacles are present in the flight path, UAVs must steer around and avoid collisions. To accomplish these tasks, the paper proposes a "dual-mode" strategy. The "safe mode" is activated in an obstacle-free area, and the "danger mode" is activated when obstacles are present in the path or there is a collision risk. The safe mode achieves global optimization as the controller considers the dynamics of all participating UAVs. In the danger mode, a novel algorithm is proposed for collision avoidance, which can generate an optimal trajectory using the geometry of the flight space [186][187]. Collision avoidance is a crucial feature of autonomous UAV flights. Various options exist for obstacle identification and avoidance, each with its drawbacks. Existing solutions can be divided into two parts: the first involves simple collision avoidance [188] by steering away from the obstacle, and the second involves more complex collision avoidance [104]. This technique does not allow the vehicle to manage the distance between it and an obstruction, which may be necessary in some situations. The second part involves mapping, location, and navigation to avoid collisions [189][190].

For multi-UAV operations, collision avoidance algorithms must be designed because some drones may need to adjust their spatial position in the swarm formation [174][176]. For collision avoidance between Automated Guided Vehicles (AGVs) and UAVs, we can learn from this work [191] how they share information about location and movement direction. The communication algorithm keeps the information up-to-date and applicable in emergencies. The application is distributed, with each UAV being managed by an individual agent using various algorithms and application approaches [192]. Optimizing Search and Rescue (SAR) operations can be effectively achieved through multi-robot systems (MRS) with autonomous support or tele-operational capabilities. These systems can assist in situational assessment, mapping, surveillance, monitoring, victim search, and establishing communication networks. Given SAR operations' wide range of environments and situations, heterogeneous and collaborative multi-robot systems can offer significant advantages [193]. The concept of a multi-robot system was introduced to demonstrate the effective use of drones by coordinating ground-based robots with aerial robots to form a cohesive team, thereby reducing human risk. For instance, aerial drones could scout the hallways during a mine cave-in, while ground-based drones could efficiently rescue personnel by digging through the rubble as directed. As previously discussed, the failure of a single drone during flight leaves first responders helpless in their search for victims or in any other general disaster management activity. Moreover, the endurance of a single drone is limited by its power consumption, and a more significant number of iterations are required to complete a complex operation over a large area. Therefore, the cooperation between multiple devices to form swarms is increasingly being considered. This applies to both homogenous swarms [32][36][51][73][19][19][196][197], consisting only of Unmanned Aerial Vehicles (UAVs), and heterogeneous swarms [10][198], consisting of multiple UAVs and Unmanned Ground Vehicles (UGVs). This technology is inspired by the swarm motion of insects, ants, and birds, utilizing artificial intelligence. The use of swarms for identifying objects of interest in water bodies has been discussed in [9]. Numerous studies have emphasized various algorithms for computing formations of multiple devices in three-dimensional space while they work towards achieving a common or varied task(s) [8]. Furthermore, a comprehensive survey on UAV- based communication in the context of civil applications, which requires intervention by such swarms, has been studied in [32]. Research is underway to streamline the coordination between drones and make it more natural, thereby minimizing the human element as much as possible. Efforts are also being made to enhance drone capabilities, such as increasing carrying capacity, equipping them with multiple tools, and building sturdier drones to withstand extreme environments like heat or cold, such as burning buildings, fires, and snowy mountain peaks [199].

VII. UAV SWARMS FOR DISASTER MANAGEMENT

One of the best ways to optimize Search and Rescue(SAR) operations is through multi-robot systems(MRS) with autonomous support or tele-operational capabilities. This can aid in situational assessment [296], mapping, surveillance, monitoring, searching for victims, and establishing communication networks. SAR operations cover a wide range of environments and situations, and thus, heterogeneous and collaborative multi- robot systems can provide the most advantages [279]. The multi-robot system started as a concept to showcase the proper utilization of drones by coordinating ground-based robots with aerial robots to form a proper team, which lessens human risk. An example would be if a cave-in happens in a mine, aerial drones can scout the hallways while ground-based drones can dig through the rubble as directed to rescue personnel efficiently. As discussed earlier, flight failure while using a single drone makes first responders helpless in their search for victims or any other general disaster management activity. Moreover, the endurance of a single drone is limited by its power consumption, and a more significant number of iterations are required to complete a complex operation that spans a large area. Hence, the cooperation between multiple devices to form swarms is increasingly been considered, both for homogenous swarms [32][36][51][73][194]-[197], consisting of only UAVs, and for heterogeneous swarms [10][198], composed of multiple UAVs and UGVs. This technology is derived from the swarm motion of insects, ants, and birds utilizing artificial intelligence. The use of swarms for identifying objects of interest in water bodies has been discussed in [9]. Several studies have emphasized various algorithms for the computation of formations of multiple devices in three-dimensional space while they work towards achieving a common or varied task(s) [8]. Moreover, a comprehensive survey on UAV-based communication in the context of civil applications, which requires intervention by such swarms, has been studied in [32]. Currently, research is being done to make the coordination between drones more streamlined and natural so that the human element can be reduced as much as possible. Research is also being done to increase drone capabilities such as carrying capacity, multiple tools to be used as needed and building sturdier drones to last in extreme environments like hot or cold, such as burning buildings/ fires and the snowy peaks of the mountains [199].

Current technological limitations and practical challenges in implementing drone swarms and AI integration are substantial and multifaceted. One of the primary challenges is the immense computational power required for real-time data processing and decision-making. Each drone in a swarm must process vast amounts of data from onboard sensors, cameras, and other input devices to navigate, avoid obstacles, and complete assigned tasks. This demand for computational power can strain the onboard systems, potentially limiting the drones' efficiency and effectiveness. Communication between drones in a swarm is another critical challenge. For a swarm to operate cohesively, it requires fast, reliable communication channels that can handle large volumes of data with minimal latency. However, interference and signal loss, particularly in urban environments or areas with dense foliage, can disrupt communication. Ensuring that all drones in a swarm remain connected and can effectively share information is a significant technological hurdle. AI algorithms play a crucial role in managing the coordination of drone swarms, enabling them to operate autonomously and avoid collisions. Developing such sophisticated AI is challenging because it involves creating algorithms that can adapt to dynamic environments, make split-second decisions, and learn from new data in real-time. The complexity of these algorithms increases exponentially with the number of drones in the swarm, making it difficult to ensure seamless operation and prevent malfunctions. Security is another vital concern when it comes to drone swarms and AI integration. Ensuring that the communication networks and control systems are secure from hacking and unauthorized access is paramount. A breach in security could lead to catastrophic consequences, including loss of control over the drones, data theft, or misuse of the technology for malicious purposes. Practical implementation of drone swarms also involves navigating a complex regulatory landscape. Regulations governing the use of drones vary widely between regions and are often stringent, particularly concerning safety, privacy, and airspace management. Compliance with these regulations can be time-consuming and costly, posing barriers to widespread adoption. Safety and privacy concerns are paramount, as the deployment of drone swarms can raise issues about the potential for accidents, invasions of privacy, and the ethical implications of their use. These concerns necessitate the development of robust safety protocols and ethical guidelines to govern the use of drone swarms in various applications.

A. Swarm Algorithms

In the case of swarm drones, different types of algorithms can be used, as mentioned earlier, such as the Anytime algorithm, which can optimize the path of quality dependent on the computation time. The algorithm can produce solutions to any given computational time interval, and the solutions get better results with increased computation time. Each of the UAVs produces a path, and the communication between each UAV allows the sharing of paths between each of them so that they can reach a specific geographical position without any collision. An adaptive path planning algorithm is used to coordinate UAVs that are deployed for land-based surveillance. This algorithm uses a global cost function to generate different paths for the UAVs, and it can adapt to the exceptions in the path that might occur. The algorithm performs a random search for a feasible solution by mutating, evaluating, and selecting members with higher fitness within a population of possible solutions. A novel algorithm is proposed for collision avoidance among swarm drones; this algorithm can generate an optimal trajectory using the geometry of the flight space [200]. The algorithm leverages local edge density to partition the frame into two separate sections. The first is an unstructured or homogeneous area, such as a sky region, while the second is a structured area, such as high-contrast clouds or terrain sections. The planes are recognized using distinct algorithms in two sorts of areas. The algorithm was designed to run in an embedded environment with low power consumption, making it suitable for small or mid-sized UAVs. Furthermore, other algorithms of interest in heavy use, research, and development include Voronoi-based space partitioning of planes and Ant colony optimization. Voronoi Partitioning, also referred to in the literature as Voronoi Tessellation, Dirichlet Tessellation, Thiessen Polytopes, Voronoi Polygons, Voronoi Decomposition, or Voronoi Partition, is a scheme for partitioning a plane into regions close to each of a given set of objects. The objects may range from points sampled over the space of interest to victims considered in disaster management. A Voronoi portioning of a 2D image or plane results in a Voronoi diagram consisting of the same plane but with overlapping Voronoi nodes, Voronoi cells, and line segments. The Voronoi Cells, also called Thiessen Polygons, consist of all points of the plane closer to that node than any other. They can be imagined as a result of the equally paced growth of circles in a direction outward from a set of points distributed over a plane, where the adjacent circles form line segments of the Voronoi diagram. Nodes are sometimes also referred to as sites or seeds. A Voronoi cell consists of every point in the Euclidean plane whose distance to the site is less than or equal to its distance to any other site. The line segments in the Voronoi diagram are all the points in the plane that are equidistant to the nearest sites, whereas the Voronoi vertices (nodes) are the points equidistant to three (or more) sites. The fundamentals behind the construction of the Voronoi diagram are distance metrics, the most commonly used being Euclidean distance. In contrast, Manhattan and Manholobis distances have also been used, but different metrics result in differently shaped cells. The distance of each point in the Euclidean plane to every site or node in the Voronoi diagram is calculated using the chosen metric. Then, the grouping of points of interest in space is done based on whether they share the same nearest node, thus giving rise to cells. There are various algorithms through which the Voronoi partitions are constructed; these methods are differentiated based on the direct formulation or indirect formulation of the diagrams. The indirect method involves calculating the Delaunay triangulation, which is a dual graph of the Voronoi, using which the Voronoi line segments are calculated. This method uses the Bowyer- Watson algorithm. Delaunay triangulation is a collection of triangles built using our original set of points as vertices, such that no triangle's vertex should lie inside the circumcircle of other triangles in the formation. The triangle's vertices form the nodes of the desired Voronoi diagram. To get the Voronoi diagram from the Delaunay triangulation, the circumcenters of each triangle are connected to the circumcenters of the neighboring triangles.

Direct Methods include Fortune's Algorithm, Jump Flooding Algorithm, Lloyd's Algorithm and its generalization via the Linde-Buzo-Gray algorithm (aka k-means clustering). Lloyd's algorithm is processed in steps, starting with a set of seed points and then moving onto steps in which the seed points are moved to new locations that are more central (centroidal) within their cells. These steps converge the partitions to form a specialized version of Voronoi Diagrams known as the Centroidal Voronoi Tessellation (CVT) [286], where the nodes are moved to points that are also the geometric centers of their cells. Similarly, there are some other variants of the Voronoi diagram, such as the weighted Voronoi diagram. Application of Voronoi diagrams in SAR and plenty of other operations carried out by a multi- quadcopter system is made possible through the formulation of search effectiveness models of sensors [201]. Because cameras' effectiveness as sensors is reduced in such complex operations with the increase in distance from the center pixel, a method for formulation of the cameras' effectiveness model is shown [284]. Moreover, the use of the formulated model for successfully applying Voronoi diagrams in simulated operations has been demonstrated with the apparent scope of expanding the usage from simulated to natural environments [201].

Effective communication among drones in coordinated swarm operations is achieved through sophisticated protocols and technologies designed to ensure seamless coordination and collaboration. Each drone within the swarm typically communicates with neighboring drones and a central control unit using wireless communication protocols such as Wi-Fi, Bluetooth, or specialized mesh networking protocols. These communication systems enable drones to exchange real-time information about their positions, velocities, sensor data, and mission objectives. This shared data allows drones to maintain situational awareness, avoid collisions, and collectively achieve mission goals. Centralized or decentralized algorithms govern swarm behavior, dictating how drones adjust their positions and behaviors based on input from neighboring drones and the environment. Key challenges in swarm communication include ensuring low latency, high reliability, and scalability as the number of drones increases. Techniques like adaptive routing, dynamic spectrum allocation, and distributed consensus algorithms are employed to optimize communication efficiency and resilience. Moreover, redundancy in communication links and fail-safe mechanisms are critical to maintaining operational continuity in challenging environments where connectivity may be compromised. Research and development continue to focus on enhancing swarm communication capabilities, particularly in scenarios with limited bandwidth, high interference, or complex terrain. Advances in artificial intelligence and machine learning enable drones to autonomously adapt their communication strategies based on real-time conditions, thereby improving overall swarm coordination and effectiveness in diverse operational settings.

The power consumption challenges faced by UAV swarms are critical in determining their operational effectiveness and endurance. Each UAV's battery life directly impacts the overall operational time of the swarm. The limited battery capacity of most drones constrains their flight duration, often requiring frequent recharging or swapping of batteries. This challenge becomes even more pronounced in swarm operations, where the coordination of multiple drones increases the demand on their power systems. Battery life is influenced by various factors, including the drone's weight, the efficiency of its propulsion system, and the power consumption of its onboard systems, such as sensors and communication equipment. Advances in battery technology, such as the development of lithium-sulfur and solid-state batteries, show promise in extending flight times, but they are not yet universally adopted. Moreover, the energy density of current batteries still limits the operational duration, necessitating ongoing research into higher-capacity energy storage solutions. Recharging infrastructure is another significant challenge. Traditional recharging stations are often insufficient for the rapid turnover required in swarm operations. This has led to the exploration of innovative solutions such as wireless charging pads, solar charging stations, and autonomous recharging drones that can replenish the batteries of other drones in- flight. These solutions aim to reduce downtime and maintain the swarm's operational tempo, especially in extended missions. Power-efficient algorithms also play a crucial role in mitigating power consumption. Advanced algorithms are being developed to optimize flight paths, reduce power-hungry computations, and enhance the overall energy efficiency of drones. Techniques such as dynamic voltage and frequency scaling (DVFS), where the power consumption of the UAV's processors is adjusted based on the task load, and energy-efficient routing protocols, which minimize the distance traveled by drones, are critical. Machine learning algorithms are also being integrated to predict and manage energy consumption dynamically, adjusting flight patterns and operational parameters in real-time to conserve power.

VIII. CHALLENGES, LIMITATIONS AND FUTURE SCOPE OF UAV'S IN DISASTER MANAGEMENT OPERATIONS

Drones have seen an increase in civilian applications in re- cent years, including collecting time-sensitive information from disaster sites, delivering commodities, and managing traffic. Due to the restricted battery life and field of view for certain activities, such as covering huge geographic areas and giving crucial information, their usage encounters limitations [202]. To overcome these restrictions, a swarm of drones could work together to solve the problem. This will allow for more efficient work completion while providing broad geographic coverage. Swarms have improved the influence of drones in coordination, enabling more excellent coverage, flexibility, and robustness. In the control system, each drone serves as a simple agent. Communication is one of the critical aspects of the proper functioning of a swarm [96]. Self-assembly methods and self- organizing formation control in the lack of global communication is thus an important emerging advancement in multi-robot coordination and has attracted a significant amount of research interest since conceptualization [96]-[99][203][204] becoming the most prominent study in the field. To overcome the limitations of drone swarms, researchers have made advances in wireless communications and power calculations [205]. Most of these initiatives are aimed at assisting in developing centralized control drone systems, which have some limits in terms of scalability and security.

The ethical and legal dimensions of drone usage, particularly concerning privacy and surveillance, are increasingly complex as technology evolves. Drones have the capability to collect vast amounts of data and conduct surveillance in ways that were previously impractical or impossible. This capability raises significant concerns about individual privacy, data security, and the potential for misuse or unauthorized surveillance. Regulatory responses vary globally, with some regions implementing strict guidelines on drone operations, data collection, and privacy protection. For example, the GDPR in Europe mandates stringent rules regarding the collection, storage, and processing of personal data, which applies to drone operations as well. In the United States, the FAA regulates drone flights and imposes restrictions on flying over certain areas to protect privacy and safety. Technological advancements such as geofencing, which restricts drones from flying into sensitive areas, and encryption protocols for data transmission, help mitigate privacy risks. However, challenges persist in enforcing these measures consistently across jurisdictions and ensuring compliance among drone operators, especially in urban environments where privacy concerns are heightened. Moreover, ethical considerations go beyond regulatory compliance to encompass broader societal impacts. Issues like public perception of drones, transparency in drone operations, and the equitable distribution of benefits and risks associated with drone technologies require careful attention. As drones become more integrated into various sectors including transportation, delivery services, and emergency response, addressing these ethical challenges becomes crucial. Future advancements in drone technology, such as improved AI capabilities for autonomous flight and data analysis, will likely amplify these ethical and legal considerations. There is a growing need for ongoing dialogue among stakeholders including governments, industry, academia, and civil society to develop robust ethical frameworks that balance innovation with the protection of individual rights and societal values.

In UAVs used for disaster management, data storage, trans mission, and protection are critical aspects to ensure effective and secure operations. Data collected by sensors onboard UAVs, such as imagery, environmental data, and telemetry, need to be stored securely onboard the UAV itself or transmitted in real- time to ground stations or cloud servers for further analysis and decision-making. UAVs typically have onboard storage capabilities to temporarily store data during flight. This storage needs to be robust to withstand the physical stresses of flight and capable of handling large volumes of data generated by sensors. Secure storage protocols ensure that data integrity is maintained and that it can be accessed efficiently for analysis after the flight. Real-time transmission of data from UAVs to ground stations or command centers is crucial for immediate decision-making during disaster scenarios. This transmission often utilizes wireless communication technologies, such as satellite links or high-frequency radio, to ensure reliable and fast data transfer. Encryption protocols are employed to secure data during transmission, preventing unauthorized access or interception by third parties. Protecting UAV data from unauthorized access or misuse is paramount. Access control mechanisms ensure that only authorized personnel can access sensitive data, such as imagery of affected areas or personal information collected during rescue operations. Encryption techniques, including AES (Advanced Encryption Standard), are commonly used to secure data both at rest (stored data) and in transit (during transmission). Challenges include ensuring data integrity in adverse environmental conditions, maintaining secure communication channels in remote or disaster-affected areas, and complying with regulatory frameworks for data privacy and protection. Solutions involve the use of robust encryption standards, redundancy in data storage and transmission systems, and adherence to international standards and guidelines for data handling in disaster management contexts.

Furthermore, swarm functionalities involving collision avoidance and formation management may be impaired in wireless environments where communication channels are prone to quality changes and potential malicious attacks. In this case, a drone swarm system should be developed using self-organizing features rather than relying on a known controller that would need to update the state of the entire swarm system regularly. The combination of network and computational systems, which have generally been researched in isolation, is required for the successful self-organized operation of drone swarms. The close integration of the network and computing systems is necessary for self-organized drone swarm operation. When a computational system estimates that the quality of some wireless links may be compromised due to shadowing effects, for example, or that an end-to-end path may be temporarily available, the network system should be able to find better transmission channels to neighbors and also better end-to- end paths to distant drones, resulting in increased network robustness. We also identify key research problems and open topics in developing drone swarms, such as networked control systems, including integrating networks and computers. Adapting drone behavior to respond effectively to dynamic and unpredictable disaster scenarios relies heavily on advanced algorithms designed to process real-time environmental data and adjust operations accordingly. These algorithms play a crucial role in enhancing the autonomy and responsiveness of UAVs, enabling them to navigate through challenging conditions such as changing weather patterns, terrain obstacles, and evolving emergency situations. In disaster management, where rapid decision-making is essential, algorithms for adaptive drone behavior leverage sensor data, including from cameras, LiDAR, and environmental sensors, to assess immediate surroundings and plan optimal paths. They incorporate machine learning techniques, like reinforcement learning or neural networks, to continuously learn from new data and improve decision-making in complex environments. However, challenges persist, particularly in ensuring robustness against uncertainties and unforeseen obstacles.

The integration of UAV technologies, particularly in surveil- lance and environmental monitoring, holds significant promise for societal impact but also raises important ethical considerations. In surveillance, UAVs equipped with high-resolution cameras and sensors offer enhanced capabilities for monitoring public spaces, disaster zones, and even private areas, raising concerns about privacy infringement. Ethical frameworks must address issues of consent, data ownership, and the potential misuse of collected information. Striking a balance between public safety and individual privacy rights is crucial to ensure responsible deployment of surveillance UAVs. On the environmental front, UAVs play a pivotal role in monitoring ecosystems, wildlife habitats, and climate change impacts with unprecedented precision and efficiency. They enable real-time data collection over large and remote areas, aiding in bio- diversity assessments, disaster response, and natural resource management. However, ethical considerations emerge regarding wildlife disturbance, airspace congestion, and the environmental footprint of UAV operations, including noise pollution and carbon emissions. Sustainable practices and regulations are essential to mitigate these impacts while harnessing UAV technology for environmental stewardship.

IX. CONCLUSION

As drone technology continues to rapidly evolve, its potential across diverse industries, including disaster management, is becoming increasingly evident. While these unmanned systems advance and gain broader adoption, concerns regarding safety and operational challenges are actively being addressed. Re- searchers in academia and industry are pivotal in driving these advancements forward, pushing the boundaries of what drones can achieve. However, assertions of industry dominance should be grounded in empirical evidence and supported by case studies to provide a clearer understanding of how drones are trans- forming various sectors and addressing practical challenges. Moving forward, the integration of artificial intelligence (AI) tools holds promise for enhancing drone capabilities, enabling greater autonomy and effectiveness in critical operations. Safety remains a paramount concern, particularly within regulatory frameworks and operational practices, due to potential risks to human safety and infrastructure integrity. Regulatory bodies worldwide enforce stringent guidelines to manage these risks effectively. Ongoing research efforts focus on developing robust safety protocols, implementing risk mitigation strategies, and advancing accident prevention technologies to enhance the reliability and safety of drone operations. Despite technological advancements in AI-powered drone modules promising to enhance disaster management operations, significant challenges persist in translating theoretical potential into practical implementation. Real-time AI processing, seamless integration with existing infrastructure, and ethical considerations surrounding AI-driven decision-making pose critical barriers that require careful navigation. Addressing these challenges comprehensively will be essential to fully realize the benefits of AI in dis- aster management, ensuring that drones contribute effectively to emergency response efforts while upholding ethical standards and maintaining operational reliability. The integration of AI- powered drones into disaster management introduces promising advancements yet also raises significant ethical considerations that demand careful deliberation. Issues surrounding autonomy, accountability, and decision-making in critical scenarios under- score the need for robust ethical frameworks. These frameworks are essential for guiding the responsible deployment of drone technologies in disaster management and other sensitive do- mains. By engaging in thoughtful discussions and implementing comprehensive ethical guidelines, stakeholders can effectively navigate these challenges, ensuring the ethical and responsible use of AI to enhance disaster response capabilities while prioritizing human safety and societal well-being.

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