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Uncrewed Aerial Systems for Emergency Medical First Response: A Market Research Report

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Abstract

This report presents the findings from market research conducted for NASA's Aerial **Ai**d Convergent Aeronautics Solutions (CAS) exploration project, which aims to assess the current state of the market and technological readiness for Uncrewed Aerial Systems (UAS) for medical emergency first response. The research reveals a robust and rapidly growing market for UAS, with a notable emerging sector for Drones as First Responders (DFR). Despite this growth, DFR applications are currently limited by regulatory, technical, and other challenges, which restrict their use primarily to manned remote video surveillance, and therefore are primarily employed by police units. To our knowledge, there is no evidence of UAS being utilized by medical first responders for scene assessment. Limited evidence exists for closely related applications; however, these are mostly confined to pilot programs for the delivery of medical supplies or equipment. Although there has been discussion around fully autonomous DFR applications for medical purposes such as UAS ambulances or patient transport drones, these applications are generally not yet operational in practice. The technology for full autonomy, especially in guidance and control, has seen significant advancements, and recent Federal Aviation Administration (FAA) regulations are likely to accelerate adoption. Computer vision algorithms for fully autonomous medical emergency response scene surveillance are primed for advancement and deployment. A notable gap likely exists between advancements in computer vision research and what is being integrated in the commercial DFR sector. This gap is primarily due to challenges such as quality assurance for autonomous systems, the availability of application-specific training datasets for computer vision algorithms, regulatory constraints, and public perception and privacy concerns.

Contents

1 Introduction

NASA's Convergent Aeronautics Solutions (CAS) project invests in innovative ideas and challenges to advance aeronautics and related industries [1]. The CAS project has identified an opportunity to enhance human health through the use of Uncrewed Aerial Systems (UAS), also known as Uncrewed Aerial Vehicles (UAV) or drones, for medical applications, currently being explored by an effort called Aerial **Ai**d. Aerial **Ai**d focuses on Drones as First Responders (DFR), a paradigm in which UAS are deployed to emergency scenes in advance of or alongside traditional resources such as fire and medical first response units. DFR uses UAS to provide reliable situational awareness to ground units prior to their arrival. Equipped with cameras, sensors, and communication devices, the drones can send live video feeds to the remote pilot and other stakeholders including responding officers, fire departments, and command personnel—giving them near real-time situational awareness before they arrive on the scene. The benefits of these programs include faster response times, improved safety for both officers and the community, and cost-effectiveness compared to traditional aerial support like helicopters [2, 3].

Within DFR, Aerial **Ai**d emphasizes the use of Artificial Intelligence and Machine Learning (AI/ML) toward automatic scene mapping and perception technologies, leveraging advances in commercially available computer vision capabilities such as object detection[1] and semantic segmentation[2]. Advances in UAS sensors and data streams (e.g., positioning, inertial data, network signals) enable the creation of detailed 3D models of emergency scenes without manual input [4]. Furthermore, automatic scene perception technology seeks to identify and report on critical environmental information for first responders. This could include such tasks as identifying safe routes of ingress and egress, patient count and location, bi-stander count and location, an indication of certain patient vitals such as respiration rate, the presence of hazards such as fire, and more, providing a comprehensive operating picture for emergency personnel.

1.1. Report Objectives

This report aims to inform Aerial **Ai**d's efforts to promote the expanding role of drones in emergency medicine and their potential to enhance patient outcomes. It highlights the current state of DFR and related AI/ML, discusses scene assessment relevant datasets for training AI/ML from a UAS perspective, and reviews gaps and challenges which may be inhibiting the integration of drones into Emergency Medical Services (EMS).

Currently, key research, including limited deployments, is underway for DFR applications for emergency medicine including delivering Automated External Defibrillators (AEDs) to cardiac arrest victims, transporting blood and blood products, delivering emergency medications such as Naloxone and Epinephrine, and assisting in search and rescue operations with advanced imaging and communication capabilities such as deep learning for emergency hand signal and drowning victim iden-

[1] https://www.tensorflow.org/hub/tutorials/object_detection

[2] https://www.tensorflow.org/tutorials/images/segmentation

tification [5]. However, the widespread adoption of medical drones faces several challenges. Challenges limiting UAV autonomy have a special impact on the utility of DFR for emergency medicine. Challenges exist that include limiting autonomy such as regulations by authorities like the FAA and the European Union Aviation Safety Agency, safety and privacy concerns, the efficacy and reliability of AI/ML capabilities for computer vision and decision making, and hardware limitations such as battery life and payload capacity. Despite these challenges, future opportunities exist for integrating drones into existing EMS and 9-1-1 systems, gaining public acceptance through education, and evaluating the cost-effectiveness of drone networks. Case studies highlight the effectiveness of drones in delivering AEDs and blood products and enhancing search and rescue missions, demonstrating their potential to improve emergency medical response [5]. Academic research shows promising advancements in AI/ML including computer vision, and new FAA legislation indicates more widespread autonomous flight in the near future.

UAS technology is a broad and growing field. Within UAS research, this report specifically seeks to contribute to a broader understanding of the DFR market by assessing the technological capabilities of relevant AI/ML, the availability of training datasets, and the use of assurance measures related to training data and model outputs for medical scene assessment. Therefore, the primary objectives of the report are to investigate the following knowledge areas:

1. State of DFR use within the UAS industry
2. State of AI/ML for UAS scene assessment, with an emphasis on medical DFR applications
3. Availability of public datasets for training UAS scene assessment models
4. Quality assurance concerns for learning-enabled UAS systems, with an emphasis on DFR applications
5. Gaps and barriers to adoption for medical DFR systems

1.2. Research Methodology

Research for this report is conducted solely via resources available over the internet. These resources specifically are websites, patents, academic and other technical articles, and published reports. Generative AI is employed in the compilation and organization of this research and in draft writing; however, all research is augmented and fact-checked by a human being. The final draft of the report is written, edited, and proof-read solely by human subject matter experts.

1.3. Scope and Limitations

For this report, effort is made to keep the scope focused on DFR with an emphasis on emergency medical response when possible. Additional emphasis was placed on AI/ML technologies and related datasets, capability gaps, and challenges to the industry adoption of medical DFR. These emphases are intended to inform Aerial

Aid's proposed contributions. Further, this report benefits from several comprehensive reports and review papers [4,6–15]. Several of these resources provide significant detail on technology and capability aspects of the DFR topic which would be impossible and duplicative to completely convey here. Our intention is a highlighted survey of the subject area, and if additional details are desired by the reader, comprehensive source summaries are provided in the Appendices.

The primary limitation of this study is that it was conducted completely using resources available over the internet. As a result, there is likely some bias; for example, proprietary data concerns may inhibit commercial vendors from publishing data or technical details about their capabilities. Websites pose a particular problem in that it is not always possible to ascertain how current and reliable the information is. The age and reliability of journal articles is less uncertain; however, information is often dated by several years which is a consideration for a technology as rapidly changing as UAS and AI/ML.

1.4. Organization

The rest of the report is organized as follows. Section 2 gives an overview of the DFR industry - applications and technological advancements. Section 3 presents our findings on the current state of the art for AI/ML technologies relevant to autonomous DFR operations. Section 4 presents an overview of publicly available training datasets relevant to UAS based scene assessment, while Section 5 discusses assurance concerns when considering learning-enabled components for safety-critical systems such as DFR. Section 6 presents the gaps and barriers we have identified for this problem space, and Section 7 concludes.

2 State of the Drones as a First Responder Industry

The UAS sector is experiencing rapid growth. The value of drone activity in the United States increased from $40 million in 2012 to about $1 billion in 2017, and is projected to have an annual impact of $31 billion to $46 billion on the U.S. GDP by 2026 [6]. Various stakeholders, including government agencies and private investors, are directing funds towards the development and deployment of UAS technologies. For the DFR subsector specifically, approximately 10% of funding comes from public safety agency budgets, 15% from forfeited funds, and the majority 46% from donations [16]. The number of agencies adopting UAS for DFR increased by over 82% between 2016 and 2017, with states like Texas, California, and Wisconsin leading the pack [16]. Of public safety agencies deploying UAS, 63.7% are law enforcement and only 20.4% fire and EMS combined [16].

These market forecasts reflect the growing demand for DFR technologies. However, the extent to which machine learning and computer vision-based technologies are being integrated into the DFR industry is not confidently assessed. The volume of academic research for AI/ML technologies for capabilities such as UAV-based scene assessment has grown significantly in recent years, but it is unclear how much of this technology is being deployed in the field. Available information about commercial drone capabilities from company websites appears to be vague and promotional; AI/ML or computer vision techniques being deployed in the field are either unknown or little detail is given. Most DFR concepts are used by law enforcement agencies and generally function as a remote video imaging platform where the controls and image processing is mostly or completely performed by a human [2]. A primary task of law enforcement is surveillance, thus piloted drones serve a current need; however, increasingly autonomous DFR concepts would likely embolden wider adoption. In the future, more autonomous DFR concepts may work to free up constrained human resources for other tasks; however, this remains to be seen. The following section reviews the current state of DFR capabilities and applications.

2.1. Corporate Interest and Involvement

Companies like Draganfly [17], Paladin Drones [18], and BRINC [19] are leading the charge by offering comprehensive UAV solutions designed to enhance emergency response through real-time data capture and surveillance. Draganfly, for instance, alleges that its DFR platform currently provides high-zoom RGB cameras and thermal imaging enhanced by target tracking via optical recognition [17].

British company PELA Systems and AI Robotics Drones Solutions focus on integrating UAV technology into urban, defense, industrial, and surveillance applications. PELA Systems states that their PELAmesh technology integrates instrumentation, visual, and communication protocols for comprehensive scene assessment, for purposes of allowing first responders to capture real-time data and make informed decisions before deploying human resources [20]. Similarly, AI Robotics Drones Solutions offers UAVs designed for 24/7 autonomous operation, providing real-time video, data analytics, and integration with other systems with a stated relevance to scene assessment and emergency response [21].

The MITRE Corporation is a not-for-profit organization that operates federally funded research and development centers and works across government and industry [22]. The MITRE Corporation offers first responders affordable UAS initiatives tailored to fit their communities' specific needs and interests. MITRE's initiatives in the DFR industry focus on designing drones that meet specific needs, providing training standards for first responders, and developing tools to help agencies select the best drones for their purposes. They also conduct technical analyses of commercial drones and invent drone adapters for specialized tasks such as hazardous materials detection [3].

The public sector is also involved in advancing DFR capabilities. AIRT Inc's DRONERESPONDERS program, a non-governmental organization, provides standardized training, certifications, and resources for aerial first responders, emergency managers, and search and rescue specialists [23, 24]. DRONERESPONDERS has entered into a three-year partnership with NASA's System-Wide Safety project, and aims to enhance emergency management through UAS operations and automated air safety systems [25]. The DRONERESPONDERS Public Safety Summit, hosted in September 2024, provides case studies, workshops, and networking events to support the development of UAS programs for first responders [24]. The National Institute of Standards and Technology (NIST) and the Public Safety Communications Research Division host the First Responder UAS Challenges to advance UAS technology for public safety applications. These competitions focus on scene assessment, search and rescue, and emergency response, allowing participants to showcase innovative solutions like 3D mapping and indoor navigation to improve first responders' situational awareness and effectiveness [26]. The Department of Homeland Security (DHS) emphasizes the use of small UAS for public safety tasks, including search and rescue and firefighting, via their Systems Assessment and Validation for Emergency Responders (SAVER) program [27]. A SAVER hosted focus group report summarizes discussions on assessment criteria for integrating UAS in public safety highlighting the "Blue UAS Cleared List" from the Department of Defense, which helps agencies acquire reliable UAS technology [8].

Training and consulting organizations like Skyfire Consulting and UAV Coach offer turnkey solutions and guides to help public safety agencies establish and manage DFR programs. Skyfire supports DFR program development with real-time video streaming and situational awareness tools [28], while UAV Coach provides comprehensive overviews of DFR programs, their benefits, and guidance on navigating FAA regulations [29]. Argus Rising provides specialized drone training for first responders, emphasizing law enforcement and fire rescue applications, covering aspects like UAS flight safety, search and rescue, and thermal imaging [30].

2.2. Applications and Use Cases

DFR applications span several critical areas in emergency response. Within **search and rescue**, drones are assessed for their capability to provide aerial views that help locate missing persons, assess their conditions, and identify the safest and quickest access routes for ground responders. Equipped with thermal imaging cameras, drones can operate in low-visibility conditions, including at night, enhancing their utility in these scenarios [7, 8].

In **firefighting**, drones are assessed for their capability to assist fire departments using the drones to assess fire scenes, monitor fire spread, and identify hotspots [8]. Fire departments also use drone video at traffic collisions to determine needed equipment and whether occupants are trapped inside. Additionally, DFR drones offer valuable oversight of wildfires, including hotspot locations, access points, and direction of travel [2].

Within **law enforcement**, as of August 2023, there are at least 16 police departments with active DFR programs and another 100 or so that are exploring the concept; the primary uses of drones for these departments is in advanced situational awareness, de-escalation, and as a force multiplier [2]. Drone derived video feeds help law enforcement de-escalate scenerios by determining if suspects possessing objects believed to be weapons are actually weapons; this takes place before officers ever interact with the individual(s) whose actions prompted the police response [2]. As a force multiplier, drones can augment or increase the efficiency of law enforcement resources. For example, the Chula Vista Police Department reports that, in approximately 25% of the cases in which a drone is dispatched, no ground units are needed, freeing personnel to answer other needs; other departments with DFR programs report similar results [2].

For **medical response**, studies in the US and Europe suggest that drones can assist in medical emergencies by delivering medical supplies such as Naloxone, antiepileptics, and blood products; and by transporting AEDs to cardiac arrest victims faster than ground vehicles [6, 10, 31]. Blood delivery drones are already being used in Rwanda and Ghana with significant reductions in response time compared to human responders [31], while organizations like Zipline and Volansi have demonstrated success in using drones for delivering prescription medications and vaccines to remote areas [5]. Drones are also being utilized in emergency medical response to supplement ground teams and manned aircraft, particularly in hazardous situations or where traditional vehicles are costly. During the COVID-19 pandemic, drones delivered Personal Protective Equipment (PPE), tests, lab samples, and vaccines; they also conducted remote patient evaluations using drones fitted with two-way video communication devices and sensors to monitor temperature, pulse rate, and respiratory rate [5]. A 2020 patent describes a medical DFR concept, with special focus on describing communications technologies for coordinating with other UAVs and emergency personnel during the response [32]. Finally, studies have been conducted to assess the value in using UAV to triage patients. In one study on multiple casualty accidents, triage with a drone was 3.5 minutes slower but could arrive 93% faster than first responders [9].

2.3. Technological Advancements

There have been a high number of recent technological advances which serve to enable autonomous DFR capabilities across a range of UAS concerns. For **autonomous flight and control systems**, significant advancements in autonomous flight technology such as detect-and-avoid technologies, versatile location technologies, integrated air-traffic-management systems, system failure responses, dynamic routing. Hand-offs between human and machine controllers are expected to enable drones to operate with minimal human intervention, making them more effective for applications such as scene assessment and surveillance in dynamic and hazardous environments [6]. A 2023 survey paper cites nonlinear control systems as a critical element for the future of UAVs in smart cities; however, advancements in computer vision technologies are also needed [7].

For **sensor integration and hardware support**, drones can now be equipped with a variety of sensors, including high-definition cameras, thermal imaging, LiDAR, and gas detectors, allowing them to capture comprehensive data from a scene [8]. This also includes improved battery life and energy density, which is increasing at a rate of 5% to 8% per year; this allows drones to operate for longer durations, covering more ground and providing extended support during emergency operations [6].

Finally, for **communications**, infrastructure and paradigms to coordinate data streams and response logistics are an essential component to autonomous emergency response. A 2018 patent describes a communication system for coordinating autonomous UAV response to emergencies including receiving vehicle data, detecting emergencies, and dispatching UAV concepts to execute emergency response tasks [33].

2.4. Focus Group Insights

In November 2023, the US Department of Homeland Security's SAVER program held focus groups with fire and law enforcement representatives to gather criteria, scenarios, and product suggestions for evaluating UAS technology. Over two days, 13 participants from various US states, experienced in UAS operations, contributed to these discussions. The following focus group insights were collected from the resultant report published in 2024 entitled "Blue Unmanned Aircraft Systems for First Responders Focus Group Report" [8].

The feedback gathered from these preliminary focus groups yield some valuable insights. First, when asked about **capabilities and criteria of an acceptable DFR system**, the groups highlighted critical needs for DFR drones, including high-quality cameras, flight duration, reliable command and control links, low latency, and rapid redeployment times. Specifically, they identified 18 assessment criteria, emphasizing "capability" and "deployability" as the most important categories. Critical capabilities includ "camera visual acuity" for clear imagery, "command and control link quality" for reliable data transmission, "communication latency" for minimal delay in data reception, and "time to redeploy" for quick battery changes and return to flight.

When discussing potential **operational scenarios**, groups recommended specific operational scenarios for evaluating DFR drones, such as search and rescue operations, post-incident damage assessment, situational awareness exercises, and night operations. These scenarios assessed various capabilities of the drones under different conditions, such as locating individuals in diverse terrains, inspecting infrastructure during disaster relief, providing detailed intelligence during unplanned incidents, and operating in low-light conditions. Evaluators highlighted the importance of using both manual and automated flight modes, dealing with varying lighting conditions, and handling different types of terrain and obstacles.

2.5. Summary

To conclude, contributions are being made to DFR from both the private and public sectors, driven by technological advancement, investments, and the recognition of the value drones bring to emergency response scenarios. Companies offer UAV solutions with specific application to DFR [3, 17–22] and services to develop and manage DFR programs [28–30]. Public and non-profit sector initiatives focus on education, training, analysis, and regulatory support to enhance the effectiveness of UAVs in emergency response [8,23–27]. DFR applications cover critical areas such as search and rescue, firefighting, law enforcement, and medical response, leveraging technological advancements in autonomous flight, sensor integration, and battery technology to enhance effectiveness [2, 5, 6, 8, 10]. However, gaps exist in the DFR sector. Of particular interest to Aerial **Ai**d, integration of computer vision technologies toward increased drone automation appear lacking especially outside of the area of navigation and control. Limiting automation reduces the utility of DFR concepts particularly for applications beyond law enforcement such as emergency medical response.

3 State of Artificial Intelligence/Machine Learning for Drones as a First Responder

A comprehensive survey of existing literature and review papers reveals a scarcity of AI/ML approaches applied to DFR scene assessment, especially for medical first response; however, there is extensive research on general computer vision including research specific to UAS-based applications. This section reviews relevant computer vision methodologies for UAS scene assessment, encompassing applications such as object identification and tracking. Despite significant academic advancements in computer vision technology, its integration into the commercial DFR is largely unknown and likely limited. Currently, drones for DFR scene assessment appear to primarily function as remote video sensors, relaying data to human operators who perform the scene assessment and analysis. This section presents a high-level overview of the state-of-the-art for both computer vision research and UAS-based scene assessment.

3.1. Computer Vision for Uncrewed Aerial Systems-based Scene Assessment

The field of computer vision has changed dramatically over the past decade, and consequently so have the algorithms available for computer vision related to scene assessment. For example, between 2016 and 2021 there has been 3.5x increase in the publication of academic papers related to object detection [14]. There has been a general shift toward computationally complex algorithms, particularly those based on Convolutional Neural Networks (CNNs) and Deep Learning (DL), which are well suited to tasks such as object detection and tracking. In a 2018 review paper on computer vision for emergency response and detection, the authors describe algorithms specialized to execute feature extraction or classification tasks in roughly equal proportion to those which perform object detection or tracking [11]. However, review papers published in 2021 [12] and 2022 [4] on aerial surveillance focus almost entirely on deep learning algorithms such as Faster R-CNN, YOLO, and Single Shot Detection (SSD). We now briefly survey some of the various computer vision algorithms which have been described for aerial surveillance and emergency response and detection; for a more detailed treatise, the reader is referred to the review articles which provided the sources for this brief summary [4, 11, 12, 14].

Computer vision algorithms in aerial surveillance and emergency response and detection-related literature focus primarily on feature extraction (color, shape/texture, temporal) and machine learning. Feature extraction can be used to aid in detecting visually distinctive emergency-specific elements of interest, utilizing spatial, motion, or other data to differentiate between normal and emergency situations. The machine learning algorithms enhance the detection and response capabilities of computer vision systems by leveraging their strengths in handling complex, nonlinear, and temporal data. Most machine learning algorithms mentioned in aerial surveillance papers in open literature focus on object detection and tracking with a direct application to DFR; for example, the algorithms might handle identification of individuals in disaster areas so that rescue teams can be given their

Algorithm		Description
Color	Color Feature Extraction	Identifies the distinctive colors of materials and events which lack specific shapes but have characteristic colors, such as fire, smoke, and water. Approaches are customized to particular color models, such as RGB, HSI, HSV, YCbCr, and CIELab.
Shape	Shape and Texture Feature Extraction	Identifies the distinctive shapes and textures of materials, events, or actors within a scene. This can include vague shapes such as smoke or fire, or more concrete shapes such as human bodies. Example approaches include Histogram of Oriented Gradients (HOG) [34] and analysis of local binary patterns in pixels [35].
Temporal	Optical Flow	Estimates the motion of objects in consecutive frames; identify moving threats, analyze crowd dynamics, and detect anomalies. Example approaches include Lucas-Kanade and its derivatives [36].
	Background Subtraction	Separates moving objects from a static background to detect anomalies given a "normal" environment. Primarily useful in stationary viewpoint scenarios. Example approaches include Stauffer and Grimson [37].
	Object Tracking	Identifies and tracks objects as unique individuals across consecutive video frames. Object representations vary based on approach, and could take the form of individual points, basic geometric shapes, or sophisticated outlines depending on system needs.
Machine Learning	Neural Networks	Handles imprecise and complex nonlinear data, making them suitable for detecting specific features, classifying events, and improving accuracy in detection tasks given specific training data.
	Support Vector Machines (SVM)	Used for classification and regression problems, particularly in binary classification tasks (such as crash/no crash), effectively working in high-dimensional spaces and performing well even with limited data. One-class SVMs can detect anomalies in complex systems like crowded areas.
	Hidden Markov Models	Recognize temporal patterns in emergency situations, including sequences of movements or events, such as crash detection or monitoring crowd behavior to identify abnormal events.

Table 1. Descriptions of a selection of feature extraction and machine learning algorithms used to perform common computer vision functions [11, 38].

exact locations [38]. A high-level description of a range of algorithmic approaches to perform computer vision tasks are presented in Table 1.

Among the machine learning family of algorithms, deep learning neural networks are receiving a great deal of attention. **Two-stage networks** such as RCNN [39], R-FCN [40], and Faster-RCNN [41] are popular for their performance when handling multi-scale challenges in aerial object detection. As the name suggests, these architectures typically involve two main stages: proposal generation (identify regions of interest) and classification (proposals are refined, classified, and further processed). R-CNN variants, combined with other networks, have shown success in competitions like VisDrone [42] and the Tiny Object Detection [43] challenges. Of the two-stage network architectures, Faster R-CNN is the first near-real-time deep learning detector. It combines a pre-trained CNN for feature extraction with two trainable subnetworks: the Region Proposal Network (RPN), which generates object proposals, and the Classification Network, which predicts the actual class of the object. The main contribution of Faster R-CNN is the introduction of the RPN that enables nearly cost-free region proposals. It offers higher detection quality than RCNN and Fast RCNN, performs classification and regression training in a single stage, and eliminates the need for separate memory storage for feature extraction. The real-time frame rates are achieved due to the design of the RPN. Multi-scale object detection (a general challenge in computer vision), is improved by using a Feature Pyramid Network (FPN) that generates multi-scale feature representations at high-resolution levels. Faster R-CNN has been used for both UAV-based detection and tracking, implemented on desktop and embedded GPUs, achieving fast and accurate results, and studied on the Stanford drone dataset [44].

One-stage, or "single shot" networks, on the other hand, are favored for their speed and efficiency compared to two-stage approaches; networks like RetinaNet [45], EfficientNet [46], SSD [47], and YOLO variants [48] are widely used in aerial object detection due to their lower computational requirements. YOLO, or "You Only Look Once", is particularly known for its extreme speed. It combines feature extraction and object localization into a unique monolithic entity, eliminating the need for separate classification or detection modules and repeated region proposals. YOLO performs feature extraction, boundary box regression, and classification in one output layer. Its quick inference time makes it suitable for edge devices. Despite its speed, YOLO has suffered from a drop in localization accuracy compared to two-stage detectors, especially for small objects; however, improvements have been made in more recent versions to address this issue. Most recently, SSMA-YOLO proposed in a 2024 paper has shown improved performance and efficiency compared to YOLOv8n when applied to a small object dataset [49].

Anchor-free networks are especially effective for UAV-acquired images where varying object scale, densities, and resolutions present challenges to object detection. These networks use points instead of anchors (such as bounding boxes). CenterNet [50], FCOS [51], CornerNet [52], FreeAnchor [53], and RRNet [54] are notable examples. GPU computing has pushed more research toward anchor free designs in recent years. RRNet employed a hybrid object detection approach to achieve high performance on the on the VisDrone2018 dataset, achieving the highest scores in several evaluation metrics (AP50, AR10, and AR100) and was runner-up in the

ICCV VisDrone2019 Object Detection in Images Challenge [54].

Network ensembles combine multiple different detectors, which can enhance performance by leveraging their respective strengths. Multi-stage detectors reduce false negatives, while single-stage detectors improve bounding box quality. This strategy, used by winners of the VisDrone 2020 object detection challenge (DP-NetV3) [42], utilized an ensemble approach with backbones such as HRNet-W40 [55], Res2Net [56], Libra R-CNN [57], and Cascade R-CNN [58].

This short summary of relevant object detection algorithms demonstrates a partial view of the advances over the past decade. The pace of research in this area has significantly increased in recent years, and the reader is encouraged to consult literature for an understanding of new approaches which may not have been conveyed at the time of this writing.

3.2. Application to Commercial Drones as a First Responder and Challenges

The current state-of-the-art in the use of computer vision for commercial DFR scene assessment reveals limited details, likely at least partly due to proprietary information handling. Draganfly employs high-zoom RGB and infrared cameras for the stated purpose of "comprehensive target tracking capabilities" and disaster area assessment, hinting at the possible use of computer vision [17]. BRINC Drones features obstacle avoidance and autonomous navigation capabilities, a function suggesting the use of computer vision and possibly other machine learning technologies [19]. In a 2022 patent entitled "Systems and Methods for Tracking, Evaluating, and Determining a Response to Emergency Situations Using Unmanned Airborne Vehicles", computer vision is implied in many of the described applications and explicitly specified in the description of an "obstacle avoidance module" [59]. However, details about the algorithms employed in these examples are lacking. Similar implications are made in a 2023 patent describing an emergency UAV monitoring network; however, specific AI/ML strategies are not directly described [60]. A limited search into non-DFR commercial UAS scene assessment indicates computer vision may be deployed more widely in other industries. For instance, Dedrone's DedroneTracker.AI platform claims to utilize AI/ML for autonomous threat detection and classification by integrating multiple sensors such as radio, radar, video, and acoustics to provide comprehensive airspace security [61].

Airborne UAS-based scene assessment has a set of unique machine learning related challenges both in the areas of computer vision and also availability of computational resources. The 2023 NOMAD dataset addresses the challenge of occluded human detection in aerial views, evaluating models like YOLOv8, FasterRCNN, and RetinaNet for their effectiveness in real-world emergency response scenarios [38]. Challenges to computer vision algorithms unique to UAS-based scene assessment are summarized in Table 2 [38, 62]. In addition to these challenges, availability of computational resources is also of great consequence to UAS-based scene assessment algorithms.

We focus here on computational resources in particular due to hardware design impacts for an AI/ML UAV application relevant to Aerial **Ai**d. Two computational

Challenge	Description
Small Resolutions	Objects may appear extremely small due to high flying altitudes.
Multiple Scales	Instances of the same class, such as people, can vary significantly in shape, size, and scale.
Extreme Views	Objects may appear in overhead, angled, or distorted views, which are uncommon in standard object detection.
Moving Cameras	The airborne platform's movement causes abrupt or continuous changes in object views, adding challenges like motion blur and the need for camera stabilization.
Non-Uniform Distribution	Objects may be densely clustered in urban areas or sparsely distributed in search and rescue missions.
Illumination	Variations in lighting and illumination due to wide area coverage create non-linear local lighting conditions.
Noisy Data	Environmental factors such as clouds, fog, haze, rain, and wind can obstruct scenes and complicate video stabilization.
Dynamic Transition of Moving Objects	The changing positions and speeds of moving objects add complexity to detection and tracking.
High Density of Objects	In urban areas, the high concentration of objects makes individual detection and tracking more difficult.
Complex Background	The varied and detailed backgrounds in aerial views can hinder accurate object detection.

Table 2. Summary of challenges to computer vision algorithms when applied to UAS-based scene assessment.

scenarios exist: executing the scene assessment capabilities either (a) on the network edge or (b) on a remote server. Edge implementations process data directly using the limited onboard resources, critical for real-time applications such as obstacle avoidance [59] and immediate hazard detection, mitigating any network latency issues. Server implementations may handle more complex data processing tasks which require significant computational power, and are useful for detailed analysis and long-term data storage. However, in DFR scenarios where UAVs may need to operate in areas with limited connectivity and visibility to operators, edge-implemented computer vision tasks may be required [63]. Additionally, there is a desire to push vision tasks to edge platforms in general in order to achieve more autonomy via lower latency, higher reliability, improved security and privacy, reduced cost, and reduced energy consumption [63]. Solutions to such resource constraints at the edge include: training smaller networks, model compression techniques (e.g., pruning, quantization, low-rank factorization, and knowledge distillation), data/model parallelism, hardware approaches, hardware and software co-design, federated learning, and block-chain [13]. In this case, lightweight algorithms offering a trade-off between accuracy and performance have been proposed for emergency response scenarios [64]. Derivatives of YOLO such as Edge-YOLO [65] and other detectors based on MobileNet, have been argued to show promise for edge implementation of object detection; however, each approach has drawbacks which should be considered [15].

4 Publicly Available Datasets for Drones as a First Responder

The utility and accuracy of an AI/ML algorithm largely depends on the data available for training. Dataset size, diversity, and relevance are important factors in the efficacy of a training dataset. In our search, we were unable to identify any datasets specific to medical DFR, including injuries or medical emergencies, from an aerial perspective. However, there are many publicly available datasets relevant to training an object detection algorithm for UAV-based scene assessment. Such datasets can be accessed online [66, 67]. One such resource, "Papers With Code", offers a robust assortment of 10,104 datasets available for training machine learning algorithms including 114 for pose estimation, 245 for image classification, 270 for object detection, and 318 for semantic segmentation [67]. In this section, we describe a range of the available datasets that are relevant to advancing AI/ML scene assessment capabilities of interest to Aerial **Ai**d. For additional datasets beyond those discussed below, please see [4, 12, 67].

4.1. Human Target Observation

Datasets in this section cover scene assessment tasks focused on human targets. These tasks include target identification and re-identification, target tracking, crowd density mapping, crowd flow estimation, target behavior identification, pose estimation, and target interaction (both human/human and human/non-human). These datasets demonstrate UAV capabilities of interest to Aerial **Ai**d due to related needs of interest to medical first response such as patient and bi-stander number identification and location, patient behavior, and patient pose and orientation. Select datasets highlighting this area are detailed below and summarized in Table 3. In addition to the datasets described in this section, the MULTIDRONE datasets website provides 36 UAV-based visual detection and tracking datasets. Within MULTIDRONE, only the DroneCrowd dataset [68] is detailed below; for details on the other 35 datasets, the reader is referred to the MULTIDRONE website [69].

The **Stanford Drone dataset (2016)** [44] is intended to demonstrate human behavior in complex environments with multiple non-human targets. The dataset includes over 929,499 frames and captures more than 19,564 targets at 100 scenes (road, roundabout, sidewalk, etc.) over six areas on a university campus. The targets include 11,216 pedestrians, 6,364 bicyclists, 333 skateboarders, 244 golf carts, 1,292 cars, and 115 buses. There are approximately 185,000 target-target interactions (e.g., a pedestrian avoiding a skateboarder) and 40,000 target-space interactions (e.g., a bicyclist maneuvering a roundabout). The scenes are annotated with target IDs, trajectories, and detailed interaction labels, allowing for comprehensive analysis of multi-target interactions and social navigation behaviors. Each scene is

		Stanford Drone	UAV123	CrowdFlow	Drone-Action	TinyPerson	P-DESTRE	UAV-Human	DroneCrowd	AG-ReID.v2
TAR-GETS	Humans	X	X	X	X	X	X	X	X	X
	Motorized Vehicles	X	X							
	Non-motorized Vehicles	X	X							
ENVIRONMENTS	Beaches / Coastal		X			X				
	Building Interiors							X		
	Farmland							X		
	Fields / Parks		X						X	
	Forest							X		
	Mountains							X		
	River / Lakeside							X		
	Rural				X			X		
	Streets / Roadways	X	X	X	X			X	X	
	Urban / City	X	X	X	X		X	X	X	X
	Varied Seasons	X						X		
	Varied Times							X	X	X
	Varied Weather							X	X	X
LABELS	Activity		X		X		X	X		
	Age						X			X
	Appearance						X	X		X
	Bounding Box		X		X	X	X			
	Class	X	X			X				
	Gender						X	X		X
	Pose / Posture				X			X		
	Target Interactions	X								
	Target Trajectories	X		X					X	

Table 3. Summary of publicly available aerial datasets for human target observation operations.

captured using a 4K camera mounted on a quadcopter, providing top-view perspectives of the interactions at an altitude of approximately 80 meters. The dataset supports research in multi-target tracking, activity understanding, and trajectory prediction.

The **UAV123 dataset (2016)** [70] is a comprehensive collection of 123 high-definition video sequences, amounting to 112,578 frames, captured from low-altitude UAVs. The dataset is divided into three subsets: 103 sequences captured between 30 and 96 frames per second (FPS) at 720p and 4K resolutions using a DJI S1000 UAV with a Panasonic GH4 camera, 12 sequences captured from a low-cost UAV (details not provided), and 8 synthetic sequences generated by a custom UAV simulator using Unreal4 Game Engine at 30 FPS. The videos feature a wide range of environments including urban landscapes, roads, fields, and beaches, and involve various targets such as cars, trucks, boats, and people engaged in activities like walking, cycling, and swimming. The sequences are annotated with upright bounding boxes at, or interpolated to, 30 FPS, highlighting challenges like fast motion, occlusions, scale and aspect ratio changes, and illumination variations.

The **CrowdFlow dataset (2018)** [71] provides an optical flow benchmark focused on the estimation of movements of pedestrians, especially in highly crowded scenes. The dataset, generated synthetically using the Unreal Engine, consists of 10 sequences (5 unique sequences each with on static CCTV and one dynamic UAV perspective) with a total of 3200 frames, rendered at a resolution of 1280 x 720 pixels and a frame rate of 25Hz. Each sequence features between 371 and 1451 individuals and simulates various crowd behaviors such as structured flows and panic situations. The dataset is designed to evaluate the performance of optical flow algorithms in densely crowded scenes, addressing challenges such as precise motion estimation and long-term temporal consistency. Detailed labels and metadata for both foreground and background motion are included.

The **Drone-Action dataset (2019)** [72] comprises 240 high-definition video clips recorded at 25 FPS in high definition (HD) resolution (1920 x 1080 pixels) from a 3DR SOLO rotorcraft drone flying slowly at low altitudes (8–12 m), capturing a total of 66,919 frames. The dataset features 13 dynamic human actions, including walking, jogging, running, clapping, punching, and various other activities performed by 10 volunteers. Some actions were recorded while the drone was hovering (e.g., kicking, stabbing, and punching), and others were recorded while the drone was following the subject (e.g., walking, jogging, and running). The dataset was recorded in an outdoor setting to simulate real-world scenarios, and the videos were annotated with subject IDs, action classes, and bounding boxes. Additionally, body joint estimations were computed using the OpenPose algorithm. This dataset is particularly useful for research in action recognition, surveillance, situational awareness, and gait analysis.

The **TinyPerson dataset (2020)** [73], is a benchmark dataset with the primary focus of improving detection of persons in images taken from a long distance (perhaps less than 20 pixels in height), a task complicated by low signal-to-noise ratios within complex backgrounds. The TinyPerson dataset was constructed from high-resolution videos collected from various online sources. The dataset consists of 72,651 annotated objects across 1,610 images. The data is divided into training and validation sets, with 794 images in the training set and 816 in the validation set. Annotations are categorized into "sea persons" and "earth persons," depending on their location, and further subdivided into "normal," "ignore," "uncertain," and "dense" based on attributes like visibility and grouping. The authors tested the effectiveness of a proposed approach called "Scale Match" using the TinyPerson dataset. This method aims to align object scales between the pre-training dataset and the detector training dataset in order to improve small target detection accuracy.

The **P-DESTRE dataset (2020)** [74], developed through a collaboration between the University of Beira Interior (Portugal) and JSS Science and Technology University (India), is a collection of UAV-based pedestrian detection, tracking, re-identification, and search data. This dataset includes over 14 million frames captured by DJI Phantom 4 drones at 4K resolution (3,840 x 2,160 pixels) and 30 FPS, stored in MP4 format with H.264 compression. The data was collected in two urban campus environments under varied conditions, simulating real-world scenarios. The dataset features 269 volunteers (261 known identities), mostly aged 18-24, with 65/35% males/females, and of predominantly two ethnicities (e.g., “White” and “Indian”). Each pedestrian is annotated with bounding boxes and 16 soft biometric labels, such as gender, age, height, body volume, ethnicity, hair color, hairstyle, beard, moustache, glasses, head accessories, body accessories, action, and clothing information. Drones operated at altitudes between 5.5 and 6.7 meters with camera pitch angles between 45° and 90°. The annotations are frame-level, providing detailed information for each pedestrian, making the dataset suitable for various pedestrian analysis tasks. Additionally, the dataset supports research on UAV-based person search, including consistent unique identifiers for each pedestrian maintained across multiple days, prohibiting reliance on clothing-based features for identification.

The **UAV-Human dataset (2021)** [75] is a large-scale benchmark designed to advance human behavior understanding using UAVs. Multiple data modalities are collected using a UAV with sensors including a fisheye camera, a night-vision sensor, and an Azure Kinect DK. The dataset is annotated for multiple tasks, including 67,428 multi-modal video sequences for action recognition with 22,476 frames involving 119 subjects performing 155 different activities, pose estimation with 22,476 frames annotated with 17 keypoints, person re-identification with 41,290 frames of 1,144 identities, and attribute recognition with 22,263 frames annotated for seven attributes (gender, hat, backpack, upper clothing color and style, and lower clothing color and style). The data was collected across 45 diverse sites, including urban and rural areas, forests, riversides, mountains, farmlands, streets, gyms, and inside buildings, over a period of three months covering both summer and fall, during both day and night. It includes various weather conditions such as sunny, cloudy, rainy, and windy, and different illumination settings from bright daylight to dark nighttime. The dataset presents significant challenges due to its diverse environments, varying UAV flight attitudes, and extensive subject variations.

DroneCrowd (2021) is one of the MULTIDRONE Datasets (see [69]). The DroneCrowd dataset comprises 112 video clips with a total of 33,600 HD frames, captured by drone-mounted cameras (i.e., DJI Phantom 4, Phantom 4 Pro and Mavic) covering various scenarios such as campuses, streets, parks, parking lots, playgrounds, and plazas in four different cities in China (Tianjin, Guangzhou, Daqing, and Hong Kong). Videos were shot at 25 FPS at a resolution of 1920 x 1080 pixels. Each video frame contains between 25 and 455 people and an average of 144.8 objects for a total of over 20,800 annotated people trajectories and 4.8 million head annotations. The dataset features diverse attributes like illumination conditions (cloudy, sunny, night), scale (large and small objects), and density (crowded and sparse). It is designed for training and benchmarking algorithms in density map estimation, localization, and tracking in crowded scenes captured by drones [68].

The **AG-ReIDv2 dataset (2023)** [62] is a video image collection designed to facilitate person re-identification (ReID) from both aerial and ground perspectives. Over a period of five months, data was collected on a university campus using three different types of cameras: a DJI M600 Pro UAV equipped with an XT2 camera with resolution of 3840 x 2160 pixels which captured images at 30 FPS from altitudes between 15 and 45 meters, a Bosch Closed-Circuit Television (CCTV) camera with resolution of 800 x 600 pixels which captured ground-level footage at 30 FPS, and a Vuzix M4000 wearable camera which captured 4K images at 30 FPS to provide stationary first-person perspectives. The dataset comprises 100,502 images featuring 1,615 unique identities, annotated with 15 soft-biometric attributes such as age, gender, and clothing style. The images reflect diverse real-world scenarios, capturing pedestrians in various states of motion and environmental conditions, such as different times of day and weather.

4.2. Disaster and Emergency Response

These datasets contain visual data from UAV or other aerial observed disaster areas and emergency response scenerios. Data includes scenes with annotations of various levels of building damage and related features resulting from disasters such as fires, floods, and hurricanes. Also included is the NOMAD dataset which features actors, partially occluded by objects, intended to provide data for search and rescue response scenarios. The disaster and emergency response datasets are summarized, along with the aerial scene assessment datasets, in Table 4.

The **Aerial Image Database for Emergency Response (AIDER) dataset (2019)** [63, 64] contains images of four disaster events (320 images of fire/smoke, 370 for Flood, 320 for rubble, and 335 images for traffic accidents), as well as “normal” (1200 images). Data was collected both manually from UAV-generated images available on the internet and using a UAV (details about the platform used for the dataset collection were not clear). Since the images were collected from a diverse set of sources, most of which were not under direct control by the authors, characteristics such as image resolution, lighting, and viewpoint varied. To address this, efforts were made to standardize feasible aspects such as image size. Image augmentation strategies were applied to vary characteristics such as orientation, shifting, blurring, etc., which produced a larger 8,540 image dataset. The dataset was designed with the intention of training a convolutional neural network which was demonstrated on a UAV platform with both embedded and remote processing for aerial object classification.

The **RescueNet dataset (2023)** [76] consists of high-resolution UAV imagery

		DER				ASA				
		AIDER	**RescueNet**	**NOMAD**	**LADIv2**	**ISPRS Vaihingen**	**ISPRS Toronto**	**UAVDT**	**VisDrone2018**	**UAVid**
TAR-GETS	Humans			X					X	X
	Buildings	X	X		X	X	X			X
	Landscapes	X	X		X	X	X			X
	Vehicles	X	X					X	X	X
ENVIRON-MENTS	Beaches / Coastal	X	X							
	Rural / Remote	X		X	X					
	Streets / Roadways	X	X		X	X	X	X	X	X
	Urban / City	X	X	X	X	X	X	X	X	X
	Varied Seasons	X		X	X					
	Varied Times	X			X			X	X	
	Varied Weather	X		X	X			X	X	
LABELS	Damage - Buildings	X	X		X					
	Damage - Roads		X		X					
	Damage - Trees / Landscape		X		X					
	Debris / Rubble	X			X					
	Fire / Smoke	X								
	Flooding	X			X					
	Target Class	X	X	X	X	X	X	X	X	X
	Target Location		X	X	X	X	X	X	X	X
	Target Visibility			X				X	X	
	Topology					X	X			
	Traffic Accident	X								

Table 4. Summary of publicly available aerial datasets for disaster and emergency response and general-purpose aerial scene assessment.

collected after Hurricane Michael made landfall at Mexico Beach, Florida, over 80 flights conducted between October 11–14, 2018. The dataset was collected using DJI Mavic Pro quadcopters producing and comprises 4,494 images at a resolution of 3000 x 4000 pixels. Images were annotated by providing semantic masks for 10 classes: trees, water, vehicles, road-clear, road-blocked, building-no damage (4011 masks), building-medium-damage (3119 masks), building-major-damage (1693 masks), and building-total-destruction (2080 masks). The dataset is designed to improve the accuracy and efficiency of damage assessment in post-disaster scenarios by facilitating comprehensive scene understanding supporting both semantic segmentation and image classification tasks.

The **Natural, Occluded, Multi-scale Aerial Dataset for emergency response scenarios (NOMAD) (2023)** [38] is developed to provide training data for object detection algorithms for UAV emergency response with an emphasis on search and rescue. The dataset consists of 42,825 frames extracted from 5.4k resolution videos, featuring actors performing sequences of hiding, laying, and walking under different levels of occlusion by an obstacle. Videos were collected at 30 FPS at a resolution of 5,472 x 3,078 pixels from a sequence of five progressively more distant locations from the target (ranging from 10m to 90m). Details of the UAV used for data collection are not clear. All frames are annotated with bounding boxes and visibility labels categorized into 10 different levels based on the percentage of the human body visible. NOMAD features a demographic diversity of 100 actors, with a 50/50 male/female distribution and aged 18 to 78, from various racial backgrounds including White Caucasians, Latinos, African descent, Asians, South Asians, Middle Eastern, and Pacific Islander. Twelve filming locations provided a variety of natural and man-made environments, such as field, lake, forest, and school, ensuring rich environmental diversity and included a range of weather conditions.

The **LADIv2 dataset (2024)** [77] consists of 9,963 images, split into 8,030 train examples, 892 validation examples, and 1,041 test examples. The training and validation examples are drawn from federally declared disasters across the United States between 2015-2022, and the test examples are drawn from disaster declarations in 2023. The images were captured using both small manned and unmanned aircraft from altitudes, perspectives, geographies, and lighting conditions. Details are not provided on the aircraft or photographic equipment used. Each image is annotated with multiple labels by a team of 46 trained Civil Air Patrol volunteers. The labels include various levels of building damage (unaffected, affected, minor damage, major damage, and destroyed), as well as other relevant features such as debris, flooding, and damage to roads and trees.

4.3. Aerial Scene Assessment

These datasets are focused on general aerial scene assessment. General city-scape data collected from UAV and non-UAV aerial perspectives is available, including a range of annotated objects such as buildings, cars, and trees. Variation in object type and object scale is reflected, as well as, variation in scene conditions such as lighting and weather. Additionally, perspectives address aerial object identification challenges such as moving object recognition and temporal consistency. In addition to the datasets referenced below, the reader is referred to "BayesNet for remote sensing" (Sagar et al., 2024) which refers to four additional widely recognized UAV-based remote sensing datasets of interest to Aerial **Ai**d [78]. The aerial scene assessment datasets are summarized, along with the disaster and emergency response datasets, in Table 4.

The International Society for Photogrammetry and Remote Sensing (ISPRS) publishes benchmark datasets for urban scene classification and 3D building reconstruction. The **ISPRS Vaihingen dataset (2013)** [79] is an urban dataset composed of non-UAV captured imagery collected in four areas of the city of Vaihingen: Area 1 ("inner city"), Area 2 ("high rise"), Area 3 ("residential area"), and a large "roads" area. For each area, the following data is available: digital aerial images and orientation parameters, digital surface model and truth orthophoto mosaic, and airborne laser scanner data. The dataset includes true orthophotos and digital surface models with a ground sampling distance (GSD) of 9 cm. Aerial image data was collected at an altitude of 900m, and laser scanner data is collected at an altitude of approximately 500 meters. The **ISPRS Toronto dataset (2013)** [79] provides non-UAV aerial imagery captured over three scenes, Area 4 (mixed density buildings), Area 5 (high rise), and Entire Data, at an altitude of approximately 1600 meters above downtown Toronto. In addition to the high altitude imagery, laser scanning data is also available for the Toronto dataset from an altitude of 650m.

The **UAVDT dataset (2018)** [80] was developed to enhance training for computer vision applied to UAV surveillance tasks. The dataset comprises about 80,000 representative frames from 100 video sequences. The video data was taken using a DJI Inspire 2 UAV platform at 30 FPS with a resolution of 1080 x 540 pixels from various urban locations representing scenes such as squares, arterial streets, toll stations, highways, crossings, and T-junctions. Data is annotated with 14 kinds of attributes such as weather conditions, flying altitude, camera view, vehicle category, and degree of target occlusion with 841,500 target bounding boxes. This benchmark is designed for tasks like object detection, single object tracking, and multiple object tracking.

The **VisDrone2018 dataset (2018)** [81] includes 263 video clips and 10,209 static images, with a total of 179,264 video frames and over 2.5 million annotated object instances. The data was acquired by various drone platforms including DJI Mavic and Phantom series 3, 3A, 3SE, 3P, 4, 4A, and 4P; maximum video and static image resolutions are 3840 x 2160 pixels and 2000 x 1500 pixels, respectively. Captured across 14 cities in China, the annotated data covers diverse urban and suburban scenarios and various weather and lighting conditions. This dataset is designed for training and benchmarking algorithms in object detection and tracking tasks in drone-captured images and videos.

The **UAVid dataset (2020)** [82] consists of 30 video sequences capturing 4K images (either 4096 x 2160 pixels or 3840 x 2160 pixels) from a height of about 50m by DJI Phantom 3 Pro and DJI Phantom 4 vehicles. For each sequence, 10 images were annotated at five second intervals for a total of 300 labeled images. The dataset is designed for urban scene analysis and features eight classes: building, road, tree, low vegetation, static car, moving car, human, and clutter. UAVid aims to improve

UAV scene understanding by addressing challenges like large-scale variation, moving object recognition, and temporal consistency.

In this section we highlighted datasets of special relevance to Aerial **Ai**d. Review of additional dataset papers beyond those discussed above may produce additional datasets of interest to the reader; however, to the best of our knowledge, there are no publicly available datasets labeling patients for medical first response scenarios beyond search and rescue.

5 Assurance of Learning-Enabled Uncrewed Aerial Systems

The term "assurance" has a range of different contexts and connotations depending on the domain in which it is being used. For aerospace systems, "assurance" has a very specific meaning due to the risks and hazards posed by the potential failure of said systems, though a precise definition still remains elusive. DO-178C, one of the preeminent guidance documents for developing aviation software in compliance with safety and airworthiness regulations, defines assurance as "the planned and systematic actions necessary to provide adequate confidence and evidence that a product or process satisfies given requirements" [83]. Under Strategic Thrust 6: Assured Autonomy for Aviation Transformation, NASA's Strategic Implementation Plan for 2023 refers to the goals of assurance in this way: "...to ensure autonomy technologies for traditional aviation applications that unequivocally show improvements in overall safety without sacrificing other factors, [and for novel aviation applications that enable] their business cases and safe integration of new vehicles and missions into the [national airspace]" [84]. From these descriptions, it is clear that, for an aviation system to operate in the national airspace, there must be rigorous demonstration of compliance with safety and airworthiness requirements; this includes any learning-enabled components that may exist on those systems.

For UAS, assurance research efforts have been applied with great success to more traditional aviation functions, such as geofencing and containment; navigation, tracking, and collision avoidance; and general safety and airworthiness. For geofencing, Hayhurst et al [85] propose a hazard partitioning framework to isolate and mitigate risk relevant to location-constrained UAS operations; here, the authors stress that "the assured part of the assured containment concept comes from being able to build a safety argument, sufficient for certification purposes, that the [uncrewed aircraft] will remain in a specified area in the presence of common vehicle, autopilot, sensor and actuator failures". Bateman et al [86] assure geofence boundaries by applying tiered allowable zones, parameterized to the vehicle's turn radius. At NASA, the SAFEGUARD project [87,88] manages geofencing and speed and altitude limits via a small set of formally verifiable functions, disparate sensors providing redundant capabilities, and killswitch methods to terminate flight if necessary. For navigation, tracking, and collision avoidance, detect-and-avoid assurance (particularly in urban environments) is one of the most popular topics both for individuals [89–91] and swarms of vehicles [92, 93]. For general safety and airworthiness, Denney and Pai [94] explore the feasibility of written arguments to support

Fairness	"AI systems must include considerations regarding how to treat people, including refining solutions to mitigate discrimination and bias, preventing covert manipulation, and supporting diversity and inclusion."
Explainability and Transparency	"Solutions must clearly state if, when, and how an AI system is involved, and AI logic and decisions must be explainable. AI solutions must protect intellectual property and include risk management in their construction and use. AI systems must be documented."
Accountability	"Organizations and individuals must be accountable for the systems they create, and organizations must implement AI governance structures to provide oversight. AI developers should consider potential misuse or misinterpretation of AI-derived results (intentional or otherwise) and take steps to mitigate negative impact."
Security and Safety	"AI systems must respect privacy and do no harm. Humans must monitor and guide machine learning processes. AI system risk trade-offs must be considered when determining benefit of use."
Human-Centered, Societal Benefit	"AI systems must obey human legal systems and must provide benefits to society. At the current state of AI, humans must remain in charge, though future advancements may cause reconsideration of this requirement."
Scientific and Technical Robustness	"AI systems must adhere to the scientific method NASA applies to all problems, be informed by scientific theory and data, robustly tested in implementation, well-documented, and peer reviewed in the scientific community."

Table 5. NASA Framework for the Ethical Use of Artificial Intelligence [96]

safety cases for UAS airworthiness at design-time, while Avram et al [95] present a framework that monitors a UAS for loss of effectiveness in rotors and for faults in the controller software. This selection of works is by no means exhaustive, but it illustrates the wide range of non-learning-enabled functions for which assurance methods have been successfully demonstrated. The rest of this section is dedicated to a discussion of assurance frameworks and methods that have been proposed for AI/ML systems at large and for UAS specifically. We highlight, in particular, the lack of current work on learning-enabled UAS for emergency medical response.

5.1. Frameworks for Ethical and Trustworthy Artificial Intelligence/Machine Learning

The recent surge in interest in AI/ML systems and their applicability to all areas of human life has inspired a related interest in defining what it means to be ethical in our development, application, and interpretation of the data and outputs offered by such systems. In response to a series of executive orders issued from the White House on the need for frameworks to guide the ethical use of AI, NASA proposed their own framework [96], as summarized in Table 5. The framework names six principles - **Fairness**, **Explainability / Transparency**, **Accountability**, **Security / Safety**, **Human-Centered Societal Benefit**, and **Scientific and Technical Robustness** - by which AI/ML systems should abide in order to promote social good and minimize harm. Similarly, Bharadwaj [97] identifies three assurance objectives that must be met to assure autonomy for aviation and Department of Defense applications: (1) **Safety** (specifically in enumerating, accounting for the full spectrum of possible real-world operating conditions), (2) **Reliability** (demonstrating resilience against adversarial samples with specifically-crafted statistical characteristics), and (3) **Trust** (building human-understandable explanations of internal functions that are transparent and don't rely on additional opaque models). DARPA's eXplainable AI (XAI) program [98,99] also identified three principles for AI development - (1) **Deep Explanation**, or "...modified or hybrid [deep learning] techniques that learn more explainable features or representations or that include explanation generation facilities", (2) **Interpretable Models**, or "...[machine learning] techniques that learn more structured, interpretable, or causal models", and (3) **Model Induction**, or "...techniques that experiment with any given [machine learning] model - such as a black box - to infer an approximate explainable model".

The Aerospace Corporation's "Trusted AI" framework [100, 101] goes even farther than this. The framework organizes assurance efforts according to four "threads": (0) Formulation, Value Proposition, and Stakeholders; (1) AI Objective, Model, and Data Specification; (2) Assess and Enhance Trust; and (3) Deployment, Monitoring, and Control. Thread 0 refers to tasks involved with information-gathering and confirming mutual understanding with all relevant stakeholders before any technical activities ever begin. Thread 1 describes tasks relevant to concrete specification of expectations and requirements for the high-level objective of the AI functionality, the model being used, and the data on which it will be trained and tested. Thread 2 presents principles by which stakeholder trust in the correctness and completeness of the design and implementation may be improved; these principles are summarized in Table 6 and bear resemblance to NASA's proposed principles. Finally, Thread 3 describes activities for deploying the learning-enabled component to its operating context, monitoring its function within that context, and controlling the resultant behavior. Representatives from the Aero Corp and JPL have since followed up the framework proposal with a case study retrospective [102], in which they applied the framework to the Machine learning-based Analytics for Automated Rover Systems (MAARS) and Ocean Worlds Life Surveyor (OWLS) projects and discussed lessons learned. While this is a unique and highly useful demonstration of assured autonomy in aerospace, it still lacks detail in how the required level of evidence demonstrating regulatory compliance was achieved.

Traceability	"...the process by which all artifacts involved in the implementation and evaluation of a system are documented and maintained to facilitate a clear and reversible development, V&V, deployment, monitoring, and upgrade trajectory."
Stability	"...a measure of the consistency and validity of an AI-based system's performance when provided inputs that fall within the nominal scope."
Pertinence Awareness	"...the ability to discern when inputs fall outside the nominal domain, providing bounds for very low prediction confidence, user alerts, or complete prediction abstinence."
Uncertainty Quantification	"...the calibrated estimation of the credibility of an AI's predictions across the nominal range of input parameters."
Adversarial Resilience	"...the ability to detect and provide stable output even when presented with intentionally misleading input."
Interpretability	"...the degree to which a user can understand the cause-and-effect of an AI algorithm prediction, both in terms of overall behavior and the internal calculations performed."
Fairness	"...the degree to which an AI algorithm provides equitable outcomes to all subgroups and the thorough characterization of residual biases."
Familiarity	"...the measure of comfort and ease with which a user successfully operates a system."

Table 6. Aerospace Corporation's Principles of Trusted AI [100, 101]

5.2. Current Research on Artificial Intelligence/Machine Learning Assurance

Contemporary research efforts in AI/ML assurance provide starting points for assuring learning-enabled UAS operations, even if the work is not explicitly intended as such. Verma and Maroney [103] describe a methodology for breaking down and allocating responsibility in human-machine teams for UAS. Hawkins et al [104] propose a framework for writing safety assurance arguments for ML-based components in an autonomous system, but make sweeping assumptions that appropriate requirements, validation and verification activities, and all necessary evidence can and have been supplied. Feather et al [105] present a use case for the framework proposed in [104] where the assurance case approach is applied to a simplified scenario of optical communication between earth and space. Hernandez et al [106] propose a taxonomy of aspects and activities to guide the development of and build trust in AI/ML-enabled air traffic management systems, but also lack concrete guidance on demonstrating compliance.

Dmitriev et al [107] provide the most concrete examples of how existing aircraft certification guidance can be massaged to accommodate learning-enabled components. In [107] and [108], the authors demonstrate feasibility of learning-enabled components complying with Design Assurance Level (DAL) D, as described in DO-178C [83]. In [108], the authors provide a proof-of-concept system built on YOLOv2 to perform runway sign recognition during aircraft taxiing. In [109], the authors expand this work further by proposing that two dissimilar models targeting DAL D can provide DAL C functionality, since "ARP4754A allows to reduce the design assurance level if a system is implemented by two or more dissimilar components". To achieve this, the authors lean on best practices from DO-178C and ARP4754A to demonstrate independence of the dissimilar models, propose "qualifying" the ML training process to provide requirements traceability, and embrace behavioral requirements coverage through testing. It is true that the body of work put forth by Dmitriev et al provides a glimpse into the possibility of certifying aircraft carrying learning-enabled components; however, the hand-waving around requirements traceability indicates a significant gap which still needs to be addressed.

When considering research for assuring machine learning models outside of an aviation context, there are some highly relevant recent works. Gopinath et al [110] build on the successful Reluplex framework [111] and propose an updated methodology to infer formal properties about a neural network. However, both works are limited only to those networks which use ReLU as an activation function, since "the on/off activation status of neurons [using ReLU] is our key building block in defining network properties" [110]. This is a major limitation since commercial models have moved beyond ReLU; for example, the YOLOv8 model uses SiLU as its activation function, but only applies it during CONV blocks[3]. Katz et al [112] propose a methodology for identifying adversarial inputs to a trained neural network, but only test their solution on ResNet and VGG with the CIFAR-10 data set. As such, it is currently unclear how well the solution will scale to commercially popular models such as YOLOv8. Leino et al [113] design a "self-correcting" layer which can be appended onto neural networks to enforce safe ordering constraints on classification output vectors; it is unclear, however, whether this approach can also be extended to safety properties beyond the ordering of output values. While great progress has been made in this area, there is still a long way to go before such assurance methods can be acceptable for real-time airborne systems.

6 Gaps and Barriers to Adoption for Medical Drones as a First Responder

In this section, we will discuss various gaps and barriers related to DFR with an emphasis on medical first response. By examining issues such as the capability differences between academic research in computer vision and commercial DFR, quality assurance, and regulation we aim to highlight the critical areas that should be addressed in order to promote adoption of medical DFR.

[3]https://blog.roboflow.com/whats-new-in-yolov8/

6.1. Challenges Specific to Emergency Medical Systems and Medical First Responders

Medical emergency first responders using UAS for scene assessment represents a significant gap in DFR. Limited examples of surveillance for medical response do exist: examples include surveillance of disaster sites and monitoring of threats such as the presence of sharks in swim areas or the spread of diseases [5]. However, we found no evidence in the literature of emergency first responders employing UAVs to provide scene assessment for anticipated medical DFR purposes such as scene safety, triage, or patient condition. This gap presents an opportunity for research of interest to Aerial **Ai**d to identify and address the obstacles that are preventing the adoption of UAS for scene assessment in medical first response.

There have been a small number of efforts to use UAS to provide other medical response services beyond scene assessment. The company Zipline spent two years researching technological solutions before opting for drone deliveries of medical supplies. In 2016, they made their first delivery of blood to a hospital in Rwanda, subsequently expanding their operations to multiple distribution centers across the country. By 2018, Zipline extended its services to Ghana and five other African countries. In 2020, they began delivering PPE in the U.S., followed by pharmaceuticals and other products for Walmart in Arkansas and Intermountain Health in Utah in 2021. By 2023, Zipline developed a platform for short-distance deliveries to homes, targeting restaurants and other retailers, and now has contracts with over 20 health systems, restaurants, and retailers in the U.S., the U.K.'s National Health Service, and Japan. It appears that Zipline's technologies, outside of Africa, are focused on non-emergency medicine [114].

In Clemmons, North Carolina, starting in September 2024, drones equipped with AEDs will respond to cardiac arrest calls with plans to arrive several minutes before Emergency Medical Technician (EMT)s or ambulances [115]. This initiative, led by the Forsyth County sheriff's office in collaboration with local emergency services, Duke University's Clinical Research Institute, and company Hovecon, aims to improve survival rates for cardiac arrest victims. A 2023 Swedish study in The Lancet [115] found that drones reached cardiac arrest scenes faster than ambulances two-thirds of the time; this is a crucial finding for UAS-based solutions as cardiac arrest victims face a 10% decrease in survival odds for every minute without help [115]. Emerging drone programs in the U.S. are also exploring applications for drug overdoses, trauma, and drowning rescues, with Tampa General Hospital, Manatee County, and emergency drone services provider AFRS launching a program to deliver AEDs, tourniquets, and Narcan within a 1.5-mile radius [115].

The concept of a "drone ambulance" re-imagines traditional emergency response vehicles as single-person drones, modeled after quad-copters [115]. These drones, designed to be dispatched with no pilot onboard to emergency scenes require only a single EMT for patient stabilization and transport, present a novel approach to urgent medical care. Argodesign, a Texas-based firm specializing in innovative technology design, has been identified as a leading contender in developing this concept [115]. However, as of July 22, 2024, no information was available on their website related to this technology. Key challenges include the drone's one-seater design, preventing an EMT from accompanying the patient during transport, urban legal restrictions on drone flights, and the high cost of approximately $1 million per unit. EHang, another company in this space, appears to be the closest to actualizing the drone ambulance vision. It has had its air operator certificate application accepted by the Civil Aviation Administration of China, indicating that while the technology exists and is being certified, it is not yet operational for medical transport as of July 2024 [116].

6.2. Regulatory Barriers

Another barrier to DFR adoption is the challenge to fully autonomous UAS flight posed by regulation. Regulations such as those related to Beyond Visual Line-of-Sight (BVLOS) operations are crucial for enabling autonomous drone deployment. Autonomous deployment is desirable in emergency response scenarios that would benefit from removing the time and financial cost of requiring a human operator, or enabling scenarios such as emergency detection where long-term monitoring could be performed efficiently by one or multiple networked autonomous UAS. As of a 2017 article, regulations required stringent safety and detect-and-avoid technologies to ensure that drones can safely navigate complex environments and avoid collisions, particularly in urban settings where emergency responses are frequently needed [6]. Additionally, regulations relevant to the development of infrastructure such as charging stations, vertiports, and integration with existing air traffic management systems were stated factors. These regulations are designed to ensure safety and security but can limit the operational flexibility of DFR technology. For example, drones must remain below 400 feet above ground level without a waiver, and operations over people are generally prohibited without special approval.

A positive development is that FAA Regulatory Updates in 2023 have expedited the first responders BVLOS waivers through a checklist template available through DRONERESPONDERS, making the approval process significantly faster [2]. Additionally, the introduction of new technologies, such as pre-positioned 360-degree camera nodes and drone-in-a-box systems, are poised to reduce reliance on rooftop pilots and visual observers, mitigating the most significant cost of UAV operations [2]. Additionally, on May 15th 2024, the U.S. House of Representatives passed the FAA Reauthorization Act of 2024 reauthorizing the FAA through Fiscal Year 2028 [117]. Notably, this bipartisan legislation requires the FAA to propose rules for UAS BVLOS operations within four months and a final rule for powered lift aircraft operations within seven months. The FAA has commented that their focus is on the development of standard rules to make BVLOS operations routine, scalable, and economically viable [118].

6.3. Public Perception and Buy-in Challenges

Public perception is another critical factor which influences the adoption of DFR technologies. Concerns regarding safety, privacy, and data security are significant barriers that impact public acceptance of drones in emergency response scenarios. Despite this, relatively few studies have been done to assess public perception of UAS for medical first response [5]. A study in Australia found general safety acceptance with concerns about privacy and misuse. Studies involving AED-equipped drones in simulated emergencies reported positive feedback, with participants feeling comfortable and appreciating the delivery of life-saving equipment. The acceptance of drone-delivered AEDs was high, though more community-based research and public education are needed.

Assessing the comfort level of EMS and Centers for Medicare and Medicaid Services with drone technology and integrating that technology into healthcare systems is also essential [5]. For widespread adoption in the US, buy-in from hospitals and insurance companies is necessary requiring established feasibility, safety, and cost-effectiveness. A theoretical model in North Carolina suggested that a network of drones carrying AEDs could improve cardiac arrest survival, but more cost-effectiveness analyses are needed for insurers.

Privacy is also a barrier. Some civil liberties groups are concerned that FAA regulations may not provide enough protection from drone cameras for people on the ground [118]. For example, organizations such as the American Civil Liberties Union and the Electronic Frontier Foundation fear that video data collected by UAVs could expand beyond what is required for emergency response. These organizations, and others, have objected to the collection of video data by UAVs traveling to and from the scene of an emergency, and even sued for the public release of such video data [2].

To facilitate increased adoption of DFR, there may be a need to shift public perception from viewing drones as invasive or novelty items to recognizing them as valuable tools for enhancing public safety. Highlighting successful use cases and the positive impact of drones in emergency scenarios can help in changing public attitudes. Engaging with community organizations that may have reservations about drone use, providing transparency through regular updates, and ensuring civil liberty and privacy protections are essential strategies for gaining public trust and acceptance [2].

6.4. Financial and Integration Barriers

UAVs offer a significant cost savings over traditional methods in several medical emergency response scenerios [5]; however, costs must be weighed against the benefits of DFR capability investment. The cost of acquiring and maintaining advanced DFR technology may include the initial UAV investment as well as sensors, communication systems, maintenance, insurance, and supporting infrastructure. Capability level can effect the cost-to-benefit ratio for an organization. For example, small UAVs serving as remote video surveillance platforms are relatively inexpensive but require a dedicated human operator; on the other hand, a future fully autonomous UAV could obviate the need for the human operator. High capability drones, such as those envisioned for autonomous patient transport, could cost $1 million per vehicle [115]. Especially for smaller or under-funded agencies, budget constraints may limit the ability to invest in cutting-edge technology or expand existing drone programs. Exploring creative funding solutions, such as public-private partnerships and government grants, can help mitigate these financial barriers [2, 6].

Once obtained, effective integration of drones into existing emergency response systems is essential. This includes seamless interoperability with communication networks, data management platforms, and other response units. Ensuring that drones can easily share data and communicate with other technologies in the field, including existing 9-1-1 and other emergency dispatch systems, is crucial for their practical utility [5, 8]. Some work in this area is described in patents from 2018 and 2020 [32, 33].

6.5. Capability Gaps between Academia and Industry

Significant gaps exist between the sophisticated computer vision capabilities developed in academic research and the capabilities which are available to and in use in the commercial DFR industry. As discussed in Section 3, there are limited examples of AI/ML technologies being deployed in DFR contexts; what information is available about commercial UAV capabilities primarily comes from vendor websites and is thus considered potentially unreliable. We posit that this dearth of information is due to the difficulty of scaling research-grade algorithms to meet the complex requirements of fielded applications.

For AI/ML models, how well the training and test data used in development map to the real-world conditions of the fielded system is a major challenge. This challenge is augmented when the model is destined for use in a safety-critical system (discussed further in Section 6.6). Although many high-performing computer vision algorithms are available which have been pre-trained on large amounts of general data, ensuring high accuracy for specific tasks requires, among other things, training with application-specific data, which may be costly or time-consuming to collect. For medical UAS scene assessment, this data should include information relevant to domain features of interest, such as patient condition or behavior data. For this current work, we were unable to find any publicly available datasets specific to emergency medical first response (though descriptions of more general-purpose aerial datasets may be found in Section 4). Training datasets play a key role in image classification and object detection, and the lack of such data has been identified as a main barrier for UAV object detection research [12]. Thus, this lack of publicly available training data specific to medical first response represents a gap in enabling fully autonomous medical DFR.

Finally, regulation, as discussed above, plays a role in limiting the deployment of computer vision algorithms for DFR operations. This is because drone autonomy, such as BVLOS flight applications, is heavily restricted; this results in a limited need for computer vision in-flight due to the assumed presence of an operator within line-of-sight. For many academic and lab-based research settings, this limitation can be worked around by testing proposed models on simulated rather than physical flight vehicles. When attempting to deploy the model to a fielded flight system, however, regulation can no longer be avoided. Due to the interrelated nature of the factors resulting in this capability gap, research which addresses one factor is likely to also effect the rest. For example, research which demonstrates explainable, reproducible quality assurance outcomes for AI/ML models is also likely to ease pressure due to regulatory restrictions on aerial autonomy, therefore promoting their implementation in real world applications such as medical DFR.

6.6. Quality Assurance

In addition to the gaps and barriers listed above, there are a range of challenges which must be addressed before AI/ML components can be fully assured for a medical UAS use case. This section summarizes those challenges, based on the state of the art in AI/ML assurance research and our discussions with stakeholders.

The first challenge is building a performant model for a niche problem domain. Medical emergencies constitute a huge range of potential scenarios to which emergency medical services may be tasked to respond; this could encompass anything from vehicle accidents (cars, trucks, vans, bicycles, motorcycles, with pedestrians, without pedestrians, etc.) to medical incidents (heart attacks, strokes, seizures, diabetic fits, heatstroke, overdose, etc.) to interpersonal conflicts (personal fights with(out) weapons, large-scale violence, etc.) and more. The amount of specialized data required to cover this range of scenarios in order to develop a comprehensive scene assessment model is enormous, but ultimately a fairly mechanical task. Assuming that the data is collected, the problem becomes crafting a model architecture that is highly performant but able to operate in a resource-constrained environment (such as onboard a UAS). There will be trade-offs to consider, such as whether to transition to a more coarse-grained, lower-performing model to save battery or whether to increase the data transmission back to the base station when an emergency is identified. While these are highly labor-intensive and specialized tasks, they are reasonably achievable with sufficient resources.

The second challenge is to manage risk when the model is wrong. No model can be correct 100% of the time. However, in a medical context - and particularly, in an *emergency* medical context - the possibility of the model outputting incorrect or misleading information may have significant implications. Incorrect diagnosis or misinterpretation of the scene could lead to emergency medical services bringing the wrong equipment to a scene, or placing themselves or the victims in danger through lack of situational awareness. If the UAS was being used in a different supporting role, such as delivering equipment to the site, a navigation error could result in a dose of Narcan or an extra first aid kit being dropped off in a public park instead of the incident site. Therefore, stakeholders would ultimately require assurance that, if these kinds of system errors and failures occur, it is not through misbehavior on the part of the AI/ML model. For traditional safety-critical systems, this assurance would take the form of "number of 9's", that is, the number of 9's that follow the decimal point when specifying the percentage of time that the system will operate safely. As an example, for an AI/ML model where 95% accuracy is considered state-of-the-art, a requirement for 99.99999% accuracy in a safety-critical system such as DFR is an incredible challenge to satisfy.

The third challenge is two-fold: to prove that the system meets stakeholder needs, and, ultimately, to secure public trust and buy-in. The twin aspects of this challenge are intertwined; one builds on (or undermines) the other. As mentioned above, there will always be cognitive overhead involved in learning a new system, integrating it into existing procedures. Therefore, an emergency medical response organization will not adopt a new technology - and acquiesce to this burden - if that technology does not provide a significant improvement to their existing processes without imposing an undue cognitive cost. Similarly, if there are privacy or data usage concerns surrounding the use of a pervasive sensing AI/ML model, or resistance to the use of UAS due to noise and sound pollution, then a lack of buy-in on the side of the public will also provide a significant barrier for medical service providers.

7 Conclusions

This market research for Aerial **Ai**d has identified significant trends and challenges in the UAS market for medical emergency first response. The market for UAS is robust and expanding rapidly, with a burgeoning sector for Drones as First Responders (DFR). Despite the potential, DFR applications are currently constrained by challenges related to regulation, technology, finance, public perception, assurance, and integration, limiting their role to remote video surveillance predominantly used by police. The adoption of increasingly autonomous UAS by Emergency Medical Services (EMS) for medical first response is not observed, with related medical emergency uses mainly in pilot programs testing the delivery of medical supplies and equipment.

The concept of fully autonomous DFR for medical applications, including UAV ambulances and patient transport drones, remains largely unrealized. The technological foundation for full autonomy is likely in place; however, regulations and concerns related to safety and privacy have thus far presented a roadblock in the further development and implementation of this technology. Significant advancements have been made in computer vision algorithms applicable to medical scene assessment, yet there is insufficient evidence of these technologies being effectively integrated into the commercial DFR market. This highlights a gap between research and industry implementation.

Reasons for this gap include challenges related to quality assurance and the lack of application-specific training datasets for AI/ML models. With FAA regulatory updates passed in 2023, fully autonomous UAVs able to operate beyond visual line-of-sight may not be far out. Addressing the challenges to computer vision for fully autonomous medical DFR scene assessment through demonstrated research advancements, improved regulatory frameworks, integration of quality assurance measures, and public engagement are recommended pathways for advancing the use of UAS in medical emergency first response and addressing the apparent gap between research grade computer vision technologies and autonomous medical scene assessment needs.

Appendices

A Source Summary - Uncrewed Aerial Systems and Drones as a First Responder

Sources used in this work are summarized below, organized by type and in chronological or alphabetical order where appropriate.

A.1. General Uncrewed Aerial Systems

- Cohn et al. (2017): “Commercial drones are here: The future of unmanned aerial systems” - This report by McKinsey & Company providing an in-depth analysis of the commercial drone market, focusing on the value chain, investment trends, and regulatory challenges. It highlights the potential applications of drones in various sectors, including emergency response, environmental monitoring, and industrial inspections. The report also discusses the technological advancements needed to fully realize the benefits of UAVs and the strategic considerations for stakeholders in the industry. [6]
- Abbas et al. (2023): “A Survey: Future Smart Cities Based on Advance Control of Unmanned Aerial Vehicles (UAVs)” - This paper provides a survey of UAV applications in future smart cities, emphasizing the integration challenges, potential applications, and control theory challenges and solutions for effective UAV deployment in urban environments. [7]
- FAA Re-authorization Act (2024): This website provides the full text of the Federal Aviation Administration (FAA) Reauthorization Act of 2024, which outlines the reauthorization of the FAA through Fiscal Year 2028 and includes provisions for UAS operations beyond visual line of sight, powered lift aircraft operations, and various measures to support advanced aviation and autonomy. [117]

A.2. General Drones as a First Responder

- King et al. (2023): “Drone as First Responder Programs: A New Paradigm in Policing” - This document from MITRE Corporation outlines the implementation and benefits of using drones in emergency response scenarios. These programs, known as DFR (Drone as First Responder), involve dispatching drones ahead of police units to provide real-time situational awareness. The drones are equipped with video cameras and other sensors to relay critical information to officers, enhancing decision-making and safety. The document discusses the origins, benefits, and challenges of DFR programs, highlighting faster response times, improved safety, and cost-effectiveness compared to traditional methods. However, it also addresses concerns regarding privacy, regulatory restrictions, and community acceptance. The report emphasizes the need for transparency, community engagement, and adherence to best practices to ensure the success and sustainability of these programs [2].

- MITRE Corporation (2023): "First Responder Drone Initiatives" - This document outlines several key initiatives designed to enhance the capabilities of first responders through the use of drones. These initiatives include developing drones for persistent overwatch, specialized training for drone pilots, tools for selecting appropriate drones, and adapters for hazardous materials detection. The goal is to improve situational awareness, reduce resource requirements, and increase safety for both first responders and the communities they serve. [3]

- Expo UAV (2023): This website describes "DRONERESPONDERS Public Safety Summit," a two-day event focused on educating and preparing first responder UAS program managers and remote pilots for public safety UAS operations. The summit includes case studies, workshops, and networking events. [24]

- NASA (2023): This website describes the NASA Partnership with AIRT/DRONERESPONDERS to advance automated air safety systems for UAS in the national airspace, enhancing emergency response operations through automated safety management systems. [25]

- NIST and PSCR (2023): This website describes "First Responder UAS Challenges," a series of competitions hosted by NIST and the Public Safety Communications Research Division. These challenges are designed to advance UAS technology for public safety applications, specifically focusing on scene assessment, search and rescue, and emergency response. The competitions offer participants the opportunity to demonstrate their innovative solutions in various scenarios, such as 3D mapping and indoor navigation, which are critical for enhancing first responders' situational awareness and effectiveness in emergency situations. [26]

- Dooley et al. (2024): "Blue Unmanned Aircraft Systems for First Responders Focus Group Report" - This Department of Homeland Security (DHS) report provides an overview of discussions between emergency first responders and representatives from the DHS's National Urban Security Technology Laboratory's SAVER program. The report distills the outcome of primary discussion objectives such as gathering assessment criteria, possible evaluation scenarios, product suggestions and product selection specifications for future SAVER assessments related to the integration of small UAS in public safety operations such as search and rescue, firefighting, and post-incident reconstruction. Top assessment criteria identified include camera's visual acuity, flight duration, command and control link quality, latency, and time to redeploy, in addition to other recommendations for assessment criteria such as integration with emergency response protocols. The report highlights the importance of capability, deployability, and usability in UAS platforms, in addition to the Department of Defense's (DoD) Blue UAS Cleared List, which supports responder agencies in acquiring compliant UAS that meet DoD standards. [8].

- Department of Homeland Security: This webpage from the Department of Homeland Security (DHS) discusses the use of small unmanned aerial systems (UAS) by first responders for public safety tasks like search and rescue, firefighting, and post-incident analysis. It highlights the "Blue UAS Cleared List" created by the Department of Defense, which includes vetted drones that comply with DoD policies, aiding responder agencies in acquiring reliable UAS technology. See also the related focus group report. [27]
- My Drone Services: This website provides a comprehensive overview of how drones are being integrated into public safety operations. It details the types of drones used, their applications in law enforcement, firefighting, and emergency medical services, and discusses funding sources and regulatory considerations. [16]

A.3. Medical Drones as a First Responder

- Johnson et al. (2021): "Impact of Using Drones in Emergency Medicine: What Does the Future Hold?" - This 2021 article explores the expanding role of drones in enhancing emergency medical services, focusing on their use for rapid delivery of defibrillators, blood products, and emergency medications. It highlights the current applications, challenges related to regulation and technology, and future opportunities for integrating drones into EMS systems to improve response times and patient outcomes [5].
- Sanz-Martos et al. (2022): "Drone applications for emergency and urgent care: a systematic review" - This paper examines the use of drones in emergency and urgent care, highlighting their benefits such as faster victim location, preliminary triage, and safe operation in hazardous conditions. The study concludes that while drones offer significant advantages over traditional methods, further research and community education are needed to enhance their integration into emergency healthcare systems. [9]
- Roberts et al. (2023): "Current summary of the evidence in drone-based emergency medical services care" - This review article explores the potential of using drones to deliver time-sensitive medical supplies such as automated external defibrillators (AEDs), naloxone, antiepileptics, and blood products in emergency medical situations. The study highlights the promising data indicating that drones can reduce the time to intervention, which is crucial for improving patient outcomes in emergencies like cardiac arrests and opioid overdoses. However, it also addresses existing barriers and knowledge gaps, emphasizing the need for further research to integrate drones effectively into emergency medical services (EMS) systems. The authors call for real-world functionality demonstrations and studies to fully realize the potential of drones in EMS. [10]
- Drone Emergency Response (2023): "Drones in Emergency Response: Delivering Narcan and AEDs" - This article discusses the use of drones to provide emergency medical responses, including delivering Narcan for opioid overdoses

and AEDs for cardiac arrest, highlighting recent initiatives and programs in the U.S. that aim to speed up life-saving treatments. [118]

- Ambulance Drone Evolution (2023): "The Evolution of UAVs: The Ambulance Drone" - This article explores the development and potential of ambulance drones, which aim to enhance emergency medical services by rapidly delivering critical supplies like defibrillators to the scene of medical emergencies, or conducting patient transport, thereby reducing response times and improving survival rates. [115]

- Surman and Lockey (2024): "Prehospital Drones: Applications and Implications for Emergency Medical Services" - This paper discusses the increasing utilization of UAVs in pre-hospital emergency medicine. It highlights their roles in rapid delivery of medical supplies, such as defibrillators and blood products, to improve response times and patient outcomes in emergencies. The review also covers challenges and future research areas. [31]

- Field (2024): "Zipline's Milestone: 1 Million Commercial Drone Deliveries" - This Forbes web article reports on the company Zipline reaching the milestone of one million commercial drone deliveries, highlighting the company's innovative use of drones to deliver medical supplies and other products, and discussing its plans for future expansion and technology advancements. [114]

B Source Summary - Datasets

- ISPRS (2013): "ISPRS Test Datasets for Urban Classification and 3D Reconstruction" - This document provides detailed descriptions of two non-UAV aerial imagery datasets: Vaihingen and Toronto. The datasets support computer vision tasks such as scene classification and 3D building reconstruction, and are designed to enhance the development and evaluation of aerial image processing algorithms. [79]

- Robicquet et al. (2016): "Forecasting Social Navigation in Crowded Complex Scenes" - This 2016 paper presents a large-scale dataset capturing images and videos of various targets, such as pedestrians, bikers, skateboarders, cars, and buses, navigating in real-world outdoor environments of a university campus. This dataset, collected by researchers at Stanford University, aims to improve trajectory forecasting and target tracking by incorporating social interactions and behaviors in complex scenes. [44]

- Mueller et al. (2016): "A Benchmark and Simulator for UAV Tracking" - This 2016 paper introduces UAV123, a large-scale dataset and benchmark for evaluating visual tracking algorithms specifically in UAV-based scenarios. It includes 123 high-resolution video sequences captured from a low-altitude aerial perspective, totaling over 110,000 frames. The dataset is designed to address the unique challenges posed by UAV tracking, such as abrupt camera motion, scale variations, and occlusions. [70]

- Schroeder et al. (2018): “Optical Flow Dataset and Benchmark for Visual Crowd Analysis” - The CrowdFlow dataset is introduced in this paper. CrowdFlow is an annotated synthetic optical flow dataset for visual crowd analysis, to address challenges in crowd behavior analysis and benchmarking optical flow algorithms. [71]

- Zhu et al. (2018): “VisDrone-VDT2018: The Vision Meets Drone Object Detection in Image and Video Challenge Results” - The VizDrone dataset is introduced in this 2018 paper. VizDrone is a large-scale annotated drone acquired visual object detection and tracking benchmark aimed at advancing visual understanding tasks on the drone platform, highlighting the challenges and solutions in object detection and tracking in urban/suburban environments. [81]

- Du et al. (2018): “UAVDT: A Benchmark for Object Detection and Tracking in UAV Videos” - This paper introduces the UAVDT benchmark, a large-scale annotated dataset for object detection and single/multiple object tracking in urban scene UAV-captured videos. [80]

- Kyrkou and Theocharides (2019): “AERIAL Image Dataset for Emergency Response (AIDER)” - This paper introduces AIDER, and ERNet, a lightweight CNN for aerial image classification, to highlight real-time disaster management using UAVs. AIDER trained ERNet is demonstrated on a UAV with both an embedded and remote image classification processing configuration. [63]

- Perera et al. (2019): “Drone-Action: An Outdoor Recorded Drone Video Dataset for Action Recognition” - This paper introduces a dataset aimed at supporting research in aerial human action recognition. The dataset is designed to capture detailed human body movements in outdoor settings, providing valuable data for applications such as surveillance, situational awareness, and gait analysis. [72]

- Aruna Kumar et al. (2020): “P-DESTRE: A Fully Annotated Dataset for Pedestrian Detection, Tracking, Re-Identification, and Search from Aerial Devices” - The P-DESTRE dataset, described in this 2020 article, was created by researchers from the University of Beira Interior (Portugal) and JSS Science and Technology University (India). It aims to facilitate research on pedestrian detection, tracking, re-identification, and search from aerial data. The dataset was collected using DJI Phantom 4 drones flown over university campuses to simulate real-world urban environments. It includes detailed annotations to support various research tasks, enabling the development of robust models for pedestrian identification from aerial footage. [74]

- Lyu et al. (2020): “UAVid: A Semantic Segmentation Dataset for UAV Imagery” - This paper introduces the UAVid dataset, a high-resolution UAV semantic segmentation dataset designed for urban scene understanding. [82]

- Yu et al. (2020): "Scale Match for Tiny Person Detection" - TinyPerson, the benchmark dataset described in this paper, is introduced along with the "scale match" technique for detection of small objects in a frame (perhaps less than 20 pixels in size). The emphasis is on the identification of distant persons especially in complex real world environments. [73] The TinyPerson dataset is also referenced in another relevant paper by the same authors which describes the Tiny Object Detection Challenge [43].

- Li et al. (2021): "UAV-Human: A Large Benchmark for Human Behavior Understanding with Unmanned Aerial Vehicles" - This paper presents a comprehensive dataset aimed at advancing the field of human behavior analysis using UAVs. [75]

- Wen et al. (2021): "DroneCrowd Dataset: A Large-scale Drone-captured Dataset for Crowd Analysis" - The DroneCrowd dataset is introduced in this paper. DroneCrowd is a large-scale annotated drone-captured dataset for crowd analysis, highlighting the challenges and solutions in density map estimation, localization, and tracking of objects in crowded scenes using drones. [68]. DroneCrowd is one of the MULTIDRONE Datasets (see [69]).

- Nguyen et al. (2023): "AG-ReID.v2: A Fully Annotated Dataset for Aerial-Ground Person Re-Identification" - This paper introduces a comprehensive dataset designed for person re-identification (ReID) tasks, encompassing images from both aerial (UAV) and ground sources (CCTV and wearable cameras). This dataset contains over 100,502 images and 1,615 unique identities, annotated with 15 soft-biometric attributes. The dataset addresses the complexities of aerial-ground ReID, providing significant variations in viewpoint, resolution, and lighting conditions. [62]

- Rahnemoonfar et al. (2023): "RescueNet: A High-Resolution UAV Semantic Segmentation Dataset for Natural Disaster Damage Assessment" - This paper introduces the RescueNet dataset, a high-resolution UAV semantic segmentation dataset for natural disaster damage assessment taken after the landfall of hurricane Michael, highlighting its applications and utility in improving scene understanding and damage assessment in post-disaster scenarios. [76]

- Bernal et al. (2023): "NOMAD: A Benchmark for Human Detection under Occluded Aerial Views in Search and Rescue Missions" - This paper introduces the NOMAD dataset, a benchmark for human detection under occluded aerial views, designed to improve the effectiveness of aerial search and rescue missions by addressing the challenges of occlusion in emergency response scenarios. [38]

- Scheele et al. (2024): "LADI v2: Multi-label Dataset and Classifiers for Low-Altitude Disaster Imagery" - This paper introduces a curated collection of approximately 10,000 disaster images captured in the United States by the Civil Air Patrol from 2015 to 2023. The images are annotated for multi-label classification by trained volunteers, aiding in emergency management operations. The paper also compares the performance of two pretrained baseline classifiers against state-of-the-art vision-language models in multi-label classification tasks. [77]

- The Open MULTIDRONE Datasets website, hosted by the Aristotle University of Thessaloniki, provides access to 36 UAV video datasets (including the DroneCrowd dataset [68]) created within the MULTIDRONE project. These datasets, totaling approximately 260 GB, support research in visual detection and tracking of objects such as bicycles, boats, and human crowds. [69]
- Papers with Code: This website provides a comprehensive and organized repository of datasets used in machine learning research. The platform categorizes datasets across various domains such as computer vision, natural language processing, and audio processing. Each dataset entry includes relevant details such as its name, description, associated tasks, and links to papers that utilized the dataset, facilitating easy access for researchers. The website also features tools for searching and filtering datasets by different criteria, enhancing the ability to find specific datasets for various AI/ML applications. [67]
- Shaip: The Shaip website provides a collection of open datasets for AI/ML training purposes. These datasets cover various domains such as automotive, healthcare, finance, and general AI. Each dataset is designed to enhance machine learning models by providing high-quality, annotated data. The website details offerings like image and video datasets, audio and speech datasets, and text and document datasets. [66]

C Source Summary - Artificial Intelligence/Machine Learning

Several original papers publishing specific object detection algorithms are relevant to this section of the source summaries were referenced in this writing. These papers are not summarized here due to the obvious nature of their content [34, 35, 37, 39–41, 43, 45–48, 50, 52, 53, 55, 57, 58, 65].

- Lopez-Fuentes et al. (2018): "Review on Computer Vision Techniques in Emergency Situations" - This paper provides an overview of how computer vision technologies can be applied to various emergency scenarios. It categorizes emergencies into natural and human-made, detailing the computer vision methods used for prevention, detection, response, and understanding of these situations. The review highlights situational awareness and the role of different sensors and algorithms in enhancing emergency management. [11]
- Chen et al. (2019): "RRNet: A Hybrid Detector for Object Detection in Drone-Captured Images" - This paper presents a novel hybrid object detection model called RRNet, specifically designed to handle the unique challenges of object detection in images captured by UAVs (drones). The primary challenges addressed include the varying scales and densities of objects in urban scenes.

This is achieved primarily via a hybrid detection approach (combining anchor-free detection methods with a re-regression module) and adaptive resampling augmentation. [54]

- Du et al. (2020): "VisDrone-DET2020: The Vision Meets Drone Object Detection in Image Challenge Results" - This paper presents the outcomes of the VisDrone-DET2020 challenge, held in conjunction with the European Conference on Computer Vision (ECCV) 2020. The challenge focused on advancing object detection in images captured by drones, addressing unique challenges such as small object sizes, diverse object categories, and complex backgrounds. [42]

- Kyrkou and Theocharides (2020): "EmergencyNet: Efficient Aerial Image Classification for Drone-Based Emergency Monitoring Using Atrous Convolutions" - This 2020 paper extends the deep learning-based approach introduced in [63] for aerial image classification for drone-based emergency monitoring, proposing a further developed CNN architecture known as EmergencyNet, and referencing the dedicated aerial image dataset known as AIDER for emergency response applications. [64]

- Ramachandran and Sangaiah (2021): "A review on object detection in unmanned aerial vehicle surveillance" - This article provides a comprehensive review of the methods and applications of object detection in UAV surveillance. The study categorizes existing object detection techniques into traditional image processing and deep learning methods, summarizing their applications in various fields such as agriculture, disaster management, and security. The authors propose a secure onboard processing system to enhance the robustness of object detection frameworks in precision agriculture, with the intention of mitigating identified research gaps. [12]

- Nguyen et al. (2022): "The State of Aerial Surveillance: A Survey" - This review paper provides an overview of the state of aerial surveillance, focusing on RGB imaging sensor data analyzed by computer vision and deep learning for tasks such as detection, tracking, identification, and action recognition. These tasks primary cover "human-centric" applications such as border patrol, search and rescue, maritime surveillance, protest monitoring, drug trafficking monitoring, military IED tracking, and crime fighting. It highlights the unique challenges faced in aerial surveillance compared to ground-based methods, discusses the available public datasets for each task, and reviews the approaches and techniques used to address these challenges. The paper also identifies gaps in current research and suggests future directions for the field. [4]

- McEnroe et al. (2022): "A Survey on the Convergence of Edge Computing and AI for UAVs: Opportunities and Challenges" - This paper provides a comprehensive analysis of the convergence of edge computing and artificial intelligence (AI) for unmanned aerial vehicles (UAVs). It discusses the benefits, such as lower latency, improved energy efficiency, and enhanced security and privacy, while also addressing the challenges of resource constraints, network reliability, and implementation difficulties in deploying edge AI for UAV applications. [13]

- Zou et al. (2023): "Object Detection in 20 Years: A Survey" - This survey paper provides a comprehensive review of the technological evolution of object detection from the 1990s to 2022. It covers milestone detectors, key datasets, metrics, fundamental building blocks of detection systems, and recent state-of-the-art methods. The survey highlights the transition from traditional handcrafted feature-based detectors to deep learning-based techniques, emphasizing advancements in accuracy and speed. It also explores speedup techniques, the integration of contextual information, and the evolution of loss functions and non-maximum suppression methods, aiming to offer readers an understanding of the field's progress and potential future directions. [14]
- Setyanto et al. (2023): "Near-Edge Computing Aware Object Detection: A Review" - This review paper provides a comprehensive overview of current object detection methods with a focus on their deployment on near-edge devices like drones and autonomous vehicles. The paper discusses the challenges of implementing computationally intensive object detection algorithms on resource-constrained edge devices and explores various model compression and optimization techniques to address these limitations. It emphasizes the need for balancing model efficiency and accuracy in real-time applications where processing capabilities and energy consumption are critical concerns. [15]
- Han et al. (2024): "SSMA-YOLO: A Lightweight YOLO Model for Ship Detection in Drone-Aerial Images" - This paper proposes a lightweight YOLO model with enhanced feature extraction and fusion capabilities. The proposed model enhances the YOLOv8n architecture to address the challenges of detecting ships in satellite remote sensing images, where ships often appear with a small pixel area, leading to insufficient feature representation and suboptimal performance. The complexity of backgrounds and vessel clustering further complicates detection. [49]
- Sagar et al. (2024): "BayesNet for remote sensing" - This paper introduces BayesNet, a Bayesian neural network-driven CNN model designed for remote sensing scene understanding with quantifiable uncertainties, highlighting its application and performance across multiple UAV-based remote sensing datasets. Four datasets of interest to Aerial **Ai**d are referenced in the paper. [78]

D Source Summary - Patents

Relevant patents references in this work are summarized below, organized by type and in chronological or alphabetical order where appropriate.

- Kumar et al. (2018): "Controlling Autonomous Vehicles to Provide Automated Emergency Response Functions" (US 2018/0144639 A1) - This patent outlines methods and systems for controlling UAVs for autonomous emergency response. The system uses a computing platform to receive vehicle data, detect emergencies, and dispatch autonomous vehicles to execute tasks such as delivering supplies, providing medical functions, and capturing incident data. [33]

- Walker et al. (2020): "Unmanned Aerial Vehicles in Medical Applications" (US 10,814,978 B2) - This patent outlines methods and systems for using UAVs to enhance medical emergency responses. The patent details UAV capabilities for delivering medical equipment like automated external defibrillators (AEDs), assessing patient conditions, providing real-time communication with first responders, and coordinating with other UAVs. [32]

- Burks et al. (2022): "Systems and Methods for Tracking, Evaluating, and Determining a Response to Emergency Situations Using Unmanned Airborne Vehicles" (US 2022/0177130 A1) - This patent describes various embodiments of a fully autonomous drone designed for purposes of emergency scene assessment. The drone, or drones, would be deployed and recovered using automated deployment and docking technologies covered in the patent. The drone is also equipped with various sensors and communication systems to provide real-time situational awareness and support to first responders. Additional features are described such as automatic charging and the ability to relay critical information to emergency personnel, improving the speed and effectiveness of emergency response. [59]

- Trundle and Slavin (2023): "Drone-Augmented Emergency Response Services" (EP 3 356 857 B1) - This patent describes methods and systems for utilizing a network of drones and control systems to perform emergency monitoring, response, and communications tasks. Surveillance data collected by drones is processed using a "monitoring application server" which performs tasks including threat determination, such as identification of unauthorized persons, implying although not directly specifying some use of artificial intelligence or computer vision. Drones can perform tasks such as delivering medical supplies, conducting surveillance, and relaying critical information to law enforcement officials. [60]

E Source Summary - Commercial Vendor Websites

Relevant websites of commercial vendors referenced in this work are summarized below, organized by type and in chronological or alphabetical order where appropriate.

- AI Robotics Drones: AI Robotics Drones Solutions provides various UAV solutions for urban, defense, industrial, and surveillance applications. Their drones are designed for 24/7 autonomous operation, offering real-time video, data analytics, and integration with other systems. [21]

- AIRT: AIRT Inc focuses on using drones for public safety and disaster response. Their DRONERESPONDERS program enhances emergency management through UAS operations. [23]

- Argus Rising: Argus Rising provides specialized drone training for first responders, covering various aspects of UAV operations including law enforcement and fire rescue applications. [30]

- BRINC Drones: BRINC Responder Drone is designed for public safety, providing features like real-time video, thermal imaging, 2-way communication, and emergency payload delivery. [19]

- Draganfly: Draganfly's DFR platform provides comprehensive UAV solutions for first responders, enhancing emergency response through real-time data capture, surveillance, and efficient scene assessment. [17]

- EHang Autonomous Aerial Vehicle: This webpage details EHang's Autonomous Aerial Vehicle (AAV) technology, focusing on its design, functionality, and applications in urban air mobility, including passenger transportation, logistics, and emergency response services. [116]

- Paladin Drones: Paladin Drones provides Drone as a First Responder (DFR) technology, offering real-time situational awareness and resource allocation for emergency response. [18]

- PELA Systems: PELA Systems scene assessment focuses on providing tools for real-time data capture, unmanned device deployment, and communication infrastructure to protect first responders and the public. Their PELAmesh range integrates instrumentation, visual, and communication protocols for comprehensive scene assessment. [20]

- Skyfire Consulting: The website "Drone First Responder" offers turnkey solutions for Drone First Responder (DFR) programs, enhancing emergency response with drones to improve situational awareness and decrease response times. [28]

- UAV Coach: "Drone as a First Responder (DFR) Guide" provides a comprehensive overview of Drone as a First Responder (DFR) programs, their benefits, and how to start one. [29]

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14. ABSTRACT

This report presents the findings from market research conducted for NASA's Aerial **Ai**d Convergent Aeronautics Solutions (CAS) exploration project, which aims to assess the current state of the market and technological readiness for Uncrewed Aerial Systems (UAS) for medical emergency first response. The research reveals a robust and rapidly growing market for UAS, with a notable emerging sector for Drones as First Responders (DFR). Despite this growth, DFR applications are currently limited by regulatory, technical, and other challenges, which restrict their use primarily to manned remote video surveillance, and therefore are primarily employed by police units. To our knowledge, there is no evidence of UAS being utilized by medical first responders for scene assessment. Limited evidence exists for closely related applications; however, these are mostly confined to pilot programs for the delivery of medical supplies or equipment. Although there has been discussion around fully autonomous DFR applications for medical purposes such as UAS ambulances or patient transport drones, these applications are generally not yet operational in practice. The technology for full autonomy, especially in guidance and control, has seen significant advancements, and recent Federal Aviation Administration (FAA) regulations are likely to accelerate adoption. Computer vision algorithms for fully autonomous medical emergency response scene surveillance are primed for advancement and deployment. A notable gap likely exists between advancements in computer vision research and what is being integrated in the commercial DFR sector. This gap is primarily due to challenges such as quality assurance for autonomous systems, the availability of application-specific training datasets for computer vision algorithms, regulatory constraints, and public perception and privacy concerns.

15. SUBJECT TERMS

UAS, UAV, scene, EMS, first responder, AI, computer vision

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