International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 5, Sep-Oct-2026, ISSN (Online): 2395-566X

AI-Powered Drones for Disaster Search and Rescue: A Review of Human Detection, Autonomous Navigation and Emergency Communication

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Abstract—Earthquakes, floods, landslides and building collapses cause serious damage and loss of life, and locating trapped or stranded people quickly is one of the most critical tasks for rescue teams. Ground searches are slow and often dangerous in unstable or inaccessible areas. AI-powered drones offer a faster and safer alternative by combining aerial mobility with onboard cameras, thermal sensors, GPS and computer vision. This paper reviews the design of AI drones for disaster rescue. It examines aerial datasets and deep object detectors for recognizing people, vehicles and damaged structures from above, thermal imaging for finding victims at night or under light cover, coverage path planning for searching large areas systematically, simultaneous localization and mapping for operation where GPS is unreliable, and drone networks that relay communication when ground infrastructure fails. Practical constraints of battery life, payload, onboard computing and regulation are discussed. A five-layer architecture comprising sensing, onboard edge AI, navigation and control, communication and a ground control station is proposed, followed by a research gap analysis, objectives, comparison of detection models and a discussion of challenges. The review concludes that AI drones can cover large areas quickly, reach inaccessible locations and reduce risk to rescuers, making disaster response faster, safer and more effective.

Index Terms—AI-powered drones, UAV, search and rescue, human detection, computer vision, thermal imaging, path planning, disaster management

I. INTRODUCTION

In the first hours after a disaster, the chance of finding survivors alive is highest, yet this is also when information is most scarce. Roads may be blocked, buildings unstable and floodwater widespread. Rescue teams must decide where to search with limited people and equipment, sometimes putting themselves at risk.Unmanned aerial vehicles (UAVs), or drones, can be launched within minutes, fly over obstacles and transmit live video. Erdelj *et al.* [1] describe how UAVs support monitoring, damage assessment and search and rescue across disaster phases. When combined with AI, a drone becomes more than a flying camera: it can automatically detect people in its imagery, mark their GPS coordinates and plan its own search pattern.This paper reviews AI-powered drones for disaster rescue, proposes a system architecture and discusses research gaps and challenges. It focuses on the drone platform itself, from sensing to communication, and on how it delivers actionable information to rescue teams.

II. THEORETICAL BACKGROUND

2.1 Drone Platforms And Sensors

Multirotor drones hover and manoeuvre precisely, making them suitable for close inspection, while fixed-wing drones cover larger areas with longer endurance. Typical payloads include an RGB camera, a thermal camera, GPS, an inertial measurement unit and sometimes LiDAR, loudspeakers or small supply packages. Fig. 1 classifies the functions of an AI rescue drone.

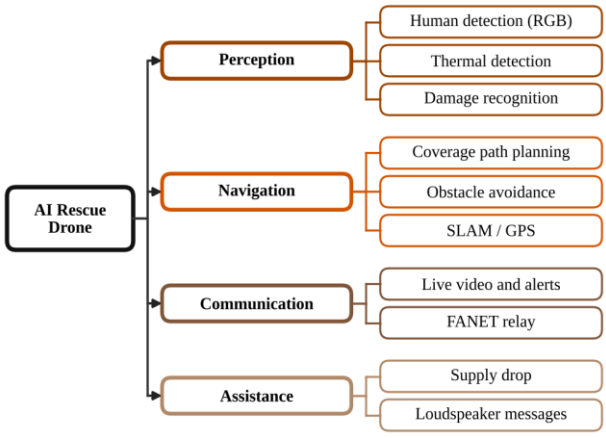


Fig. 1. Functions of an AI-powered rescue drone.

2.2 Computer Vision For Aerial Imagery

Detecting people from the air is harder than from the ground because people appear small, are seen from above and may be partly hidden. One-stage detectors such as YOLO [2], [3]

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process frames in real time, and two-stage detectors such as Faster R-CNN [4] offer high accuracy.

2.3 Survey Of Existing Approaches

Hayat *et al.* [5] surveyed UAV networks for civil applications, including search and rescue, and identified requirements for reliable, low-latency links and coordination among multiple drones. Bekmezci *et al.* [6] described flying ad-hoc networks (FANETs), in which drones relay data to each other, extending range and supporting communication where ground networks have failed.For detection, Zhu *et al.* [7] organized the VisDrone challenge with a large dataset of drone images and videos annotated for pedestrians and vehicles, and showed that small-object detection from altitude remains challenging even for state-of-the-art detectors. Rahnemoonfar *et al.* [8] released FloodNet, aerial imagery after a hurricane annotated for flooded buildings and roads. Gupta *et al.* [9] provided xBD for building damage assessment, which can guide drones to the most damaged areas.

For navigation, Galceran and Carreras [10] surveyed coverage path planning, which ensures that a robot systematically covers an area, using patterns such as back-and-forth sweeps and cell decomposition. Cadena *et al.* [11] reviewed SLAM, which allows a drone to build a map and localize itself in GPS-degraded environments such as collapsed structures or dense urban canyons. Hart *et al.* [12] introduced the A* search algorithm, widely used for shortest-path planning around obstacles.

Murphy [13] reported experiences from real disaster deployments of robots and drones, highlighting the importance of operator interfaces, the limited flight time of small drones, and the value of drones for rapid situational awareness. Table I summarizes these works.

TABLE I Summary of Literature Survey

Ref.	Authors	Year	Technique Used	Merits	Demerits
[6]	Bekmezci et al.	2013	Flying ad-hoc networks	Drone-to-drone relaying concepts	High mobility complicates routing
[10]	Galceran and Carreras	2013	Survey of coverage path planning	Methods for systematic area coverage	Energy limits not central
[13]	Murphy	2014	Disaster robotics field experience	Practical lessons from deployments	Small drones, short endurance
[5]	Hayat et al.	2016	Survey of civil UAV networks	Communication requirements for SAR	General civil focus
[11]	Cadena et al.	2016	SLAM survey	Localization without GPS	Robustness in smoke and dust
[1]	Erdelj et al.	2017	UAV support for disaster management	Roles of UAVs across disaster phases	Conceptual; few field results
[8]	Rahnemoonfar et al.	2021	FloodNet aerial dataset	Post-flood scene understanding	Single hurricane event
[7]	Zhu et al.	2022	VisDrone benchmark	Large annotated drone dataset	Urban scenes; not disaster-specific

III. COMPARATIVE STUDY

Table II compares detection models for aerial rescue. Larger two-stage detectors are accurate but slow on embedded hardware; compact one-stage detectors run in real time; and thermal-RGB fusion improves detection at night and in vegetation.

TABLE II Comparison of Detection Approaches for Aerial Rescue

Approach	Accuracy	Speed on Drone	Night Use
Faster R-CNN (RGB)	High	Slow	Poor
YOLO (RGB)	Good–High	Real time	Poor
Thermal threshold	Medium	Very fast	Good
YOLO on thermal	High	Real time	Very good
RGB–thermal fusion	Very high	Near real time	Very good

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3.1 Research Gaps

The following gaps are identified:

- Detection models trained on general aerial datasets perform poorly on partially buried people, debris and floodwater scenes.
- Fusion of thermal and RGB imagery for reliable detection is not widely evaluated in Indian disaster conditions.
- Short battery life limits search time, and energy-aware path planning is rarely integrated with detection.
- Multi-drone coordination and communication relay in the field remain largely experimental.
- Operator interfaces that present AI detections clearly to rescue teams are under-studied.

3.2 Aims And Objectives

The objectives of this review are:

- **O1:** To review drone platforms, sensors and AI techniques for disaster search and rescue.
- **O2:** To compare object detection models for human detection in aerial imagery.
- **O3:** To propose a five-layer AI drone architecture for rescue operations.
- **O4:** To examine path planning, localization and communication methods.
- **O5:** To identify challenges and future research directions.

IV. PROPOSED ARCHITECTURE

Fig. 2 shows the proposed architecture. Detection runs on the drone so that alerts can be generated even when the video link is weak.

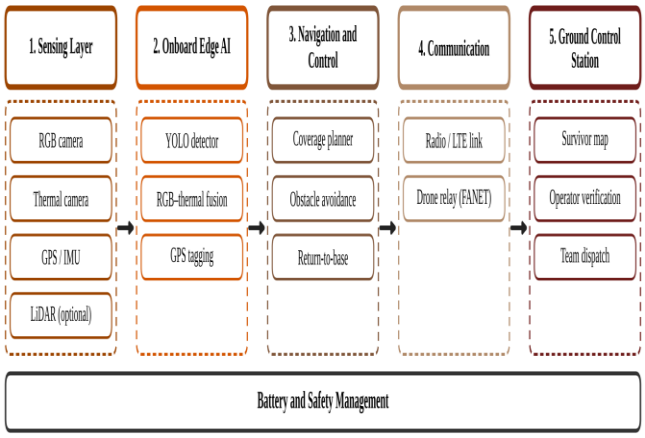


Fig. 2. Proposed five-layer architecture of the AI-powered rescue drone.

4.1 Sensing Layer

An RGB camera captures visual detail, a thermal camera detects body heat, GPS and IMU provide position and orientation, and an optional LiDAR assists in obstacle avoidance.

4.2 Onboard Edge Ai Layer

A lightweight detector such as a compact YOLO model runs on an embedded GPU module. RGB and thermal detections are fused to improve reliability, and each confirmed detection is tagged with GPS coordinates and a timestamp.

4.3 Navigation And Control Layer

A coverage planner divides the search area into strips; obstacle avoidance and SLAM maintain safe flight. The drone can hover over detections to capture closer images and returns to base when the battery reaches a reserve level.

4.4 Communication Layer

Detections, thumbnails and telemetry are sent to the ground station over radio or LTE links. Additional drones can act as relays, forming a FANET.

4.5 Ground Control Station

A map interface displays search coverage, detected survivors and hazards. Operators verify detections, assign rescue teams and can drop small supplies such as life jackets or medicine.

V. PROCESS FLOW AND EVALUATION

The workflow appears in Fig. 3. The ground sampling distance, which determines how many pixels a person occupies, is

$$GSD = (H \cdot s) / (f \cdot W_img) \quad (1)$$

where H is flight altitude, s the sensor width, f the focal length and W_img the image width in pixels. Lower altitude gives finer detail but smaller coverage. The approximate area covered in one flight is

$$A \approx v \cdot T \cdot w \quad (2)$$

where v is ground speed, T usable flight time and w the swath width. Detection quality is evaluated with precision, recall and mean average precision on annotated aerial images.

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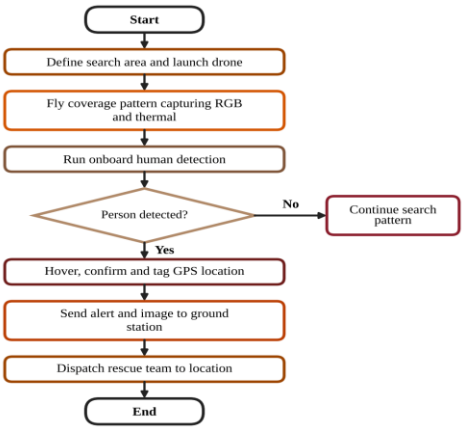


Fig. 3. Search-and-rescue workflow of the AI drone.

VI. LIMITATIONS AND FUTURE SCOPE

Table III summarizes the main challenges. Future directions include swarms of cooperating drones that divide search areas automatically, longer endurance through hybrid or tethered designs, detection of mobile phone signals to locate victims, voice communication through onboard speakers, and training datasets built from Indian disaster scenes.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Short battery life	Energy-aware planning; battery swaps
Hidden victims	Thermal sensing; low-altitude passes
Communication loss	Onboard storage; relay drones
Weather and wind	Robust platforms; flight limits
Regulation and safety	Trained pilots; airspace coordination

VII. CONCLUSION

AI-powered drones can transform disaster search and rescue by covering large areas quickly, reaching dangerous places and automatically locating people in need. The reviewed literature shows that deep object detectors, thermal imaging, coverage planning, SLAM and drone networks together form a capable rescue system. Battery life, detection of partially hidden victims, reliable communication and clear operator interfaces remain important challenges. With continued research and field testing, AI drones can make disaster response faster, safer and more effective.

7.1 Acknowledgment

The authors express their sincere gratitude to the Department of Artificial Intelligence and Data Science, Jaihind College of Engineering, Pune, for providing the facilities, guidance and encouragement needed to carry out this work. The authors also thank the faculty members and colleagues whose valuable suggestions helped improve the quality of this review.

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