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Ai-Based Disaster Response For Defence Forces: A Review Of Situational Awareness, Damage Assessment, Robotics And Resource Optimization

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Abstract—Floods, earthquakes, landslides and cyclones cause heavy loss of life and property, and defence forces are often the first organized responders, providing search and rescue, evacuation, relief logistics and emergency communication. Their operations are frequently hampered by delayed and incomplete information, limited resources, damaged infrastructure and difficulty in locating affected people. This paper reviews how Artificial Intelligence (AI) can strengthen disaster response by defence forces. It examines computer vision for automatic damage assessment from satellite and aerial imagery, machine learning on social-media and emergency-call data for situational awareness, unmanned aerial and ground robots for search in hazardous areas, prediction models for flood and hazard evolution, and optimization algorithms for routing, resource allocation and relief distribution. Human–machine teaming and resilient communication are discussed as enabling conditions. A layered command-and-control decision-support architecture integrating data acquisition, AI analytics, a common operational picture, planning and field execution is proposed. Research gaps, objectives, a comparison of AI capabilities and the challenges of data accuracy, connectivity, cost, reliability and ethics are analysed. The review concludes that AI can reduce response time and human risk and improve coordination, provided it is integrated with military doctrine and remains under human command.

Index Terms—Disaster response, defence forces, artificial intelligence, computer vision, damage assessment, UAV, robotics, resource allocation, humanitarian assistance

I. Introduction

India's armed forces regularly support civil authorities during floods in Assam and Kerala, cyclones on the eastern coast, earthquakes and Himalayan landslides. Within the national framework [1], they bring helicopters, boats, engineering units, medical teams and disciplined manpower that can be deployed quickly. The Sendai Framework [2] stresses that effective response depends on timely, accurate information and coordination among agencies.

In the first hours after a disaster, commanders face a fog of uncertainty: which areas are worst hit, where people are trapped, which roads and bridges are usable, and how to allocate limited aircraft and teams. Traditional reconnaissance and manual reporting are slow and may expose personnel to danger.

Artificial Intelligence can process satellite images, drone video, sensor data and public messages far faster than human analysts. This paper reviews AI applications that support defence forces in disaster response, proposes a decision-support architecture and discusses the conditions for effective and responsible use.

II. Background and Related Work

2.1 Phases of Disaster Management

Disaster management involves mitigation, preparedness, response and recovery. Defence forces contribute mainly to response, including search and rescue, evacuation, medical aid and restoring critical infrastructure, and to recovery logistics. Fig. 1 classifies AI capabilities that support these tasks.

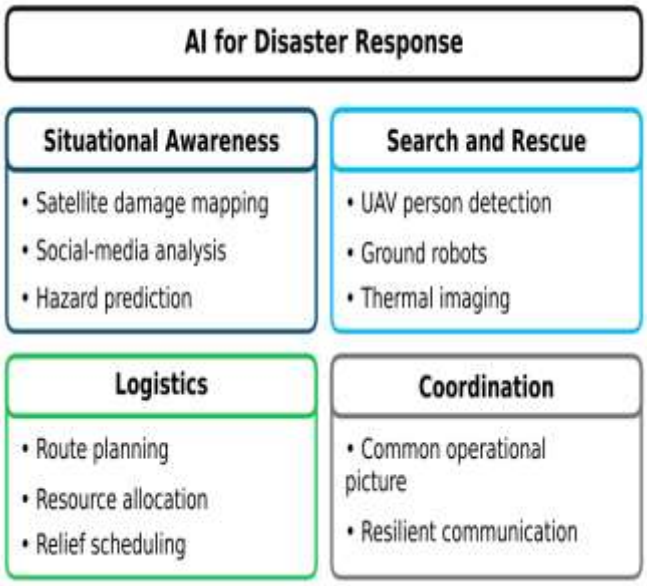


Fig. 1. AI capabilities supporting defence forces in disaster response.

2.2 Humanitarian Assistance and Disaster Relief

Humanitarian assistance and disaster relief (HADR) operations require coordination between military units, the National Disaster Response Force, state agencies and non-governmental organizations. A shared, accurate view of the situation, often called a common operational picture, is central to coordination.

2.3 Review of Related Studies

Damage assessment. Gupta *et al.* [3] created xBD, a large dataset of pre- and post-disaster satellite images with building damage labelled on a four-level scale across many disaster types, enabling deep models that automatically map damaged buildings. Rahnemoonfar *et al.* [4] released FloodNet, high-resolution aerial imagery annotated for flooded roads and buildings, supporting post-flood scene understanding. Ofli *et al.* [5] combined crowdsourced labelling with machine learning to analyse large volumes of aerial imagery after disasters quickly.

Situational awareness from social media. Imran *et al.* [6] surveyed methods for processing social-media messages during emergencies, including classification of messages into categories such as requests for help, infrastructure damage and casualties, and extraction of locations. These methods can reveal needs in areas that official channels have not yet reached.

Robots and UAVs. Murphy [7] documented the use of ground, aerial and marine robots in real disasters and showed that robots are most valuable for reaching dangerous or inaccessible places, while also identifying problems with communication and operator workload. Erdelj *et al.* [8] discussed how UAV networks support monitoring, forecasting, damage assessment and emergency communication. Hayat *et al.* [9] surveyed UAV networking requirements for civil applications including search and rescue.

Prediction and navigation. Operational flood forecasting [10] can tell commanders which areas will be inundated in the next days, helping to pre-position boats and relief. Simultaneous localization and mapping (SLAM) [11] allows robots to map collapsed or GPS-denied environments, and object detectors such as YOLO [12] identify people and vehicles in imagery in real time. Table I summarizes these works.

Ref.	Authors	Year	Technique Used	Merits	Demerits
[7]	Murphy	2014	Field study of disaster robots	Lessons from real deployments	Robots often teleoperated
[6]	Imran et al.	2015	Survey of social-media crisis processing	Classification and extraction of crisis information	Noise and misinformation
[5]	Ofli et al.	2016	Crowdsourcing + ML for aerial images	Rapid analysis of large image volumes	Depends on volunteer availability
[9]	Hayat et al.	2016	Survey of civil UAV networks	Communication requirements for SAR	Not disaster-specific in detail
[11]	Cadena et al.	2016	SLAM survey	Mapping in GPS-denied environments	Robustness in debris still hard
[8]	Erdelj et al.	2017	UAV networks for disaster management	Mapped UAV roles across phases	Battery and regulation limits
[3]	Gupta et al.	2019	xBD satellite building-damage dataset	Enabled automated damage classification	Satellite revisit delays
[4]	Rahnemoonfar et al.	2021	FloodNet aerial imagery dataset	Post-flood scene segmentation	Single event region
[10]	Nevo et al.	2022	Operational ML flood forecasting	Early warnings to large populations	Riverine floods only

TABLE I Summary of Literature Survey

III. Research Gap and Objectives

3.1 Identified Research Gaps

The following gaps are identified:

G1: AI tools are usually developed in isolation and are not integrated into military command-and-control systems.

G2: Models trained on foreign imagery may not generalize to Indian building types, terrain and weather.

G3: Communication networks in disaster zones are often damaged, limiting cloud-based AI.

G4: Little work addresses joint optimization of scarce military assets such as helicopters, boats and engineering teams.

G5: Trust, accountability and human oversight of AI recommendations in time-critical operations are under-studied.

3.2 Objectives of the Review

The objectives of this review are:

1. 1) To identify AI technologies applicable to disaster response by defence forces.
2. 2) To review computer vision, social-media analytics, robotics and optimization for HADR operations.
3. 3) To propose a layered AI-enabled command-and-control decision-support architecture.
4. 4) To compare AI capabilities in terms of maturity, data needs and operational value.
5. 5) To discuss challenges and recommend directions for adoption.

I. IV. Design of the Proposed System

The proposed architecture in Fig. 2 is designed to work on deployable edge computers at forward bases, synchronizing with headquarters when communication is available.

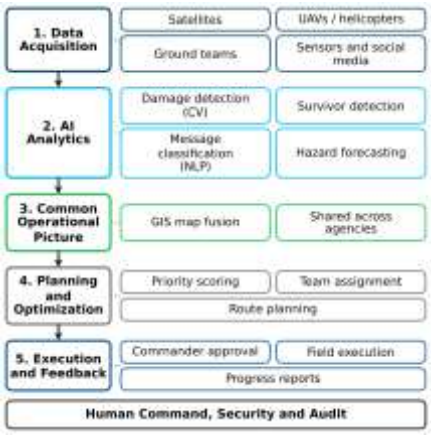


Fig. 2. Proposed AI-enabled command-and-control decision-support architecture.

3.3 Data Acquisition Layer

Data is gathered from satellites, UAVs, helicopter cameras, ground teams with mobile devices, weather and river sensors, emergency calls and social media.

3.4 AI Analytics Layer

Computer vision models detect damaged buildings, flooded roads, blocked routes and people needing help. NLP models classify messages and extract locations. Prediction models estimate how floodwater or other hazards will evolve.

3.5 Common Operational Picture Layer

Results are fused on a geographic information system map showing affected areas, survivors, hazards, usable routes, resources and unit locations, shared among all participating agencies.

3.6 Planning and Optimization Layer

Algorithms assign rescue teams and aircraft to tasks, plan routes around blocked roads using shortest-path search [13], prioritize areas by urgency and population, and schedule relief distribution.

3.7 Execution and Feedback Layer

Commanders review and approve plans, units execute them and report progress through mobile devices, and the picture is updated continuously.

3.8 Methodology

The decision-support workflow is shown in Fig. 3. Rescue priority for zone i can be expressed as

$$P_i = w_1 \cdot S_i + w_2 \cdot N_i + w_3 \cdot T_i - w_4 \cdot A_i \quad (1)$$

where S_i is estimated severity, N_i the number of people affected, T_i the time sensitivity, A_i the difficulty of access, and w_j weights set by commanders. Teams are allocated to minimize total response time subject to capacity constraints:

$$\min \Sigma_i \Sigma_j t_{ij} \cdot x_{ij} \quad \text{subject to} \quad \Sigma_i x_{ij} \leq c_j \quad (2)$$

where t_{ij} is the travel time of unit j to zone i, x_{ij} indicates assignment and c_j is the capacity of unit j.

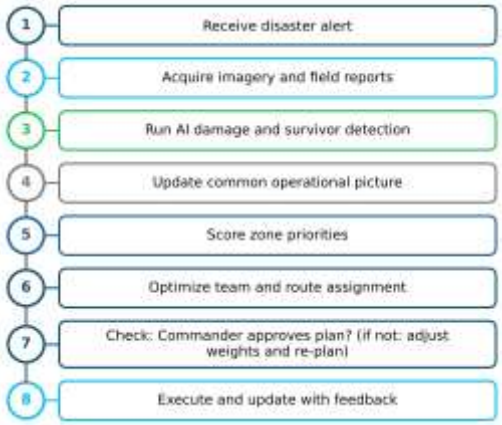


Fig. 3. Decision-support workflow for disaster response operations.

Because all recommendations are presented to a commander for approval, the system supports rather than replaces military judgement.

IV. Discussion and Comparison

Table II compares AI capabilities by maturity and operational value. Satellite damage assessment and flood forecasting are relatively mature; drone-based person detection is increasingly practical; and autonomous ground robots remain limited in rubble and water.

Capability	Maturity	Data Need	Operational Value
Satellite damage mapping	High	High	Wide-area overview
Flood forecasting	High	Medium	Pre-positioning
UAV person detection	Medium–High	Medium	Faster search
Social-media analytics	Medium	Medium	Unreported needs
Ground rescue robots	Low–Medium	Low	Dangerous areas
Resource optimization	Medium	Low	Efficient use of assets

TABLE II Comparison of AI Capabilities for Defence HADR

V. Challenges and Future Directions

Table III summarizes key challenges. Future directions include training models on Indian disaster imagery, swarms of cooperative drones, satellite and mesh communication for disconnected operations, digital twins of vulnerable regions for planning exercises, and joint training of personnel with AI tools so that trust is built before real emergencies.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Data accuracy	Multi-source fusion; human verification
Connectivity loss	Edge computing; satellite and mesh links
Cost	Dual-use systems; phased adoption
System reliability	Field trials; fallback procedures
Ethics and accountability	Human approval of all critical actions

VI. Conclusions

Defence forces are central to disaster response, and AI can significantly increase their effectiveness. The reviewed literature shows that computer vision can map damage within hours, social-media analytics can reveal unmet needs, robots and drones can search dangerous areas, and optimization can use scarce assets efficiently. Integrating these capabilities in a command-and-control decision-support system can reduce response time, minimize risk to personnel and improve coordination. Success requires reliable data, resilient communication, rigorous testing and decisions that always remain under human command.

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