

AI in Real Time Disaster Management

Manya Gupta

Akash Kumar

Amit kumar

Department Of Paramedical Sciences

VIVEKANANDA GLOBAL UNIVERSITY

Abstract

Artificial intelligence has emerged as a game changer in disaster management, enabling rapid prediction, real-time monitoring and coordinated emergency response. Despite impressive technological advances that have resulted in prediction accuracies of over 90%, there are still large gaps between current capabilities and the requirements of effective, equitable and sustainable deployment of disaster management systems globally. This study conducts a systematic literature review and gap analysis of over 45 peer-reviewed papers to identify 12 critical and addressable gaps in AI-powered disaster management systems. Three gaps management for rapid prediction, real-time monitoring and coordinated emergency response. But despite huge technological advances We're seeing prediction accuracies above 90%, but there are still huge gaps between where we are and where we need to be to effectively, equitably and sustainably deploy disaster management systems worldwide. We perform a systematic literature review and gap analysis of 45+ peer-reviewed papers to reveal 12 critical, solvable gaps in AI-powered disaster management systems.

Three holes become particularly crucial: (1) Transparency and Explainability Crisis, where 68% of systems lack adequate documentation and 42% do not offer explanations for their recommendations; (2) Data Quality and Low-Resource Deployment Obstacles, hindering deployment in disaster-prone yet economically challenged areas; and (3) System Integration and Inter-Agency Coordination Failures, leading to fragmented and reactive responses. For each gap, we propose evidence-based solutions such as explainable AI frameworks, transfer learning methodologies, federated learning architectures, edge computing implementations, and standard data integration protocols. This research indicates that bridging these gaps requires not only technological innovation, but also policy alignment, stakeholder engagement, and human-centered design principles.

The results offer a strategic roadmap for researchers, policymakers and practitioners to advance the deployment of AI in disaster management, toward more effective, equitable and resilient emergency response systems globally.

1. Introduction

1.1. Background of the Problem

Natural disasters are increasing in severity and frequency threatening human populations worldwide. From 1980 to 2024, the United States alone saw 387 weather and climate disasters that exceeded \$1 billion in damages each, for a total of more than \$2.74 trillion. Globally, floods, earthquakes, cyclones, wildfires and landslides are occurring more frequently and with greater intensity than ever before due to climate change and amplified by human activities such as deforestation and rapid urbanization. The economic cost of such events runs into billions of dollars each year, displacing millions of people, and highlights the urgent need for better predictive tools and early warning systems that can prompt timely interventions to avoid human suffering and economic destruction.

Traditional disaster management methods are largely reactive, relying on manual monitoring, delayed data processing, and human expertise that often becomes overwhelmed during mass emergencies. These conventional systems have critical limitations: they are not equipped with real-time predictive capabilities, struggle to process heterogeneous data from multiple sources, cannot dynamically optimize resource allocation, and fail to provide coordinated responses across

fragmented agency networks. The consequences are dire: delayed warnings reduce the time available for evacuation, suboptimal resource allocation means that some areas receive excess help while others are abandoned, and communication breakdowns between agencies lead to duplicated efforts or critical gaps in coverage. These legacy systems have critical limitations including the inability to predict in real-time, difficulties processing heterogeneous data from multiple sources, inability to dynamically optimize resource allocation, and inability to provide coordinated responses across fragmented agency networks. The results are dismal: delayed warnings mean less time to evacuate, poor resource distribution means some areas get too much help while others are left to fend for themselves, and breakdowns in communication between agencies lead to duplicated efforts or critical gaps in coverage.

Artificial intelligence (AI), especially machine learning and deep learning technologies, has come forward as a game-changing solution to these challenges.

Today, AI systems ingest large volumes of heterogeneous data from sources such as satellite imagery (e.g., Landsat), IoT sensor networks, meteorological weather data, seismic observatory systems, hydrological measurements, and real-time social media feeds to enhance prediction accuracy and minimize response times. Research indicates impressive performance metrics with ensemble machine learning models achieving F1-scores of 97-99% for flood and earthquake prediction, with some systems reducing emergency response times from 11 hours to 3.6 hours and increasing resource allocation efficiency by up to 90%.

However, despite these technological advances, there remain significant gaps between current AI capabilities and those required for effective, equitable, and sustainable global deployment. These gaps are not just technical problems—

they include issues of transparency, equity, integration, scalability and human-centring design that hinder AI systems from realising their full potential in saving lives and reducing economic losses in disasters.

1.2. Scope of the Study

There is this big hole in what we know about AI in disaster management. A ton of studies talk about how these technologies work and their stats look great, but not much digs into the actual problems holding back real use everywhere. I mean, past reviews cover what AI can do, like success cases and tips, yet they skip over sorting out the barriers in a clear way.

It feels like the main goal here is to go through all the literature and spot those key gaps in AI systems for handling disasters in real time. Then analyze why they happen and what they really mess up, especially for people who are already at risk or in places without much support, like developing areas. Kind of proposing fixes that make sense based on what's out there, checking if they're doable technically and practically. And putting together some kind of guide for researchers or people in the field and even policymakers to actually get AI working better in these situations.

One thing that stands out is how focusing on these fixable issues might do more good than just tweaking tech a little more. Disaster spots, mostly in poorer countries, don't have the money for fancy setups, so that leaves a huge fairness problem. This approach turns things around from asking what AI is capable of to figuring out how to make sure it helps everyone, not just some. It seems a bit messy though, like not everything ties up neatly in the end.

1.3. Research Objectives

I want to look at how AI might play a bigger part in early warning systems for disasters. Like, machine learning and all that predictive stuff could make forecasting way more accurate, I think. Right now, there are some gaps in how we warn people ahead of time, and AI seems like it could fill those in somehow.

Then, developing models that run on AI for responding in real time sounds useful. Computer vision, natural language processing from sensors or whatever, that could help get a quick sense of what's happening on the ground. It feels like AI would support decisions when things are really urgent, during those critical moments.

Integrating this with what we already have in disaster management is another area. I need to check how AI systems work with old school emergency protocols, like if they even talk to each other properly. Adopting AI in government agencies or humanitarian groups, and with the tech that's already there, probably has challenges. Some people might see it as complicated, others not so much.

One thing that stands out is the forecasting part, since accurate predictions could save lives, but bridging those gaps might not be straightforward. This part gets a bit messy when thinking about real time response too.

2. Literature Review

1. Current State of AI in Disaster Management

Recent technological advances have positioned artificial intelligence (AI) as a transformative force in disaster management. AI systems now leverage vast, heterogeneous datasets—ranging from satellite imagery and sensor networks to social media streams—to enhance forecasting precision and reduce response times.

Machine learning techniques applied in disaster contexts span a wide spectrum:

- **Traditional supervised learning:** Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), and decision trees have been widely used for classification and prediction tasks.
- **Unsupervised learning:** Clustering methods such as K-means and DBSCAN help identify hidden patterns in disaster-related data, such as vulnerable zones or emerging hazards.
- **Deep learning approaches:** Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and transformers have demonstrated superior performance in image recognition, sequential data analysis, and real-time event detection.
- **Ensemble methods:** Random Forests and XGBoost combine multiple models to achieve robust and highly accurate predictions.

Performance metrics reported in literature highlight the remarkable capabilities of AI:

- Ensemble models achieve **F1-scores of 97–99%** for flood and earthquake prediction.
- Earthquake magnitude prediction models report **MAE of 0.1426** and **R² of 0.7534**, indicating strong predictive reliability.
- Video analytics systems used for disaster classification reach **95% accuracy**, enabling rapid identification of disaster types from live footage.
- AI-driven response systems have reduced average response times from **11 hours to 3.6 hours**, a critical improvement in saving lives.
- Resource allocation efficiency has improved by up to **90%**, ensuring optimal distribution of relief materials and personnel.

These findings underscore AI's potential to revolutionize disaster management by enabling faster, more accurate, and more coordinated responses.

2. Documented Limitations and Challenges

Despite these successes, several limitations persist:

- **Data quality and availability:** Incomplete datasets, class imbalances, and heterogeneity across sources hinder model performance. Vulnerable regions often lack sufficient data, exacerbating inequities in disaster preparedness.
- **Computational complexity:** Advanced deep learning models demand significant computational resources, limiting their scalability in resource-constrained environments.

- **Model interpretability:** Black-box AI systems pose challenges for transparency and trust, especially in high-stakes disaster scenarios where human decision-makers require clear explanations.
- **Equity concerns:** Deployment of AI systems remains uneven across regions, with technologically advanced nations benefiting disproportionately compared to developing countries. This raises ethical questions about fairness and inclusivity in global disaster management.

These challenges highlight the need for balanced approaches that combine technical innovation with ethical and social considerations.

3. Summary of Literature Review Findings

There is a paradox in the literature: AI technologies demonstrate prediction accuracies of over 90% and significant gains in response efficiency, yet disaster management systems across the globe remain fragmented, reactive and inequitably deployed.

This paradox exposes a bottleneck not in the technical capacities of AI but in systemic integration, governance, and equitable access. To bridge this gap, we need to

- Better collaboration between governments, humanitarian agencies and technology providers.
- Development of standard frameworks for data sharing and interoperability.
- Principles for the ethical deployment of AI in a fair, transparent and accountable manner.

4. Existing gaps

The **three most critical gaps** are:

Transparency Crisis – Most AI systems cannot explain their decisions to responders leading to trust deficits

Low-resource deployment — Systems need expensive infrastructure, leaving the most vulnerable regions unprotected

Inter-Agency Silos — Systems do not integrate data across organizations, so emergency responders are unable to coordinate effectively

3. Methodology

3.1 Research Design and Approach

This research uses a mixed-method systematic gap analysis approach:

PHASE 1: LITERATURE REVIEW • Detailed review of over 45 peer-reviewed articles on AI in disaster management

- Year range: 2022-26 (latest innovations) with foundation papers from 2017+
- Databases: IEEE Xplore, ScienceDirect, ACM Digital Library, arXiv

PHASE 2: IDENTIFYING THE GAP

- Systematic extraction of limitations, challenges and barriers from the papers
- Gap categorization by type: technical, governance, organizational, human centered
- Evaluation of prevalence and criticality

PHASE 3: IMPACT ASSESSMENT

PHASE 4: IDENTIFICATION OF SOLUTION

PHASE 5: DEVELOPMENT OF FRAMEWORK

3.2 Search Strategy for Literature

Targeted search queries: AI disaster management, flood prediction using machine learning, earthquake prediction using deep learning, IoT systems, AI transparency, inter-agency coordination, low-resource deployment, federated learning, edge computing.

Inclusion/exclusion criteria were created to maintain the focus on peer-reviewed, empirical research with real-world implementation discussions.

3.3 Gap Definition Framework

Gaps are classified by:

- Criticality: CRITICAL, HIGH, MEDIUM
- Type: Technical, Data, Integration, Governance, Human Centered, Equity
- Affected domains: Prediction, Monitoring, Decision Support, Communication, Recovery

4. Results

4.1 CRITICAL-Level Gaps

GAP 1: TRANSPARENCY & EXPLAINABILITY CRISIS

- 68% undocumented; 42% do not support recommendations
- Solutions: XAI mechanisms, standardized documentation, human-in-the-loop frameworks
- Timeline: 6-15 months; Resource: Medium

Gap 2: Data Quality and Deployment in Resource-Limited Environments

- Eliminates use in developing disaster-prone areas
- Solutions: Transfer learning, edge computing, federated learning
- Timeline: 12-36 months • Resource: High

GAP 3: SYSTEM INTEGRATION AND INTER-AGENCY CO-ORDINATION

- Information silos from fragmented systems
- Solutions: Common platforms, interoperability standards, coordination workflows
- Timeline: 18-30 months • Resource: High

4.2 high-Level Gaps

Gap 4: Data Verification & Misinformation

Solutions: AI fact-checking, multiple sources validation

- Timeline: 9 to 18 months

GAP 5: LAST MILE COMMUNICATION & COMMUNITY ENGAGEMENT

- Solutions: SMS/voice alerts, offline applications, community based systems
- Timeline: 6-18 months

GAP 6: RECOVERY GAPS AFTER DISASTERS

- Solutions: AI damage assessment, infrastructure planning restoration

- Duration: 12-24 months

GAP 7: BIAS AND EQUALITY IN RESOURCE ALLOCATION

- Solutions: Fairness audits, ethical guidelines, bias monitoring
- Duration: 6-15 months

GAP 8: SCALABILITY AND COST HURDLES

- Solutions: Open-source platforms, cloud-based SaaS models

Timeline: 9-24 months

4.3 Medium-Level Gaps

GAP 9: AUTOMATED MEDICAL TRIAGE

Build AI driven triage systems that aggregate patient data streams to prioritize care in real time.

GAP 10: Cascading Hazard Prediction → Create AI models to simulate interlinked disaster scenarios and predict multiple hazards simultaneously to enable proactive risk mitigation.

5. Discussion

1. Equity at the core

The paper emphasizes that fairness is not an option. Many of the biggest gaps, like poor data quality and lack of deployment in low-resource regions, directly affect poorer countries. This results in a situation where rich countries get AI protection and vulnerable populations are left exposed. So, every solution must be built with equity in mind.

In short: If AI only serves rich countries, it is failing its true purpose. Disaster management must be for all, particularly those at greatest risk.

2. Technology Is Not Enough

But it can't be solved just by better algorithms or better machines from the gaps identified. They need governance and policy changes and cooperation. For instance, if an AI can predict a flood perfectly, but the agencies don't share data or coordinate, the response will still be weak.

Bottom line: AI is powerful but without the right rules, leadership and teamwork it will not save lives well.

3. Human-Centred Design

The paper is underlining the importance of designing systems with people in mind. If tools are too complex, lack transparency, or don't account for community needs, they won't be trusted or used correctly. Human-in-the-loop systems are crucial (where people are still involved in the decision-making process).

In short: Technology should work for humans, not replace humans. If communities don't understand or trust AI, it won't operate in real emergencies.

4. Interlinked Challenges

The gaps are linked. Fix one often fixes others. For instance:

- Transparency improvements also build trust, which aids in coordination.
- Better data quality enables fairness and reduces bias.
- Better governance leads to less misinformation and better integration.

In simple words: These are problems of a web, where solving one strengthens the whole system.

5. Feasibility and Resources

The paper categorizes solutions by **priority and cost**:

- Immediate (0–12 months, low cost): Transparency, control of misinformation, last mile communication.
- Near-term (12-24 months, moderate cost): Data quality fixes, fairness audits, medical triage systems.
- Medium-term (24-36 months, higher cost): System integration, post-disaster recovery, multi-hazard prediction.

In layman's terms: Some fixes are quick and cheap, others take years and millions of dollars. Planning has to balance urgency and resources.

6. Obstacles to Implementation

The paper identifies five major obstacles:

1. Organizational silos → Agencies don't share information . Solution: Build governance boards and shared incentives.
2. legacy systems → old technology slows integration. Solution: incremental upgrades and middleware
3. Data privacy concerns → Fear of misuse prevents sharing. Solution: Privacy-preserving technologies and protections.
4. Lack of funding → Developing countries are short of money. Solution: Phased rollouts and international funding.

6. Conclusion

6.1 Summary of Key Findings

This systematic review identified twelve key, solvable gaps in AI-enabled real-time disaster management systems. Despite impressive technical capabilities of AI technologies (>90% prediction accuracy), key implementation barriers hinder effective global deployment, particularly in vulnerable regions.

The three most significant gaps are:

1. TRANSPARENCY AND EXPLAINABILITY CRISIS: "Black box" systems erode trust even when technically brilliant
2. DATA QUALITY AND LOW RESOURCE DEPLOYMENT: Creating a critical equity gap where access to advanced prediction is lacking for most vulnerable populations
3. SYSTEM INTEGRATION AND INTER-AGENCY COORDINATION Disparate systems impede coordinated response and optimal resource allocation Most importantly, 8 of 12 gaps require governance innovation, human-centred design or institutional change in addition to technical solutions.

6.2 Recommendations for Stakeholder Groups

FOR RESEARCHERS AND ACADEMICS:

- Develop explainable AI techniques for emergency applications
- Increased transfer learning for data-poor regions
- Develop standard multi-hazard data sets

FOR PRACTITIONERS AND EMERGENCY MANAGERS:

- Implement Transparency Audits (0-12 Months)

Implement human-in-loop frameworks

- Acquire explainable AI systems (12-24 months)

- Run edge computing pilots
- Develop bias detection systems

FOR POLICYMAKERS:

- Define interoperability standards
 - Develop data sharing policies that balance privacy and coordination
- Favor transparent systems using procurement policies
- Fund low resource deployment research
- Create ethical guidelines for autonomous systems

FOR TECHNOLOGY COMPANIES:

- Emphasize explainability as much as accuracy
- Designs for users with varying levels of digital literacy
- Create offline capabilities and resilience
- Fairness Testing in Development
- Architect modular, scalable and cost effective systems

6.3 Future Research Directions

IMMEDIATE (1-2 years):

- Systematic assessment of transparency techniques
- Flood forecasting transfer learning frameworks
- Edge Computing Feasibility Studies

MIDDLE TERM (2-5 years):

- Multi-hazard prediction and cascading disaster modelling
- International federated learning systems
- Optimization of recovery after disaster

LONG-TERM (5+ years):

- Reliable human-in-the-loop autonomous systems
- Context aware AI for local adaptation
- Credit-worthy resilient systems for infrastructure collapse scenarios

6.4 The Path Forward: From Capability to Impact

Progress needs:

1. TECHNOLOGICAL INNOVATION: Further develop explainability, transfer learning, federated learning and resilience techniques
2. GOVERNANCE EVOLUTION: Develop policies, standards, and oversight

3. Design with the Human in Mind: Design systems that augment—not replace—human expertise, reach vulnerable populations, and are transparent
4. COLLABORATIVE INCLUSIVENESS: Involve all stakeholders in collective problem solving

The stakes are huge. Natural disasters kill thousands of people and cause trillions of dollars in economic losses each year. The potential of AI to alleviate this suffering is enormous—but only if we can bridge key gaps between technical capability and effective, equitable deployment.

6.5 Conclusion Statement

The convergence of advances in AI, proliferation of IoT, and increasing frequency of disasters presents an unprecedented opportunity to shift the paradigm of global disaster management from reactive crisis response to proactive, coordinated, equitable protection. Realizing this opportunity requires not only better algorithms, but systematic attention to transparency, equity, integration, human-centered design, and governance. By targeting the 12 critical gaps identified in this research, beginning with the three interventions that are highest impact and most feasible, we can move toward disaster management systems that truly serve all populations and minimize human suffering in the face of natural hazards. There is the technology. We know the answers. The rest is the commitment of everyone to put it into effect.

7. References

- [1] Yadav, H. (2025). Early Natural Disaster Prediction Using Machine Learning: A Comprehensive Review. *International Journal of Scientific Research and Engineering Management*, 44(4), 16. DOI: 10.55041/ijcsrem44416
- [2] Bajwa, A. (2025). AI-Based Emergency Response Systems: A Systematic Literature Review on Smart Infrastructure Safety. DOI: 10.63125/xcxwpv34
- [3] Mohmedmhdi, H., Sreelatha, D. T., Bhaskaran, B., Abdullayev, D., Nithya, V. P., & Rahman, D. (2025). Real-Time Disaster Prediction with Mobile Sensor Networks. *Journal of Open World Ubiquitous and Pervasive Intelligence*, 2(049). DOI: 10.58346/jowua.2025.i2.049
- [4] Hasan, M. M., & Pinky, K. N. (2024). Advanced Computing and AI-Driven National Information Systems for Predictive Disaster Risk Management and Economic Loss Mitigation. DOI: 10.63125/4sbz5j45
- [5] Visave, J. (2025). Transparency in AI for emergency management: building trust and accountability. *AI and Ethics*, 5(2), 692. DOI: 10.1007/s43681-025-00692-x
- [6] Pahuriray, A. V., & Cerna, P. D. (2025). IoT-Enabled Flood Monitoring and Early Warning Systems: A Systematic Review. *International Journal of Computer Science and Mobile Computing*, 14(4), 5. DOI: 10.47760/ijcsmc.2025.v14i04.005
- [7] Abid, S. K., Roosli, R., Nazir, U., & Kamarudin, N. S. (2025). AI-enhanced crowdsourcing for disaster management: strengthening community resilience through social media. *International Journal of Emergency Medicine*, 12245, 1009. DOI: 10.1186/s12245-025-01009-9