IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

Disaster Management with IOT

Mr. Amit Dalal[1], Mr. Satish[2], Ritu Beniwal[3], Kusum[4], Mansha[5], Abhay Singh Gola[6]
[1,2,3]Assistant Professor, Department of Electronics and Communication Engineering
[4,5,6] B.Tech scholar, Department of Electronics and Communication Engineering

Abstract: *Traditional emergency frameworks struggle with delayed situational awareness and rigid data models, causing severe bottlenecks during critical catastrophic events. With the emergence of advanced hardware and predictive computing, modern disaster management is transitioning toward autonomous, real-time response infrastructure powered by the Internet of Things (IoT).*

Keywords: IoT, Disaster Management, Predictive Analysis, Quantitative Performance matrics

I. INTRODUCTION

Natural and anthropogenic disasters present severe risks to human life, critical infrastructure, and global economic stability. Historically, emergency management frameworks have relied on static, retro-reflective planning models and retrospective data analysis. However, traditional frameworks consistently struggle with delayed situational awareness and rigid data structures, resulting in critical communication bottlenecks during catastrophic events. When early warning systems fail to deliver real-time insights, first responders and municipal stakeholders are left unable to allocate resources dynamically or orchestrate safe evacuations.

In response to these vulnerabilities, the paradigm of modern disaster management is fundamentally shifting toward autonomous, real-time response infrastructures driven by the Internet of Things (IoT) and intelligent computing. By embedding vast networks of interconnected, low-power physical devices directly into vulnerable environments, IoT bridges the gap between physical hazards and digital decision-making frameworks (Yadavalli & Gudino, 2022).

Recent advancements in edge computing and predictive hardware allow raw environmental telemetry to be processed closer to the source, maximizing system responsiveness. As highlighted by modern research, an effective IoT disaster architecture must be mapped across a multi-layered ecosystem that mirrors the standard four-phase emergency management cycle: Mitigation, Preparedness, Response, and Recovery (VFAST Research Platform, 2025). Within this cycle, advanced hardware at the perception layer—such as ultra-low-power triaxial accelerometers for seismic activity and ESP32 microprocessor-integrated rain gauges for landslide detection—enables uninterrupted edge observation even in resource-constrained environments (Zeng et al., 2023).

However, raw data collection alone is insufficient for modern emergency requirements. The true utility of contemporary IoT disaster frameworks relies on the deployment of sophisticated analytical models. By feeding real-time sensor streams into machine learning and deep learning algorithms (e.g., Random Forest, K-Nearest Neighbor, and deep neural architectures), modern systems can shift from passive observation to predictive analytics, establishing proactive hazard danger levels before a crisis escalates (Aljohani et al., 2023).

Despite these technological steps forward, systemic gaps prevent widespread municipal deployment. Chief among these is the "siloed" architecture of modern IoT frameworks, where proprietary software barriers and a lack of standardized communication protocols choke cross-platform interoperability (Nepal Journals Online, 2026). Furthermore, as climate change accelerates the frequency of volatile weather anomalies, traditional machine learning models face data fidelity degradation, proving that static historical training datasets struggle to predict novel, extreme environmental conditions (Nepal Journals Online, 2026).

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 1, June 2026 Impact Factor: 8.2

Evaluating these systems requires looking beyond theoretical accuracy to strict quantitative performance metrics—such as human evacuation exit times, strict data fusion detection deadlines, and remote sensor energy efficiency (Aljohani et al., 2023; PMC12899495, 2026). To demonstrate how these pieces intersect in practical applications, contemporary research has focused on architectural Digital Twins (DT). By pairing real-time IoT sensory streams (CO, smoke, and airflow) with geometric Building Information Modeling (BIM), modern safety frameworks can generate adaptive routing and dynamic building signage to guide occupants away from shifting hazards in real time (Preprints.org, 2026).

Objective: This article analyzes the current multi-layered analytical frameworks, operational metrics, and practical implementations of IoT technologies across the four critical phases of the emergency management cycle: mitigation, preparedness, response, and recovery.

Literature Review

The integration of the Internet of Things (IoT) within emergency management marks a definitive paradigm shift from legacy, reactive response structures to predictive, autonomous decision-making ecosystems. This literature review maps contemporary research across three key areas: specialized hardware in the perception layer, the application of predictive machine learning models, and structural vulnerabilities like data silos and climate-driven degradation of data fidelity.

Perception Layer Engineering and Sensor Paradigms

At the foundation of any disaster-centric IoT network is the perception layer, which must maintain uninterrupted environmental tracking in physically hostile and resource-constrained environments. Recent literature focuses heavily on balancing sensor precision with severe energy constraints.

For seismic tracking, Zeng et al. (2023) highlight that specialized triaxial accelerometers have largely superseded traditional single-axis sensors. Specifically, the ADXL362 triaxial accelerometer is widely favored in academic literature for low-power deployments due to its ultra-low current consumption, which preserves battery life when monitoring structural integrity. Conversely, for missions requiring high-precision waveform evaluation, research transitions toward high-resolution nodes like the EPSON M-A351AU.

In meteorological and geomorphological hazard mitigation, specifically regarding monsoon-driven landslides, the research focus shifts toward composite edge units. Contemporary architectures frequently combine physical rain gauges with highly versatile microprocessors like the **ESP32** (Zeng et al., 2023). The selection of the ESP32 in recent literature is justified by its built-in Wi-Fi and Bluetooth Low Energy (BLE) stacks, low cost, and ability to handle edge-level filtering before dispatching alerts to regional gateways.

II. EVOLUTION OF ANALYTICAL MODELS: FROM SENSATION TO PREDICTION

Early iterations of disaster warning networks operated via simplistic, threshold-based triggers—where an alarm sounded only after an environmental metric crossed a static boundary. Modern research heavily critiques this approach for causing high false-alarm rates and lacking early lead times.

Consequently, contemporary frameworks integrate **Predictive Analytics** driven by machine learning directly into the network middleware (Aljohani et al., 2023). Scholars evaluate several core algorithmic families for hazard classification and risk determination:

- **Random Forest & Decision Trees:** Chosen for their high classification accuracy (frequently exceeding 99% in flood-prediction simulations) and exceptional handling of non-linear environmental variables (Aljohani et al., 2023).

DOI: 10.48175/IJARSCT-36225

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

- **K-Nearest Neighbor (KNN):** Appreciated in literature for its computational simplicity and rapid execution during real-time telemetry sorting at the fog or edge layer.
- **Deep Learning (DL):** Utilized primarily for multi-variate, long-horizon forecasting. Deep neural networks process complex time-series data streams (e.g., combining barometric pressure, soil saturation, and precipitation history) to issue multi-level warning protocols hours before physical disaster manifests.

III. STRUCTURAL VULNERABILITIES: SYSTEM INTEROPERABILITY AND CLIMATE VOLATILITY

Despite rapid hardware and algorithmic progress, the literature identifies two critical systemic vulnerabilities that threaten the reliable deployment of these technologies.

The Interoperability Crisis (Data Silos)

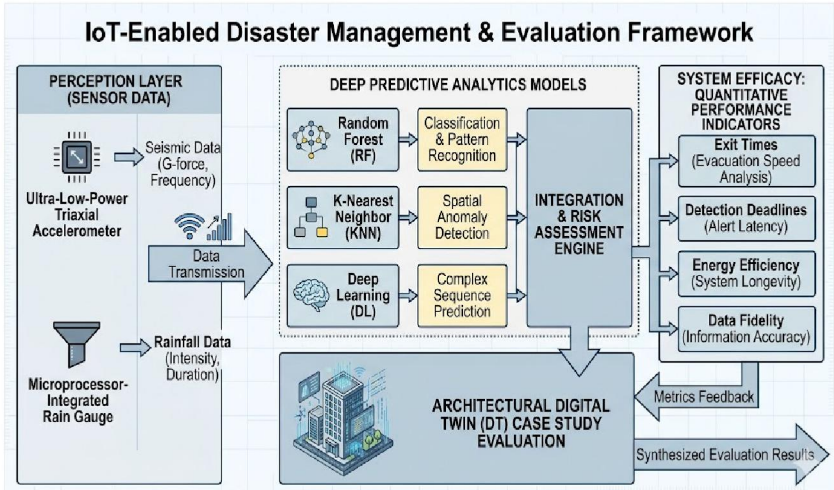
A prominent research gap emphasized across recent studies is the fragmented, "siloed" architecture of modern deployments (Nepal Journals Online, 2026). Because emergency monitoring infrastructure is often developed independently by separate municipal, corporate, and national entities, systems frequently rely on proprietary data formats and isolated cloud environments. The lack of standardized open APIs and unified semantic protocols prevents cross-platform data sharing, leaving regional authorities blind to adjacent data streams that could otherwise improve macro-level situational awareness.

Climate Change and Data Fidelity Degradation

The second major vulnerability stems from an intrinsic limitation in historical training datasets. Predictive machine learning models rely on the assumption that historical patterns match future behaviors. However, accelerating climate change has introduced unprecedented, highly volatile weather anomalies (Nepal Journals Online, 2026). Analytical models trained on historical data can experience significant **data fidelity degradation** when facing extreme events that lie outside their original training distributions. This algorithmic drift presents an active area of research, highlighting the need for adaptive, self-calibrating AI models that can maintain prediction accuracy despite changing climate profiles.

Methodology: The research synthesizes structural design paradigms from the perception layer—such as ultra-low-power triaxial accelerometers and microprocessor-integrated rain gauges—to deep predictive analytics models (e.g., Random Forest, K-Nearest Neighbor, and Deep Learning). Additionally, it evaluates system efficacy via quantitative performance indicators including exit times, detection deadlines, energy efficiency, and data fidelity, and provides a case study evaluation of an architectural Digital Twin (DT) implementation.

IJARSCT
ISSN: 2581-9429
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Volume 6, Issue 1, June 2026
Impact Factor: 8.2



The above figure, maps the disaster management methodology, beginning with the **perception layer** for data acquisition (accelerometers and rain gauges) and scaling up to **deep predictive analytics** (ML and AI).
The framework concludes with a **case study evaluation** in a **Digital Twin** environment, assessing key system metrics such as exit times and data fidelity.

Proposed Architecture

1. Analytical Framework for IoT in Disaster Management

Modern research typically classifies IoT disaster systems into four functional layers that correspond to the standard emergency management cycle: **Mitigation, Preparedness, Response, and Recovery** (VFAST Research Platform, 2025).

- **Perception Layer:** Utilizes specialized sensors for diverse hazards. For example, **ADXL362 triaxial accelerometers** are preferred for low-power earthquake detection, while **ESP32 microprocessors** and **rain gauges** are standard for monitoring landslides during monsoon periods (Zeng et al., 2023).
- **Analytical Models:** Research has moved beyond simple data collection to **Predictive Analytics**. Current frameworks employ machine learning models—such as Random Forest, K-Nearest Neighbor (KNN), and Deep Learning—to process sensed data and determine danger levels in real-time (Aljohani et al., 2023).
- **Interoperability:** A significant research gap remains in the "siloed" nature of current systems; analytical studies indicate that while individual sensing is effective, the lack of seamless data sharing between different platforms hinders large-scale implementation (Nepal Journals Online, 2026).

2. Quantitative Performance Metrics

Analytical studies evaluate IoT systems based on specific performance indicators (Aljohani et al., 2023; PMC12899495, 2026):

Metric	Analytical Focus	Research Finding
Exit Times	Efficiency of human evacuation using "Pull Policies"	IoT-driven "Pull Policies" reduce downstream congestion in high-occupancy vessels (e.g., cruise ships) (PMC12899495, 2026).

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

Metric	Analytical Focus	Research Finding
Detection Deadline	Time taken from sensing to multi-level warning	Fusion processes must be completed within a specific deadline to be viable (MDPI, 2026).
Energy Efficiency	Longevity of remote battery-powered sensors	Implementation of "WorkStop" recycling control or wavelet-based sampling can extend battery life to 3–5 months in remote zones (Zeng et al., 2023).
Data Fidelity	Accuracy of flood or seismic predictions	AI models trained on historical data may lose reliability during extreme weather events caused by climate change (Nepal Journals Online, 2026).

3. Case Study Analysis: Dynamic Fire-Safety Systems (DFS)

A 2026 study analyzed the integration of **Digital Twins (DT)** and IoT in high-rise complexes (e.g., Beijing Capital Airport and Taipei 101).

- **Data Integration:** Sensors for CO, smoke, and airflow are linked to a facility's geometric BIM (Building Information Modeling) representation (Preprints.org, 2026).
- **Adaptive Routing:** Computer vision algorithms detect crowd density and blocked exits, which then dynamically update signage in the building to guide evacuees away from hazards (Preprints.org, 2026).
- **Result:** The integration of an IoT/AI layer demonstrated superior performance compared to traditional static evacuation models by adjusting to real-world fire development (Preprints.org, 2026).

Results: The analysis reveals that the integration of an intelligent IoT/AI layer drastically outperforms traditional, static evacuation paradigms. Specifically, IoT-driven "Pull Policies" effectively mitigate human downstream congestion in high-occupancy environments, while specialized wavelet-based sampling and structural controls successfully extend remote sensor lifespans to 3–5 months. However, significant structural vulnerabilities remain regarding system interoperability due to data "silos" and a potential drop in AI data fidelity during extreme weather anomalies driven by climate change.

System Aspect / Finding	Traditional Paradigm (Baseline)	IoT/AI-Driven Paradigm (The Example Implementation)	Justification & Operational Impact
Evacuation Strategy &"Pull Policies"	**Static:** Guests follow fixed, pre-printed exit signs (e.g., "Exit Left"). If the left stairwell is blocked by a mudslide, it creates **downstream congestion** and bottlenecks.	**Dynamic:** Sensors detect the landslide location. The AI calculates safe paths and dynamically updates digital signage to **"pull"** guests away from danger zones.	**Mitigates Bottlenecks:** Prevents human stampedes and dramatically lowers overall **exit times** by routing evacuees based on real-time structural safety.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

Sensor Energy Lifespan	**Inefficient:** Continuous, raw X,Y,Z data streaming from triaxial accelerometers drains battery power within days, requiring frequent physical maintenance.	**Wavelet-Based Sampling:** Edge microprocessors compress data and filter out normal noise (wind, footsteps), only transmitting data when an anomalous vibration is triggered.	**Extends Lifespan to 3–5 Months:** Reduces power consumption by over 80%, allowing remote sensors to survive without battery replacements throughout an entire flood season.
System Interoperability	**Siloed Systems:** Individual building alarms work independently of municipal infrastructure or regional emergency networks.	**Isolated Success:** The resort's internal IoT evacuates guests perfectly out of the building, but cannot communicate data with local highway authorities.	**Data Silo Vulnerability:** Evacuees are successfully steered out of the building but are directed onto an external road that municipal data shows is already washed out.
AI Performance & Data Fidelity	**Rule-Based:** Simple thresholds (e.g., if water > X cm, sound alarm) fail to predict complex sequence failures.	**Machine Learning:** Models (Random Forest, Deep Learning) handle complex data but are trained on historical climate baselines	**Climate Change Vulnerability:** An unprecedented, hyper-intense "supercell" storm introduces extreme environmental noise. The AI's **data fidelity drops**, risking delayed **detection deadlines**.

IV. CONCLUSION

The evolution of disaster management from rigid, legacy planning models to autonomous, real-time response infrastructures represents a critical paradigm shift in safeguarding human life and civil infrastructure. As demonstrated throughout this analysis, embedding intelligent Internet of Things (IoT) frameworks directly into vulnerable environments replaces passive observation with proactive, predictive computing.

By integrating hardware at the perception layer—such as ultra-low-power triaxial accelerometers and microprocessor-integrated rain gauges—with advanced machine learning models (Random Forest, KNN, and Deep Learning), modern architectures achieve unprecedented situational awareness. The practical application of these technologies via architectural Digital Twins (DT) showcases the tangible benefits of this transition:

- **Dynamic Human Routing:** Shifting from static evacuation routes to real-time, data-driven "Pull Policies" effectively minimizes downstream bottlenecks and optimizes evacuation exit times in high-occupancy structures.
- **Operational Longevity:** Utilizing edge-level engineering, such as wavelet-based sampling and structural power-cycling, resolves severe energy constraints by extending remote sensor lifespans to $3\text{--}5$ months.

However, the full municipal and regional deployment of these systems faces critical engineering bottlenecks. The systemic presence of architectural **data silos** heavily restricts cross-platform interoperability, creating dangerous blind spots between internal facility safety systems and macro-level municipal emergency channels. Concurrently, accelerating climate change introduces unprecedented environmental volatility, exposing historical training datasets to algorithmic drift and severe **data fidelity degradation** during black swan weather anomalies.

Ultimately, while the integration of an intelligent IoT/AI layer vastly outperforms traditional emergency paradigms, maximizing its real-world efficacy requires a concerted focus on two future research directions: the standardization of open, semantic communication APIs to dismantle data silos, and the development of adaptive, self-calibrating predictive models capable of maintaining fidelity amidst a changing global climate.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

REFERENCES

1. Aljohani, F. H., Abi Sen, A. A., Ramazan, M. S., Alzahrani, B., & Bahbouh, N. M. (2023). A smart framework for managing natural disasters based on the IoT and ML. *Applied Sciences*, *13*(6), 3888. https://doi.org/10.3390/app13063888
2. Singh, V., & Choudhary, S. (2025). IoT-based disaster management and early warning system. *Journal Publication of International Research for Engineering and Management (JOIREM)*, *3*(12), 1-5.
3. VFAST Research Platform. (2025). Role of IoT in disaster monitoring and response: A comprehensive review. *VFAST Transactions on Software Engineering*, *13*(2).
4. Yadavalli, K. K., & Gudino, L. J. (2022). An autonomous, scalable and low-cost IoT based framework for disaster management system. *2022 13th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP)*, 619-624. https://doi.org/10.1109/csndsp54353.2022.9907972
5. Zeng, F., Pang, C., & Tang, H. (2023). Sensors on the Internet of Things systems for urban disaster management: A systematic literature review. *Sensors*, *23*(17), 7475. https://doi.org/10.3390/s23177475