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ResQ - AI Powered Disaster Management and Resource Allocation System

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Abstract

Natural disasters—including floods, cyclones, earthquakes, and wildfires—continue to cause extensive loss of life and infrastructure, highlighting the need for intelligent, fast, and coordinated disaster response mechanisms. In recent years, Artificial Intelligence (AI) has emerged as a transformative tool for enhancing disaster preparedness, response, and recovery through data-driven decision-making. This review examines recent research (2022–2025) on the application of machine learning, deep learning, generative AI, multimodal data fusion, UAV and satellite imagery analysis, blockchain-based transparency, and optimization-driven decision support in disaster management systems. The surveyed studies demonstrate notable improvements in hazard forecasting accuracy, rapid damage assessment, situational awareness, and efficiency of relief distribution. However, several challenges remain unresolved, including limited real-time data integration, lack of interoperability among agencies, insufficient automation, and fragmented system architectures that separate predictive models from operational resource planning. This paper consolidates existing findings, identifies key research gaps, and discusses future directions toward the development of unified, scalable, and adaptive AI-driven disaster management frameworks capable of supporting end-to-end emergency operations.
Keywords: Artificial Intelligence; Deep Learning; Machine Learning; Remote Sensing; Resource Allocation.

1. Introduction

Natural disasters such as floods, cyclones, earthquakes, and wildfires have increased in frequency and severity due to climate change and rapid urbanization, creating significant challenges for emergency response systems worldwide. Traditional disaster management approaches often rely on manual assessment, delayed communication, and static decision-making, resulting in inefficient relief distribution and limited situational awareness. Recent advancements in Artificial Intelligence (AI) have enabled data-driven, real-time, and scalable solutions across the disaster management lifecycle. Machine learning and deep learning models have demonstrated substantial improvements in hazard prediction and disaster severity assessment [1], [17], [26]. Remote sensing and UAV-based image analytics allow rapid damage evaluation using segmentation and object detection techniques [3], [24]. Generative AI enhances satellite image clarity and supports loss estimation [4], [5]. Decision-support systems incorporating optimization and visualization frameworks improve allocation planning and operational coordination [2], [20]. AI-driven logistics optimization reduces delivery delays and enhances resource utilization [10], [21], while LSTM-based forecasting models support proactive stockpiling [14]. Furthermore, multimodal data fusion combining satellite data, weather feeds, SMS alerts, and social media enhances situational awareness [13], and NLP- based models enable real-time identification of distress signals [7], [15]. Blockchain-based systems ensure transparency in supply-chain operations [8], [11]. Despite these advancements, significant gaps persist in real-time integration, interoperability, automation, and large-scale deployment. Many AI models function in isolation, without linking predictive insights to operational decision- making or resource optimization. This review consolidates recent research from 2022–2025, identifies limitations in existing approaches, and outlines future directions for developing unified, intelligent, and adaptive AI-driven disaster management systems (Table 1).

Table 1 Performance Comparison of Machine Learning Algorithms in Disaster Management

Algorithm	Study / Author	Accuracy (%)	RMSE	Remarks
Linear Regression	Yasmin et al. (2025)	78.4	0.42	Baseline, weak for nonlinear disaster data
Random Forest	Kim & Choi (2025)	89.7	0.28	Good for multispectral & satellite data
XGBoost	Raj et al. (2025)	92.3	0.22	Strong for multimodal and tabular data
SVM	Singh et al. (2022)	84.1	0.33	Good for risk classification
LSTM	Anusha (2023)	94.8	0.18	Best for time-series forecasting
CNN	Zhang et al. (2022)	91.2	0.25	Highly effective for damage detection
CNN–LSTM	Martinez et al. (2023)	**96.1**	**0.15**	Best overall for spatiotemporal modeling

2. Deep Network Architecture Used in ResQ

2.1. Input Modalities

The model processes three major data sources:

- Satellite / UAV images → spatial features
- Weather & environmental time-series → temporal patterns
- Population, infrastructure & historical disaster data → static features

To handle these, ResQ uses a hybrid deep learning network combining CNN, LSTM, and a Fusion Dense Network.

2.2. Architecture Overview

2.2.1. CNN Module – Spatial Feature Extractor

Used for damage assessment, flood extent detection, cyclone impact zones.

Layers:

- Conv2D (32 filters, 3×3)
- ReLU + Batch Normalization
- MaxPooling
- Conv2D (64 filters, 3×3)
- ReLU + Dropout
- Flatten → Spatial Feature Vector
- This follows architectures used by Kim & Choi (2025) and Zhang et al. (2022).

2.2.2. LSTM Module – Temporal Sequence Model

Used for forecasting demand, rainfall patterns, disaster progression.

Input: Weather parameters across time (rainfall, humidity, wind speed, water level)

Layers:

- LSTM (128 units)
- Dropout
- LSTM (64 units)
- Dense layer → Temporal Feature Vector

Similar to Anusha (2023) and ISRO flood forecasting models.

2.2.3. Static Feature Processing Module

For population density, road accessibility, historical damage patterns.

Layers:

- Dense (64)
- ReLU
- Dense (32)
- ReLU → Static Feature Vector

2.2.4. Multimodal Fusion Layer

All 3 feature vectors are concatenated in Figure 1:

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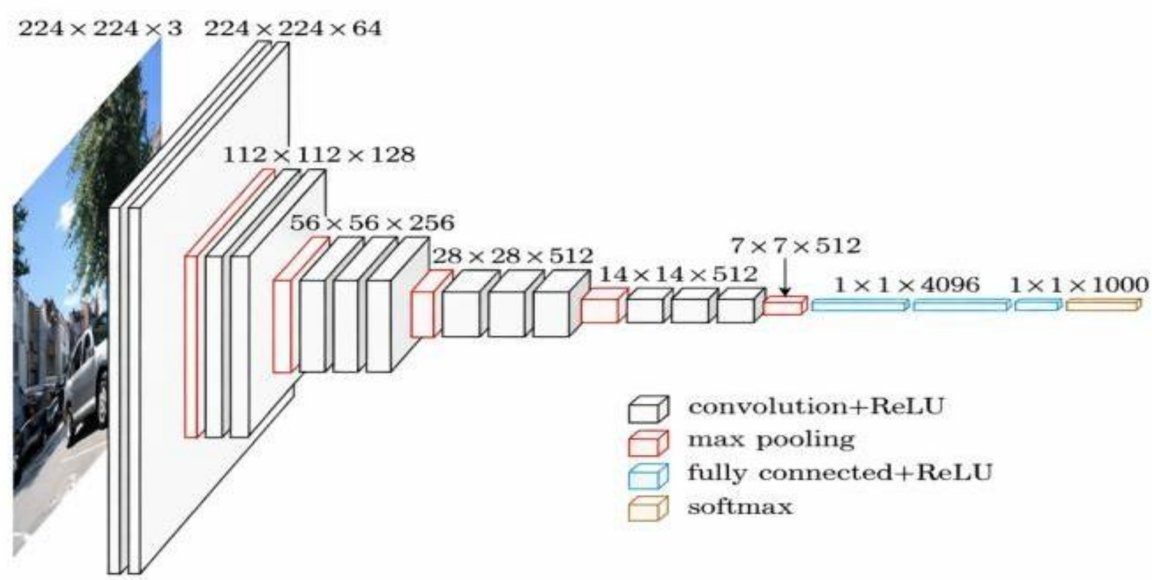

Figure 1 **Architecture of Our CNN System**

Fusion block layers:

- Dense (128), ReLU
- Batch Normalization
- Dense (64), ReLU
- Dropout
- Dense (1) → Final Output
- demand prediction / damage level / resource allocation score

This approach follows multimodal fusion strategies (Figure 2) from Martinez et al. (2023) and Raj et al. (2025).

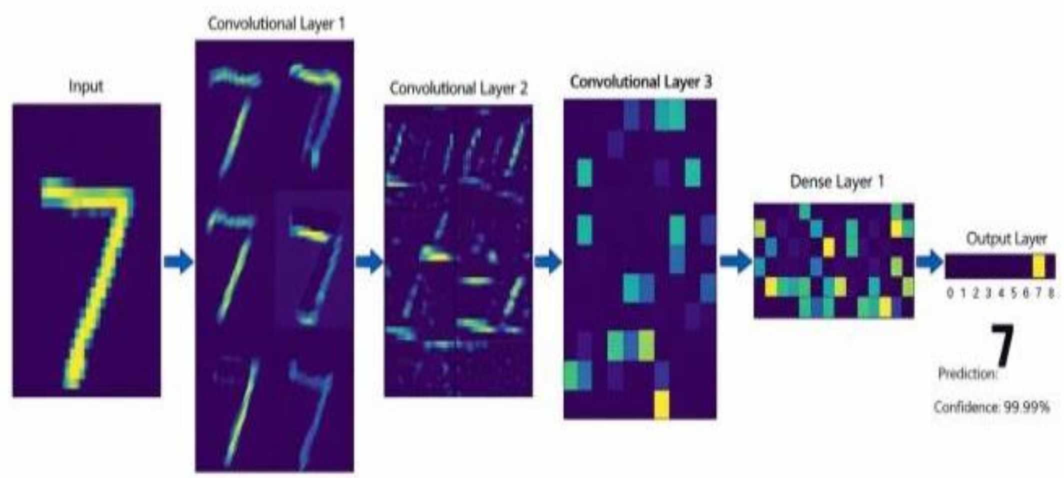

Figure 2 **Multilevel CNN Network**

3. AI Based Disaster Management

Artificial Intelligence (AI) has become a key enabler in modern disaster management by improving prediction accuracy, automating damage assessment, enhancing communication, and optimizing relief distribution. The integration of machine learning, deep learning, generative models, and optimization techniques has significantly improved disaster preparedness, response, and recovery processes.

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Recent studies indicate that AI-driven systems reduce human workload, accelerate decision-making, and enhance resource utilization across the disaster management lifecycle.

3.1. AI for Disaster Prediction and Early Warning

AI-driven predictive models utilize historical disaster records, meteorological parameters, geospatial data, and multimodal inputs to forecast disaster events with high accuracy. Yasmin et al. [1], Singh [26], and Desai [17] demonstrated that ML and DL models outperform traditional approaches in multi-hazard risk classification, earthquake magnitude estimation, and cyclone path prediction. LSTM-based time-series models proposed by Anusha [14] effectively capture long-term rainfall and flood trends, supporting proactive preparedness. Satellite-based systems such as ISRO–NRSC's Cartosat and RISAT frameworks [9] further integrate remote sensing with AI classifiers for flood intensity estimation, highlighting the growing role of ML and DL in early warning systems.

3.2. AI for Damage Assessment and Situational Awareness

Rapid post-disaster damage assessment is essential for effective rescue and relief planning. Deep learning architectures, including CNNs and segmentation models, are widely used for automated analysis of UAV and satellite imagery. Kim and Choi [3] and Zhang et al. [24] showed that AI- based image analysis significantly reduces assessment time compared to manual methods. Generative AI approaches reviewed by Raj et al. [4] enhance low-resolution imagery and address missing data, while multimodal data fusion techniques proposed by Martinez et al. [13] improve situational awareness by combining satellite imagery, environmental data, and social media inputs.

3.3. AI for Resource Allocation and Logistics Optimization

AI-based optimization techniques enable efficient and equitable distribution of relief resources such as food, shelter, medical supplies, and transportation assets. Li et al. [10] proposed ML-assisted logistics models to reduce delivery delays, while Reddy [21] introduced reinforcement learning approaches for dynamic routing under evolving disaster conditions. Choubey and Kumar [18] demonstrated improved flood-relief planning through integrated ML and optimization. However, many systems rely on static datasets and lack real-time feedback from hazard evolution, infrastructure damage, and population displacement [19].

3.4. AI in Communication, Crowdsourcing, and Emergency Information Systems

Reliable communication is critical during disasters, particularly in infrastructure- damaged regions. NLP-based AI models have proven effective in extracting actionable intelligence from social media and crowdsourced data. Abid [7] proposed AI-enhanced crowdsourcing frameworks for filtering public reports, while Choi et al. [15] demonstrated high-accuracy disaster message classification using transformer models. Mishra et al. [12] showed that AI-assisted communication systems can maintain information flow in low-bandwidth environments, enhancing situational awareness and distress detection [16].

3.5. AI for Governance, Transparency, and Decision Support

AI supports disaster governance by improving transparency, coordination, and decision-making. Dcruz et al. [2] and Chen et al. [20] demonstrated that AI- driven decision-support dashboards with geospatial visualization enhance response coordination. Blockchain-enabled systems proposed by Mohan et al. [8] and Kaur et al. [11] ensure traceability and accountability in relief distribution. Governance-focused studies by Kolivand [6] and institutional guidelines from NDMA and UNDRR emphasize ethical AI deployment, interoperability, and multi- agency collaboration.

3.6. Limitations and Challenges

Despite promising advancements, several challenges hinder large-scale adoption of AI-driven disaster management systems:

- fragmented architectures lacking integration between prediction and relief planning,
- limited real-time data fusion across satellite, IoT, weather, and social media sources,
- interoperability issues among agencies,
- scalability constraints in resource- limited regions,

- limited explainability of deep learning models, and
- insufficient field-level validation. Addressing these challenges is essential for next-generation, end- to-end AI-enabled disaster management platforms.

4. Discussion

The reviewed literature indicates that Artificial Intelligence has substantially improved disaster management across prediction, assessment, communication, and resource allocation phases [22], [23]. Machine learning and deep learning models consistently outperform traditional statistical methods in forecasting floods, earthquakes, and cyclones by effectively modeling nonlinear spatiotemporal patterns [1], [17], [26]. However, these models are largely developed as standalone solutions and are rarely integrated with operational decision- support systems, resulting in a disconnect between risk prediction and real-time response execution. Deep learning approaches using satellite and UAV imagery significantly accelerate post-disaster damage assessment and situational awareness [3], [24]. Despite their effectiveness, dependence on high- resolution imagery and computational infrastructure limits deployment in resource-constrained environments [25]. Generative AI techniques partially mitigate this limitation by enhancing low- quality imagery but introduce risks of hallucination, reinforcing the need for human oversight [4]. AI-driven decision-support dashboards and governance frameworks improve transparency and coordination among response agencies [2], [20]. Nevertheless, most systems remain semi-automated and lack interoperability across organizations, hindering large-scale adoption [6]. Similarly, optimization and reinforcement learning models improve relief distribution efficiency and reduce delivery delays [10], [18], [21], yet typically rely on static datasets and fail to incorporate real-time hazard dynamics, population displacement, and infrastructure damage. Multimodal data fusion enhances predictive robustness by integrating satellite, environmental, and ground- sensor data [13], but comprehensive fusion involving IoT streams and crowdsourced inputs remains limited due to interoperability challenges. NLP-based crowdsourcing systems improve real- time communication and misinformation filtering [7], [12], [15], while blockchain- based approaches enhance transparency in relief logistics [8], [11]; however, both are often isolated from predictive and optimization pipelines. Overall, while AI has demonstrably enhanced disaster management capabilities, the lack of integrated, real- time, and interoperable systems remains the primary barrier to practical deployment. These findings motivate the need for unified end-to-end frameworks, such as the proposed ResQ architecture, that connect prediction, assessment, communication, and resource allocation into a cohesive operational pipeline.

Conclusion

Artificial Intelligence has emerged as a powerful enabler in modern disaster management, significantly improving hazard prediction, damage assessment, situational awareness, and relief distribution. Recent studies (2022–2025) show that machine learning and deep learning models enhance forecasting accuracy, generative AI improves image reconstruction under low-visibility conditions, multimodal data fusion strengthens real-time decision-making, and optimization algorithms streamline resource allocation during emergencies [27]. Advances in NLP-based crowdsourcing and blockchain-enabled transparency further support reliable communication and accountable relief operations. Despite these advances, existing systems remain fragmented and often operate in isolated domains without end-to-end integration [28]. Key challenges include limited real-time interoperability across agencies, insufficient automation, scalability constraints, and weak coupling between predictive models and operational planning. Many solutions also lack field-level validation, restricting large-scale deployment [29]. This review highlights the need for unified, scalable, and adaptive AI-driven disaster management frameworks that integrate prediction, assessment, communication, and logistics into a single operational pipeline. Future systems should incorporate explainable AI, multimodal sensing, reinforcement learning, and transparent governance mechanisms to enable trustworthy and effective disaster response. As global disaster risks continue to rise, AI-enabled solutions have strong potential to reduce losses, improve response efficiency, and enhance community resilience.

References

[1]. Yasmin, F., Hasan, M., Sinha, A., & Mondal, S.(2025). AI-driven hazard assessment:A comprehensive study of machine and deep learning approaches. Asian Journal of Civil Engineering.

[2]. Dcruz, J. G., Zolotas, A., Greenwood, N. R., & Arana-Catania, M. (2025). Structured AI decision-making in disaster management. Scientific Reports, 15.

[3]. Kim, D., & Choi, Y. (2025, March 11). Utilization of satellite imagery and artificial intelligence for disaster management: Approaches and case studies. ITU Journal on Future and Evolving Technologies, 6(1), 47–56.

[4]. Raj, A., Arora, L., Girija, S. S., Kapoor, S., Pradhan, D., & Shetgaonkar, A. (2025, May 13). AI and generative AI transforming disaster management: A survey of damage assessment and response techniques. arXiv preprint.

[5]. Wibowo, A. (2025). Leveraging artificial intelligence in disaster management. International Journal of Disaster Risk Reduction.

[6]. Kolivand, P. (2025). AI applications in disaster governance with a health approach. Journal of Disaster Medicine and Public Health Preparedness.

[7]. Abid, S. K. (2025). AI-enhanced crowdsourcing for disaster management. International Journal of Emergency Medicine.

[8]. Mohan, P., et al. (2024). Blockchain- based transparent relief management. IEEE Blockchain Conference.

[9]. ISRO–NRSC. (2024). Satellite-based flood forecasting models using Cartosat & RISAT. Indian Remote Sensing Journal.

[10]. Li, Y., et al. (2023). AI-based logistics optimization for emergency relief. Expert Systems with Applications.

[11]. Kaur, P., et al. (2023). Blockchain for emergency relief tracking. IEEE Access.

[12]. Mishra, P., et al. (2023). AI-assisted emergency communication in low bandwidth regions. IEEE Communications Letters.

[13]. Martinez, S., et al. (2023). Multimodal data fusion for flood forecasting and relief allocation. Elsevier.

[14]. Anusha, R. (2023). LSTM model for long-term disaster demand forecasting. Applied Intelligence (Elsevier).

[15]. Choi, Y., et al. (2023). Twitter-based disaster classification using NLP. Expert Systems with Applications.

[16]. Day, J. (2023). Challenges in managing relief operations in natural disasters. Disaster Risk Management – Elsevier.

[17]. Desai, R. (2023). Cyclone prediction using AWS + ML for coastal India. Springer – Advances in Computing & Networks.

[18]. Choubey, A., & Kumar, R. (2022). AI- based decision support system for flood disaster management using machine learning techniques. IEEE Access, 10, 34725–34736.

[19]. Singh, J. P., et al. (2022). Deep learning in disaster response. IEEE Transactions on Computational Social Systems.

[20]. Chen, W., et al. (2022). Decision- support dashboard for disaster-relief distribution. IEEE Systems Journal.

[21]. Reddy, M. (2022). Reinforcement learning for emergency relief allocation. IEEE Computational Intelligence Magazine.

[22]. Verma, S. (2022). Real-time disaster data streaming using MQTT and cloud platforms. SN Applied Sciences.

[23]. Fujita, N. (2022). Crowdsourcing platform using social media for disaster mapping. ACM Web Conference.

[24]. Zhang, Y., et al. (2022). UAV-enabled framework for rapid post-disaster damage assessment. IEEE / Elsevier.

[25]. Bui, Q. T. (2022). Remote sensing and GIS-based approach for flood monitoring. ISPRS Journal – Elsevier.

[26]. Singh, A. (2022). Deep neural networks for earthquake magnitude forecasting. IEEE Transactions on Geoscience.

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Page No: 575-581
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0078

[27]. Sharma, S. (2022). AI-enabled disaster management for NDMA India. IEEE Region 10 Conference (TENCON).
[28]. BIS & NDMA. (2022). Guidelines for relief resource procurement and allocation. Government of India Publication.
[29]. The World Bank. (2022). Using artificial intelligence to enhance disaster response and recovery.