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Role of IoT in Disaster Monitoring and Response: A Comprehensive Review

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Abstract

In an age where natural and man-made disasters are increasing in frequency and intensity, the impact of technology is expanding in disaster management. One of these transformative technologies is the Internet of Things (IoT) in disaster management. IoT-based disaster management systems involve monitoring environmental conditions, such as temperature, humidity, seismic activity, rainfall, water levels, or gas concentrations, by utilizing sensor nodes deployed in the field to autonomously record relevant data. This recorded data is then transferred to a central sink node or base station, performing as a gateway node for further communication, data collection, and smart decision-making. This review article comprehensively explores the critical aspects of the Internet of Things (IoT) in off-site disaster monitoring and management. It offers a broad overview of IoT-enabled disaster management applicable across various disaster types, including earthquakes, floods, forest fires, and nuclear hazards, consisting of sensor networks, supported by wireless communication, cloud computing, and advanced data analytics, that provide real-time understanding, foresight, and automated responses across all four phases of disaster management, including mitigation, preparedness, response, and recovery. It also highlights the importance of integrating IoT with emergent technologies such as artificial intelligence (AI), edge computing, big data, and 5G, which can significantly increase the responsiveness, efficiency, and resilience of disaster management systems. IoT is leading a paradigm shift in disaster management and marking a significant step toward building safer, more resilient communities, offering faster and smarter responses, and improving the potential to predict and prevent crises.

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1 Introduction

A disaster is a significant disruption of societal functions and activities that cause extensive human, material, economic, or environmental losses, exceeding the capacity of impacted communities to manage their resources [1, 2]. Disasters not only cause massive destruction to buildings and transportation infrastructure but also severely impact critical services, such as power grids, utility lines, and communication systems, as well as the food supply chain whether it's a natural disaster (e.g., earthquakes, floods, hurricanes), technological (e.g., industrial accidents, infrastructure failures), or human-induced (e.g., terrorism, conflict, famine) [3, 4]. For instance, power blackouts, connectivity issues, and severe network congestion led to extensive telecommunication failures in the Haiti earthquake (2010) [5], Christchurch (2011) [6, 7], Japan earthquake and tsunami (2011) [8], and Nepal (2015) [9, 10]. Similar challenges were also faced during the recent earthquake in Turkey and Syria (February 2023) [11], when communication networks failed in several impacted areas, depriving thousands of victims of access to emergency services and real-time updates [12, 13]. Delaying emergency response due to affected communication system, making it more difficult for rescue crews and impacted communities to coordinate. Similar to this, prolonged communication blackouts caused weeks of delayed relief during Hurricane Maria (Puerto Rico, 2017) [14, 15][, and Cyclone Idai (Mozambique, Zimbabwe, Malawi, March 2019) [16], causing prolonged delays in relief efforts [17]. For decades, Asia has remained the most disaster-prone region in terms of weather, climate, and water-related hazards. According to the World Meteorological Organization (WMO), floods and storms caused the most reported casualties and economic damage, while heatwaves had a more severe impact [18]. The total natural and man-made (technological) disasters of various countries from 1900 to 2024 are summarized in the ***Figure 1*** [19].

Conventional disaster management approaches include initiatives such as aero-geometrical techniques, systematic risk assessments, the building of resilient infrastructure, and predictive analysis based on complex examinations of tectonic plate movements, meteorological patterns, and weather forecasts [2, 3]. Although these methodologies offer a certain level of assistance, their limited precision and reliability fail to provide absolute certainty with real-time monitoring and warning systems. However, by implementing more reliable, robust, and precise methods, a remarkable level of accuracy and reliability can be achieved, practically minimizing the chances of damage or loss. Climate change, causing more intense and severe natural disasters, emphasizes the crucial need for reliable and decentralized communication technologies and networks, for example, satellite-based IoT, edge computing, and IoT-enabled device-to-device (D2D) ad-hoc networks to ensure continuous connectivity and effective communication during crises in disaster-hit areas. The problem exists not merely in having communication technology, but in their performance under pressure and adaptability to emergencies [20, 21].

The Internet of Things (IoT) is gaining significant attention not only in disaster communication strategies but also in the wider scope of disaster management networks. Effective disaster management is based on a coordinated and continuous process intended to prevent or mitigate disasters, prepare for emergencies, respond efficiently during calamities, and recover afterward. The Global Assessment Report 2025 (GAR 2025), issued by the United Nations Office for Disaster Risk Reduction (UNDRR), presents an action-oriented view of growing disaster risk globally and the critical need for transformative investments in disaster risk reduction (DRR). The global cost of disasters now exceeds $2.3 trillion annually, making it a compelling economic and social case for prioritizing resilience [22].

In this review article, we discuss the growing significance and integration of Internet of Things (IoT) technologies in remote disaster monitoring, early warning, and management systems. It provides an in-depth exploration of IoT systems, primarily built upon Wireless Sensor Networks (WSNs), cloud computing, edge computing, and advanced data analytics, which can be effectively deployed in disaster-prone areas. This comprehensive review is structured around the

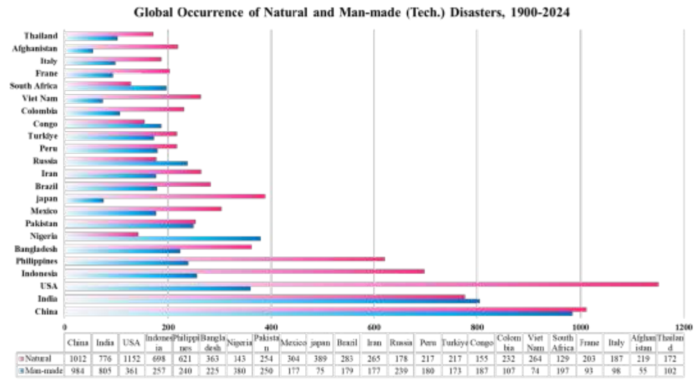

Figure 1. : Global occurrence of Natural and Man-made disasters, 1900-2024

four key phases of disaster management: mitigation, preparedness, response, and recovery, and it showcases the role of IoT integrated with other modern technologies. The discussed case studies encompass domains such as earthquake early warnings, forest fire detection, flood monitoring, and nuclear radiation monitoring. The review article also presents a general multi-layered IoT model for disaster management. It highlights that integrating modern technologies such as cloud services, edge computing, ML, and AI-driven analytics can improve prediction, actuation, and long-term resilience strategies. Additionally, it includes the scope of data analysis to enable the use of recorded data by the IoT architecture in future risk assessment and strategic planning to minimize losses.

2 Background

The Internet has rapidly evolved as a powerful global communication platform, laying the foundation for many groundbreaking technologies, including Voice over Internet Protocol (VoIP) [2]. It revolutionized telecommunications by allowing real-time conversation via the Internet. Centered on this advancement, the Internet of Things (IoT) has emerged as a paradigm that connects everyday devices, sensors, and objects to the Internet, allowing them to collect, transmit, monitor, and take action on data accordingly without direct human intervention [23, 24].

The IoT was pioneered in the early 1990s at MIT's Auto-ID Labs, where researchers envisioned automatic machine interactions [23]. One of the earliest devices to be connected to the internet was a Coca-Cola vending machine in 1982, followed by the formation of an Internet-controlled coffee pot in 1999. Additionally, the world's first internet-connected smart toaster was developed to demonstrate the feasibility of remotely controlled appliances. Ever since, the Internet of Things has widely expanded, leading to advances in sensing technology, wireless connectivity, cloud computing, safety/security management, etc [25, 26].

As Internet technologies advanced, the IoT evolved radically through different phases as summarized in ***Table 1*** [24]. Starting from Internet of Data (basic data exchange) to the Internet of Content (involving data sharing), to the Internet of Services (allowing transactional services), and finally to the Internet of Things, where billions of smart devices can independently operate and communicate autonomously. In this advanced IoT age, devices can perform pre-programmed operations and interact seamlessly across various platforms using embedded software and sensors [24, 26].

Additionally, as the IoT ecosystem matured, researchers synchronized computer science principles to create smart autonomous systems that require minimal or no human intervention, resulting in the fourth industrial revolution (Industry 4.0). Industry 4.0 revolution is a phase that involves smart manufacturing, intelligent automation, and data-driven decision-making, maximizing productivity, process optimization, and efficacy [2, 28].

Table 1. Evolution of Internet technologies through different phases [24–27]

Phases of the Internet	Description	Examples
Pre-Internet	Early networking concepts, military and academic research	ARPANET beginnings
Internet of Data	Focused on basic data exchange between computers	Early TCP/IP networks
Internet of Content	Emergence of websites, multimedia, and information sharing	WWW, Email, FTP
Internet of Services	Cloud platforms, APIs, and service-oriented architecture	SaaS, PaaS, IaaS
Internet of Things (IoT)	Devices communicate autonomously; integration of physical and digital worlds	Smart homes, industrial automation, and environmental monitoring
Internet of Everything (IoE) (Future)	Full convergence of people	AI-driven smart cities, autonomous vehicles

Technologies including cloud computing, edge computing, and AI-based sensors have advanced real-time monitoring and control in industrial manufacturing, healthcare, and infrastructure [29–32]. With IoT, new business models that were previously unimaginable can be made successful by monitoring production processes and optimizing workflows [33]. Various benefits of IoT are represented in ***Figure 2***.

The development of the Internet has significantly shaped the operations of modern communication systems. The Internet of Things (IoT) is one of its most transformative outcomes, providing a technological framework that allows billions of objects to collect, process, and share data autonomously using embedded sensors and Internet connectivity. In today's digital community, IoT has become a benchmark for smart and real-time data communication [34].

Industries are deploying sensor-based devices to automate decision-making and optimize operations as they become increasingly sophisticated and affordable. According to recent figures, more than 18 billion IoT devices are currently online, and it is expected to surpass 40 billion by 2030 [35] as summarized in ***Figure 3***. IoT-based systems are not just passive data collectors; however, they actively generate a vast amount of data, which helps derive immediate insights by processing at the local device or transmitting to the central server. The cognitive processing ability of IoT systems distinguishes them from conventional sensors. The exponential growth of IoT-based devices is driven by smart city initiatives, industrial automation, and the adoption of Low Power Wide Area Networks (LPWAN) such as LoRaWAN and NB-IoT, which has led to its deployment across various domains [35].

IoT applications have advanced the modern-day infrastructure, encompassing smart homes [36], buildings [37], smart grids [38], transportation [39], and agriculture [40]. These devices are being employed in healthcare monitoring, public safety, environmental monitoring, energy efficiency, and much more. These applications depend on new networking technologies, such as IPv6, which connects an almost limitless number of device addresses, which are essential for scaling IoT deployments globally. Despite the rapid advancement, the IoT domain continues to evolve. Breakthrough innovations, including Artificial Intelligence (AI), Edge Computing, and Federated Learning, have tremendously improved the intelligence, responsiveness, and privacy of IoT-based systems [41–43]. Additionally, blockchain integration is being investigated to advance safety, security, transparency, and

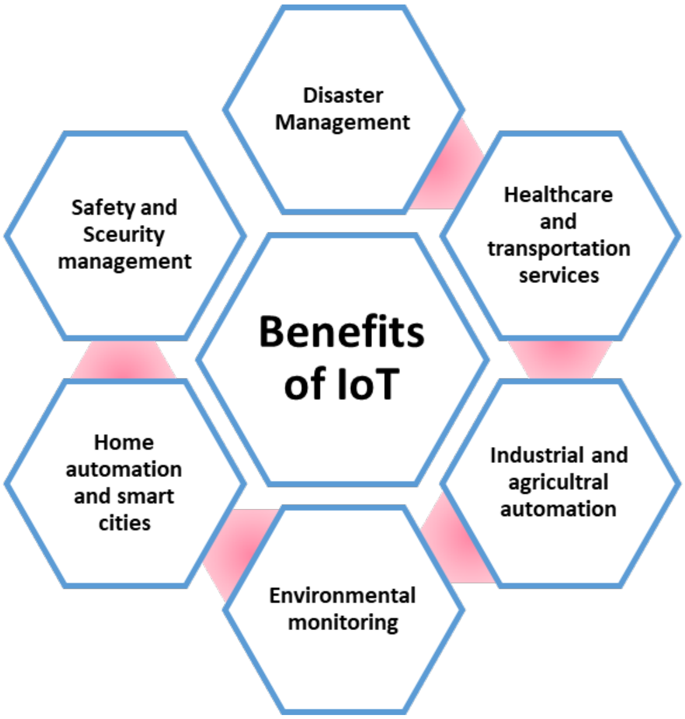

Figure 2. : Various benefits of IoT

traceability, mainly in critical areas such as supply chains and disaster response [41].

With an estimated 41.1 billion installed IoT-based connections by 2030, the global IoT market is increasingly expanding. The compound annual growth rate (CAGR) has increased in recent years, averaging between 13% to 15%, in recent years, with an outstanding 147% CAGR (2021–2023) and an estimated 62% growth rate by 2030. According to IoT analytics, Cellular 5G IoT is expected to grow at the fastest rate due to its widespread usage in connected cars, smart cities, and industrial automation [35] as summarized in ***Table 2***.

LPWA technologies, such as LoRa and NB-IoT, are suitable for low-power, long-range applications, particularly in agriculture and remote monitoring. Traditional wired IoT solutions show modest growth compared to wireless infrastructure, suggesting a market shift towards wireless devices. In the meantime, short-range communication standards, including WPAN (e.g., Bluetooth, Zigbee) and WLAN (e.g., Wi-Fi), continue to grow as an indispensable part of smart home and consumer IoT systems [35, 44, 45].

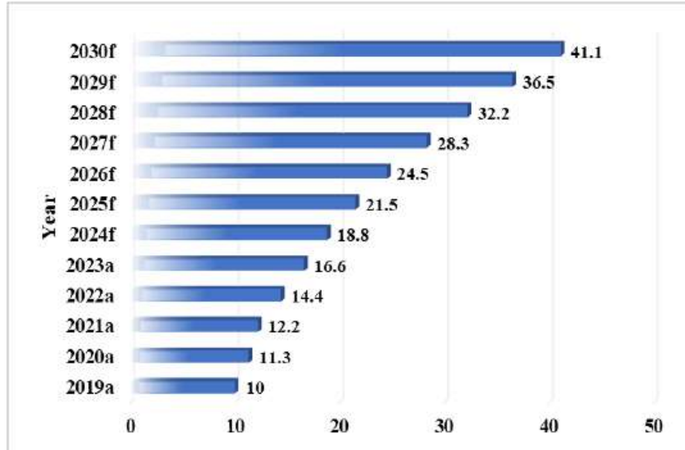

Figure 3. : Various benefits of IoT

Recent advances have efficiently improved the robustness and capabilities of IoT-based systems. One of the most significant developments is the integration of satellite-based IoT devices. Companies, including Amazon (Project Kuiper) and SpaceX (Starlink), are expanding the role of satellite IoT and proprietary networks as growing efforts to bridge the digital divide in remote and disaster-prone regions [46–48]. In addition, the emergence of Edge AI technologies, powered by devices, for instance, NVIDIA Jetson and Google Coral, enables robust and on-site processing of video and sensor data [49, 50]. This real-time monitoring and processing of sensor data minimizes the dependency on cloud servers, which becomes indispensable during emergencies like earthquakes and floods when network accessibility may be compromised. Due to current security threats, the deployment of Zero Trust Architecture (ZTA) and quantum-safe encryption is rising in IoT installations to ensure data integrity and safeguard against cyber threats [44, 51, 52].

To enhance security and reliability in deployments, researchers are exploring the integration of blockchain with IoT-based systems. This integration facilitates data integrity and tamper-proof logging, particularly advantageous in disaster prediction and emergency response systems [41, 47, 53]. Furthermore, federated learning is another increasingly adopted approach in healthcare, defense, and emergency coordination domains, where it protects user

Table 2. CAGR (%) of IoT-based connections

Connectivity Type	CAGR (2021–2023)	CAGR (2023–2030)
Cellular 5G IoT	147%	62%
LPWA (Low-Power Wide-Area)	35%	21%
Cellular IoT (excl. 5G, LPWA)	21%	11%
Wireless local area networks (WLAN)	18%	14%
Wireless neighborhood area networks (WNAN)	15%	14%
Wireless personal area networks (WPAN)	12%	13%
Wired IoT	4%	9%
Other (e.g., satellite, unclassified)	21%	17%

privacy by enabling decentralized machine learning across edge devices (Laptops, smartphones, and wearable devices) without transmitting raw data [54, 55]. To further improve the compatibility and systemic coherence, standardization initiatives such as the IEEE P2413 standard have been introduced. It provides a cohesive architectural foundation for IoT systems, which is important for building scalable, reliable, secure, and interoperable IoT systems for disaster management.

As outlined by the Institute of Electrical and Electronics Engineers (IEEE), a unified architectural framework has four layers (***Figure 4***), including physical devices, networking, data abstraction, and application logic, which addresses various concerns related to security, privacy, and service interoperability across different domains. IEEE P2413 performs a crucial role in mission-critical applications such as disaster management, where multiple organizations and systems must operate together effectively in real-time [56]. Moreover, it establishes a universal architectural foundation to facilitate the evolution of future technologies, i.e., edge AI, blockchain, and satellite communications.

Disaster management is a collaborative effort involving governmental bodies, non-governmental organizations, and corporate entities to address the growing prevalence of disasters. It includes the strategic planning and organizing resources and responsibilities to effectually manage all phases of a disaster, including preparedness, response, relief, and recovery. This framework works through a multi-level governance hierarchy, engaging local, state, federal entities, the community, and the corporate sector. The core of this framework is the disaster management cycle, which typically encompasses four key phases: Mitigation, Preparation, Response, and Recovery, as depicted in ***Figure 5*** [3, 56, 57].

Disaster mitigation refers to proactive strategies or preventive measures implemented before a disaster hits, detecting early signs of earthquakes, floods, or wildfires [58]. This comprises hazard assessment, reinforcing infrastructure, and implementing early warning systems. As per disaster management figures, mitigation is a more economical strategy than post-disaster response, as it helps to educate people, reduces the human and economic toll [22]. Through real-time monitoring, prompt automated alerts, and rigorous system verification, recent advances in IoT, edge computing, and formal verification & model checking methods have significantly enhanced the capacity to anticipate and prevent disasters. By adapting proactive measures, these technologies make communities more resilient and well-resourced to handle both natural and man-made disasters [59, 60].

Preparedness is the next phase of the disaster management cycle, which refers to the proactive measures taken before a disaster strikes. It ensures an efficient and coordinated response by developing effective emergency plans, conducting training & drills, stockpiling life-saving supplies, and strengthening communication networks and early warning systems. In recent years, technological innovations such as IoT-based monitoring, satellite connectivity, and formal verification tools have significantly advanced preparedness. These advanced technologies assist real-time detection, automated alerts, and verifi-

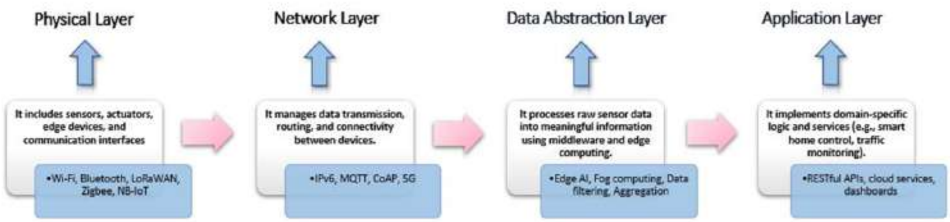

Figure 4. Various benefits of IoT

cation of mission-critical systems, helping relief teams anticipate hazards and deploy resources efficiently. As emphasized in studies, ensuring the reliability and precision of emergency systems through formal methods is key to building reliable and resilient disaster-management and safety-critical systems [60, 61].

The response phase of disaster management is the most critical, involving the urgent activities taken during or immediately after a disaster to save lives, safeguard property, stabilize the situation, provide immediate needs (i.e., food, water, shelter, sanitation, medical care), restore critical services, and coordinate relief efforts between agencies, governments, and humanitarian organizations. It requires the rapid deployment of emergency services, coordination among responsible governmental and private sectors, and access to real-time figures for up-to-date decision-making. However, recent events such as Hurricane Maria (Puerto Rico, 2017) [15], the Nepal earthquake (2015) [9], and the Turkey-Syria earthquake (2023)[12] has shown that communication failures and infrastructure collapse can severely hamper response efforts. To combat these issues, modern disaster response strategies are increasingly integrating IoT-based systems, including satellite communications, drones and UAVs, sensors, AI and Machine Learning, blockchain, and formal verification approaches to ensure system reliability under stress [47, 62, 63]. These technologies offer real-time tracking and sensing, automated updates, and secure data sharing, enhancing interoperability among diverse systems and agencies, enabling faster and more coordinated action during emergencies [61].

After the initial crisis has been addressed, the recovery phase of the disaster management cycle helps restore normalcy and rebuild communities. It encompasses short-term and long-term efforts to not only return to the pre-disaster state but to rebuild in more resilient and sustainable ways. Short-term efforts involve the recovery of essential services (electricity, water, transportation, and healthcare), reopening schools and businesses, and providing temporary housing. Whereas, long-term efforts comprise reconstructing buildings, Economic revival, and implementing new policies to avoid future risks. It involves providing support to victims through housing, healthcare, and economic revival. Being a long-term process, recovery requires sustained investment and coordination over weeks, months, or even years. Effective recovery ensues through the coordination of governments, humanitarian aid organizations, the private sector, and local communities. Additionally, now is a crucial time to evaluate risks, draw lessons from the disaster, and enhance policies for future disaster preparedness [2, 61, 63].

2.1 IoT edge in disaster management

In the past, disaster prevention depended on manual monitoring, centralized alert systems, and physical sensors positioned in disaster-prone areas. Despite their limited scalability, lower reliability, extended response times, and lack of real-time data sharing, traditional methods of disaster management were not effective [60]. However, advanced technologies such as the Internet of Things (IoT) have transformed disaster management by enabling real-time monitoring, early warning, efficient communication, and informed decision-making. IoT-based systems utilize embedded sensors, edge computing, wireless networks, and cloud platforms to gather and analyze information

Figure 5. Phases of Disaster Management Cycle

from disaster-prone areas, enabling early warnings and faster response times [30]. For instance, IoT has been deployed successfully in floods, forest fires, earthquakes, volcanic eruptions, landslides, nuclear incidents, and road accidents [63]. For example, sensors installed on trees can sense sudden rises in temperature or carbon dioxide levels, potentially indicating the onset of a wildfire. Likewise, ground vibration sensors detect earthquake tremors, whereas water level sensors in water bodies can predict flooding events [64].

Developing countries are more susceptible to natural disasters due to inadequate healthcare, poor infrastructure, limited insurance coverage, and an overall lack of emergency preparedness. With more than 90% of crisis-related deaths recorded in developing nations [22, 65], IoT holds promising potential in reducing risks by contributing reliable, cost-effective, scalable, and efficient disaster management solutions [61].

2.2 IoT across the disaster management phases

In every phase of the disaster management cycle (mitigation, preparation, response, and recovery), the Internet of Things (IoT) is essential. IoT considerably enhances reliability, resilience, coordination, interoperability, and efficiency of safety-critical systems to combat emergencies by facilitating real-time sensing, automated decision-making, and unimpeded communication and accessibility among critical systems [1, 61].

2.2.1 Mitigation and risk reduction

In the mitigation phase of the disaster management cycle, IoT helps diminish disaster risk by continuously monitoring critical environmental variables and reporting early signs of potential disaster threats. Wireless Sensor Networks (WSNs) are one of the most deployed technologies across disaster-susceptible areas to track indicators and monitor conditions such as water levels, gas levels, seismic activity, temperature, humidity, pressure, and more [66]. These sensors are usually integrated with GPS and CCTV systems to provide geo-locating surveillance and situational awareness. When threshold values are exceeded, the IoT-based sensor systems immediately notify authorities via wireless communication networks. This forms the foundation of early warning systems, public awareness campaigns, and the initiation of precautionary measures [67]. For instance, accelerometers are installed in earthquake-prone areas, helping to detect tremors before they escalate, enabling a timely response [68]. Similarly, in flood-susceptible regions, IoT-based water-level sensors are deployed to detect and notify before flooding. Modifying the safety-critical systems by integrating formal verification tools ensures their reliability even under challenging scenarios [69, 70].

2.2.2 Disaster preparedness

Although IoT cannot prevent disasters, it performs as an early warning system, significantly improving the preparedness phase of disaster management. It helps susceptible communities to take timely initiatives, issue timely alerts, and start automated rescue operations. It also allows post-disaster data collection and analysis, which can be useful for forecasting and risk mitigation in the future [69].

2.2.3 Emergency response

In the response phase, IoT also allows real-time response through automated, rapid, and coordinated actions during emergencies. For instance, temperature and smoke sensors immediately detect anomalies in temperature and smoke rise in a smart building equipped with an IoT-based fire management system. Upon sensing, the Wireless Sensor Network system (WSN) automatically directs commands to actuators, activating sprinklers, unlocking fire extinguishers, and directing residents to evacuation routes via smart signage [66]. At the same time, the system sends automated alerts to the nearest fire station via SMS, phone call, or web service, confirming quick human intervention. These IoT-enabled automated actions make the system far more reliable, responsive, accurate, and efficient, thereby outperforming traditional methods, significantly reducing potential damage and loss [71, 72]. A general architecture of IoT-enabled fire safety management system is shown in ***Figure 6***.

2.2.4 Recovery and post-disaster management

During the recovery phase and post-disaster management, IoT-enabled activities, such as assisting in missing person identification, search and rescue operations, infrastructure monitoring, and environmental restoration, were utilized. GPS tracking, RFID tags, and CCTV footage help in search and rescue operations. whereas drones and satellite-linked camera technology offer aerial views of impacted regions, facilitating damage assessment and resource allocation. For example, flood detection systems facilitate the identification of waterlogged locations in low-lying regions, allowing critical evacuation and relief efforts. Moreover, wildlife tracking sensors detect and locate animals trapped in forests during wildfires, improving post-disaster ecological response strategies. Combining edge computing with AI-driven analytics enables on-site and real-time data processing, further minimizing dependence on centralized cloud systems that may become inaccessible during widespread disasters [73]. Furthermore, the IEEE P2413 standard improves interoperability among diverse IoT-based disaster platforms, facilitating the seamless coordination and integration of recovery technologies across various governmental and non-governmental organizations [56].

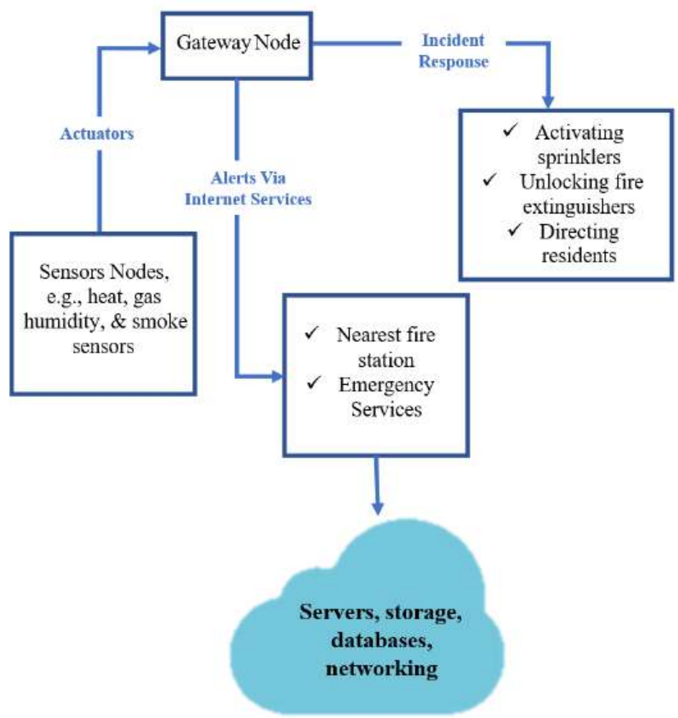

Figure 6. Architecture of an IoT-enabled fire safety management system

3 A systematic review of IoT-based disaster management systems

The Internet of Things (IoT) has become a fundamental technology in disaster management, offering robust solutions across various stages, from early detection and prevention to instantaneous response and recovery [51]. This section highlights the significance of the energy-efficient and scalable IoT-based disaster management technology. The rapid advancement of IoT has revolutionized disaster management by enabling real-time monitoring, data-based decision-making, and proactive risk mitigation. IoT-based systems remarkably enhance early warning systems, improve situational awareness, and support real-time emergency responses during natural disasters (floods, earthquakes, tsunamis, and wildfires) or man-made disasters. This section reviews recent literature on IoT-based disaster management solutions, summarized in ***Table 3***.

3.1 Early earthquake warning systems

Earthquakes typically emit a minor preliminary shock wave followed by stronger, dangerous, and destructive waves. Although the time gap between the two shock waves is just a few seconds to minutes, which is sufficient to initiate preliminary automated responses such as halting elevators, trains, or industrial machinery, minimizing casualties and infrastructure damage [74]. Furthermore, smartphones having built-in accelerometers can monitor unusual ground movements, and the combined data serve as an early warning when several devices in a disaster-prone region concurrently record comparable seismic patterns. For instance, the MyShake app demonstrates that its on-phone earthquake detection algorithm can detect ground movements from earthquakes at varying distances: M5 earthquakes up to $\sim$250 km away, M4 up to $\sim$150 km, and M3 up to $\sim$50 km [75, 76].

Anis Koubaa et al. [77] proposed a compute offloading architecture design for Internet-connected drones. They reported a comprehensive experiment to evaluate the performance of edge computing and cloud-based offloading approaches when applying deep learning techniques, specifically Convolutional Neural Networks (CNNs), in UAVs. Their investigation focused on evaluating the communication costs and computational efficacy across the two methodologies. The model was trained using data in the form of aerial images captured using UAVs.

Rabia Tehseen et al. [78] proposed a novel earthquake prediction framework based on a federated learning (FL) approach. This approach outperformed current machine learning (ML) models in terms of efficiency, reliability, and accuracy. This study employed three separate local datasets to develop multiple ML-based models, which were further integrated into a global model using the FedQuake algorithm on a central FL server, accessed through an IoT gateway. The resultant model analyzed multidimensional data within a 100 km radius in the Western Himalayas, attaining a precision of 88%.

Similarly, Gautham Pughazhendhi and fellow researchers [79] proposed an IoT-enabled warning system integrated with a machine learning classification algorithm to predict tsunamis. This model was trained on historical tsunami data dating back to 2100 BC, using earthquake parameters such as location, depth, and magnitude for prediction with an accuracy of 95%.

Irshad Khan et al. [80] employed IoT-based acceleration nodes to design an earthquake detection platform. The study explored two approaches for operating these devices as seismic sensors. The first approach is a standalone method, and the other is a client-server method. Although the client-server approach provides more accuracy, it needs a robust server and a reliable network infrastructure to process acceleration data gathered from multiple client devices. On the contrary, simpler earthquake detection procedures can be implemented independently on less powerful mobile nodes using the standalone method. Yet, this approach carries a higher risk of generating false alarms. A cooperative approach was developed to address this limitation, using information from several nearby cellphones to improve detection precision without depending on network infrastructure or centralized systems. This cooperative setup integrates adjacent mobile phones to form a decentralized seismic network that helps monitor the tremors caused by earthquakes, human activities, or mechanical vibrations. When a smartphone detects motion resembling an earthquake, it uses a key neural network-based detection algorithm to analyze the event, followed by sharing the outcome with neighboring devices via a multi-hop communication mechanism, improving overall detection reliability and performance of the system.

Hui Zhai and Yi Wang [81] utilized a combination of mobile computing, remote sensing technologies, and machine learning algorithms, particularly Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), to mitigate the effect of earthquake-related calamities. The machine learning models were trained using input features including entity types, spatial relationships, and entity identifiers. The designed system performance was assessed based on the accuracy of the models in forecasting and interpreting seismic events, representing the potential of integrating geospatial data with ML techniques for more effective disaster response management.

Mohamed S. Abdalzaher and co-workers [82] designed a potential platform for rapid detection of earthquake magnitude and location within just 3 seconds after the P-wave onset. They introduced a deep learning framework based on an autoencoder (AE) and a CNN. This model, referred to as 3S-AE-CNN, employs seismic data from three stations in Japan's Hi-net network. It was trained and verified on a dataset containing 12,200 seismic events, approximately 109,800 three-second, three-component waveform segments. The designed model provided highly accurate predictions of earthquake parameters, such as precision levels of 0.000028 degrees for magnitude, 0.0000033 degrees for latitude, and 0.0001 degrees for longitude. Additionally, the 3S-AE-CNN model quickly transmits the measured earthquake features to a centralized IoT system, which then alerts the relevant authorities to initiate timely response.

Furthermore, Siddhartha Sarkara and co-workers [83] designed a Multilayer Perceptron classifier to issue warnings based on the likelihood that tremors would exceed a predefined peak ground acceleration (PGA) threshold corresponding to destructive levels on the Modified Mercalli Intensity (MMI) scale. By using a stratified differential feature-window resampling strategy during the supervised learning phase, the model was trained using seismic data obtained from strong-motion signals after the P-wave beginning.

A deep learning algorithm was developed to monitor P-waves even under noisy conditions by employing MEMS sensor nodes to measure seismic activities. The developed model was capable of predicting the likelihood of detection before the strong tremors. It attained a P-wave detection accuracy of 98.8% in 1.5 to 2.5 seconds of wave hit [84].

Bassetti and Panizzi [85] designed a novel edge-based earthquake early warning (EEW) system that deploys IoT crowdsensing and decentralized computing to overcome limitations faced in traditional centralized systems. Their system shifts the computation to sensor nodes at the edge, which process accelerometer data locally and use a mesh network to communicate with neighboring sensors. This system exhibits prominent resilience by eliminating single points of failure and tolerating node faults or network disruptions. The architecture supports data privacy by transmitting processed detection data rather than raw sensor data. Raspberry Pi and NodeMCU devices, CrowdQuake machine learning model were deployed, offering fast detection times and scalability with minimal computational overhead. Moreover, this advanced system supports practical deployment through user-friendly mobile applications and modular IoT devices.

Jangsoo Lee and fellow researchers [86] adopted a novel machine learning-based approach for earthquake detection in both static and dynamic environments using affordable IoT devices (smartphones) equipped with accelerometers. The researchers propose a novel earthquake feature extraction technique, particularly improving the zero-crossing (ZC) method to distinguish earthquake signals effectively from noise and human activities. They advanced the performance of the developed lightweight Artificial Neural Network (ANN) model by incorporating multi-component amplitude and frequency statistics, along with Singular Value Decomposition (SVD)-based features. This developed model was validated using data from 385 earthquake events with magnitudes 4 to 8. Their experimental results have shown that the proposed model outperforms existing traditional methods, achieving high accuracy, precision, and recall on both balanced and real-world datasets. The model also simplifies well across different sensor types and remarkably performs in dynamic environments involving various human activities, making it suitable for deployment in smartphone-based or standalone seismic monitoring systems.

P Sreevidya and fellow researchers [87] focused on monitoring geological landslide events by developing a predictive model that incorporates IoT devices with a Machine Learning (ML) framework. The model was trained using data from several geotechnical parameters, for instance, soil moisture, shear strength, rainfall intensity, and terrain slope. A set of sensors is installed to capture real-time soil and terrain data, which is essential for prediction.

Aming Wu and co-workers [88] introduced CrowdQuake+, a deep learning-based seismic detection system to process large volumes of acceleration data through a dense IoT network. The system utilizes a multi-head convolutional neural network (CNN) to analyze sensor input, with the IoT network encompassing MEMS-based nodes. The researchers evaluate signal-to-noise levels along with metrics, i.e., accuracy, precision, and recall, to monitor model performance. To train and validate the model, the dataset was sourced from the National Research Institute for Earth Science and Disaster Prevention (NIED). The designed model is capable of processing input from approximately 8,000 IoT sensors, enabling earthquake detection within just a few seconds of data transmission.

Mariarosaria Falanga and co-workers [89] proposed an IoT-based potential platform for collecting, interpreting, and storing seismic data in a structured knowledge base. They developed the Volcano Event Ontology (VEO), a domain-specific ontology to classify seismic signals recorded using sensors for event monitoring. This ontology is based on the established SSN/SOSA framework, commonly employed to describe sensors, actuators, and observations. Data was sourced from seismic monitoring networks at Mt. Vesuvius (Italy) and the Colima volcano (Mexico), which were further organized within the ontology. A classification module was used to analyze the signals and detect various seismic events, including volcano-tectonic and long-period earthquakes, quarry blasts, and underwater explosions. The final dataset comprised 4008 seismic signals in SAC format, entailing an accuracy of 93% as estimated by the F1-score.

Timothy Clements [90] designed a robust Earthquake Early Warning System (EEWS) utilizing real-time alert mechanisms via the Internet of Things (IoT) network. This system incorporated MEMS (Micro-Electro-Mechanical Systems) accelerometers and an Arduino Cortex M4 microcontroller together with Machine Learning (ML) techniques to improve both the accuracy of earthquake monitoring and the speed of response. This model operated on acceleration data collected locally from the installed MEMS accelerometer nodes, enabling efficient and quick seismic event detection.

Kevin Fauvel et al. [91] proposed the Distributed Multi-Sensor Earthquake Early Warning (DMSEEW) system, based on an advanced machine learning framework, that detects medium to large earthquakes. This system processes data from both GPS stations and seismometers via a novel stacking ensemble method, which was previously validated through real-world data and reviewed by geoscientists. Built on a geographically distributed infrastructure, DMSEEW confirms rapid data processing and remains active even during partial system failures. By combining GPS and seismic data, the system exhibits remarkable accuracy and reliability towards earthquake detection, contributing to a more effective and robust early warning.

Irshad Khan et al. [92] presented a standalone earthquake detection system having a low-cost accelerometer and minimal computing resources. The performance of the designed system was initially assessed using four different acceleration sensors, and the most suitable one (MEMs sensor) with high accuracy and a lower false alert rate was selected. Using the selected sensor, they optimized the earthquake alert mechanism powered by a simple machine learning model. The model was trained on regular building vibrations, ambient noise, and historical earthquake data. This study demonstrated that these affordable sensors could efficiently detect acceleration variations arising due to earthquake tremors ranging from 0.02 g to 0.8 g. Furthermore, the model was trained using the corresponding scaled data within this range.

3.2 Nuclear radiation monitoring

In nuclear facilities, IoT-based Wireless Sensor Networks (WSNs) continuously monitor radiation levels in the air or water. If the detected radioactive emissions exceed predefined safety thresholds, the designed system automatically alerts regulatory authorities, allowing timely human intervention and remediation measures [93–95].

Muhtadan and co-workers [95] designed an IoT-based radiation monitoring system to enhance nuclear safety in the Yogyakarta Nuclear Area. The developed system integrated Geiger-Müller detectors, wireless sensor networks (WSN), and Arduino microcontrollers to monitor and transmit real-time environmental radiation data to a centralized cloud server. This setup enabled continuous, remote monitoring and smart decision-making in potential nuclear emergencies. The system demonstrated as a potential component in a nuclear disaster preparedness framework with a high accuracy rate and enhanced reliability, making it effective in detecting radiation levels.

Muhammad Saifullah et al. [96] developed an intelligent IoT-enabled system for radiation monitoring and warning, detecting and classifying harmful electromagnetic radiation levels in real-time, particularly for vulnerable populations such as infants. This system deploys a network of low-cost sensors and ultraviolet and electromagnetic radiation detectors integrated with an Arduino Mega microcontroller to record environmental radiation data. A multi-layered IoT architecture was employed, combining real-time sensor data, machine learning-based data processing, and mobile alerts to notify application users when radiation intensity surpassed safe thresholds. The remarkable accuracy of 81.77% demonstrates the robustness and reliability of the system in radiation prediction and alerting. This efficient system enhances public safety and supports the practical integration of IoT and AI in radiation hazard management.

3.3 Flood monitoring and early warning

IoT has become a leading innovation in flood prediction, involving embedded systems that record real-time data via wireless sensor networks (WSNs), transmitting it to computational platforms for analysis [97]. These IoT-powered systems facilitate robust and reliable data collection through sensors. In addition, integration with cloud computing and analytical tools enhances their response [98]. The embedded systems powered by machine learning (ML) monitor environmental parameters such as temperature, humidity, and rainfall intensity to investigate patterns and forecast floods based on climatic trends. The flood prediction has shifted from relying solely on environmental parameters to implementing mathematical models, AI-based models, Machine learning models, and algorithm-based techniques. Recent trends involve mobile-based platforms and also alert systems that utilize Arduino Uno microcontrollers connected to ultrasonic and rain sensors to collect and process data [97, 99].

Another research conducted by Muhammad Wajid and co-workers [100] has been published, focusing on the development of energy-efficient, IoT-based flood prediction and forecasting systems. This proposed solution utilizes a power-efficient IoT sensor with fog nodes and cloud computing to monitor climatic variables (i.e., temperature, humidity, rainfall) and hydrological parameters (i.e., water flow and elevation) for timely flood prediction and forecasting. Artificial Neural Networks (ANNs) are at the core of the predictive model, achieving benchmark performance compared to alternative algorithms such as Logistic Regression and Decision Trees, with an accuracy of 94.2%. The system not only provides real-time flood risk forecasts via a user-friendly interface but also provides safety interventions and location-based evacuation guidance.

A recent study by Soleyman Nezhadbasaidu et al. [101] proposed an integrated flood detection, warning, and prediction system that connects IoT with machine learning to predict flood risk and improve flood risk management. The designed platform is a non-structural, real-time monitoring approach that enables early warning. IoT-based sensors are deployed across various water bodies, including rivers, dams, canals, and lakes, monitoring environmental conditions and water levels. After a critical threshold is surpassed, automatic alerts are issued within a 5 km radius via an Android application, which displays crucial data such as temperature, water level, flood location, and predictive insights. The designed linear regression model exhibited superior performance, an accuracy of 79.01%, a recall of 91.00%, and a precision of 84.3%. This shows efficacy in identifying and reporting flood events with a minimal false alarm rate. Moreover, the system also offers real-time safety interventions by allowing users to track flood locations, evacuation routes, and nearby roads, making it even more effective.

M. Anbarasan and co-workers [102] proposed a flood detection system integrating IoT, Big Data (BD), and a Cascaded Deep Neural Network (CDNN) classifier, achieving remarkable disaster management capabilities by enabling timely and accurate decision-making. The system employs HDFS MapReduce for data cleaning and uses a rule-based approach to generate input features for classification. Performance evaluations demonstrated 93.23% accuracy with a dataset of 500 records, making the CDNN model outperform traditional DNN and ANN models across multiple metrics. This investigation highlights the potential of advanced deep learning and IoT integration in developing efficient flood detection frameworks.

Sandeep K. Sooda et al. [70] designed an integrated IoT-based smart flood monitoring and forecasting architecture that combines Big Data (BD) with High-Performance Computing. The framework determines optimal locations of IoT sensor installation by dividing geographic regions into hexagonal grid structures. Social network analysis was conducted to improve energy efficiency, whereas Singular Value Decomposition (SVD) was performed to reduce dimensionality. Flood risk was then divided into five levels by applying the K-Means clustering algorithm, and the intensity of flood was monitored using the Holt-Winter approach. The resulting system performed remarkably with fewer sensors.

3.4 Forest fire detection and response

Across forested regions, wireless sensor networks (WSNs) equipped with sensors are deployed to detect anomalies in heat, humidity, smoke, and gases (CO_2 and CO), which are indicative of early-stage wildfires [103]. These sensors also use GPS trackers, allowing emergency services to find the exact location. When sensor readings surpass critical safety figures, alerts are sent to the nearest monitoring station and emergency service organizations to initiate fire control and rescue operations [104]. In Addition, these networks also provide updates on local traffic congestion and adverse weather conditions, e.g., thunderstorms, aiding in occupants' evacuation planning and resource allocation [103, 105].

Ahshanul Haque and Hamdy Soliman [71] proposed an intelligent forest fire prediction system that deployed Wireless Sensor Networks (WSNs) supported with virtual sensors, improving data reliability and prediction accuracy. The designed system integrates machine learning models with real-time environmental data recorded via physical and virtual sensors, empowering more accurate forecasting of forest fire evolution. Virtual sensors are deployed to simulate missing, non-functional, or failed physical sensors. Experimental results demonstrate that incorporating virtual sensors significantly improves prediction performance, particularly achieving 95% accuracy in the "No fire" and "Smoke" scenarios, whereas 90% accuracy was reported in the "Fire about to Start" scenario. This investigation highlights the potential of integrating edge computing, machine learning, and sensor virtualization, building reliable, robust, scalable, and adaptive systems for early wildfire detection and monitoring.

Recent developments in IoT-enabled fire risk reduction have presented the remarkable potential of integrating heterogeneous sensor data with machine learning models to improve early fire detection in industrial environments.

The novel study by JAYAMEENA DESIKAN and co-workers [106] developed a multi-sensor, edge-based IoT architecture that employs RGB cameras, thermal sensors, gas sensors, smoke sensors, and flame sensors to record real-time environmental data. MobileNet CNN, EfficientNet, Random Forest, SVM, and Decision Tree are various ML models that were used to process sensor inputs. The application of Dempster-Shafer Theory (DST) to combine the outputs of separate classifiers, thus improving decision accuracy under uncertainty. The system outperforms standalone models, presenting a 98.2% accuracy rate, a 98.5% precision rate, and a 98.3% recall rate. This approach also offers real-time anomaly detection, facilitates feedback mechanisms, and model retraining for further enhancement. As edge computing reduces dependence on cloud infrastructure, this solution is particularly compatible for industrial environments with limited resources where prompt fire detection is indispensable.

In simple terms, IoT technologies significantly improve control across all phases of disaster management, including mitigation, preparedness, response, and recovery, from issuing early warnings to notifying authorities, from disseminating public alerts to initiating automatic safety protocols, from supporting search and rescue operations to recording disaster-related analytics for post-event analysis. IoT assists in identifying safe evacuation routes, monitoring flood levels in low-lying areas, and providing real-time information during emergencies. Consequently, IoT empowers organizations and communities to minimize losses and enhance disaster resilience effectively.

4 Generic IoT model for disaster management

The Internet of Things (IoT) has become a transformative technology in disaster management and early warning & response systems, offering real-time monitoring, early warnings, informed decision-making, and quick recovery efforts. Across all IoT-based disaster management architectures, the general flow of data and operations remains consistent across each stage of various disasters, from risk detection to post-disaster assessment [60, 69]. However, the characteristics of sensed or recorded parameters, actuation mechanisms, and response strategies vary markedly based on the specific application context, for example, earthquakes, floods, forest fires, land sliding, and nuclear radiation monitoring [1, 21]. ***Figure 7*** illustrates the general model for an IoT-enabled disaster management system, which applies to earthquakes, floods, forest fires, landslides, and nuclear radiation monitoring and management systems. There are four distinct layers, including the sensing/perception layer, network layer, data processing layer, and application layer.

These layers perform various functions, including event identification, data processing, robust and effective response, post-disaster analysis, and informed decision-making. IoT-driven Disaster management systems typically depend on Wireless Sensor Networks (WSNs) installed across critical locations, including forests, the sea, rivers, dams, nuclear facilities, bridges, coastal areas, and urban infrastructure [107–109]. In contrast to single-sensor setups, economical WSNs offer higher accuracy and reliability through real-time data recording, sensor redundancy, and spatial coverage of complex areas. Each installed sensor node in the network gathers data of environmental variables such as temperature, humidity, seismic activity, gas concentration, smoke, rainfall, or water levels, which is further transmitted to a central gateway node Via multi-hop routing techniques [110].

In addition to sensor nodes, the infrastructure comprises actuators that enable automated or semi-automated responses upon sensing threshold anomalies. These actuators are usually programmed to perform immediate responses such as opening emergency valves, activating sirens, or shutting down power systems, directing towards emergency evacuation paths and ways, or can be manually triggered using a control panel or through a mobile interface [64, 111–113].

Table 3. Comparative Analysis of Architectures, Data Sources, and Applications of IoT-based Disaster Management Systems

Article	IoT Architecture	Data Source	Environment	Parameters	Dataset Type	Application
[68]	IoT-based sensor	Multi-sensor data (temp, humidity, light, smoke, sound)	Forest field	Temp, humidity, light, smoke, sound	Real-time + historical	Fire detection
[103]	Multi-sensor edge	RGB, IR, gas, smoke, flame + historical fire data	Industrial fire risk	RGB, IR temp, gas conc., smoke, flame	Real-time + historical	Fire detection
[97]	Fog nodes, RPi	Sensors + Govt. data (Kerala)	Urban/semi-urban	Humidity, temp, rainfall, waterflow, elevation	Real-time + semi-synthetic	Flood monitoring
[98]	IoT + Android app	Water level	Rivers, dams, canals, lakes	Temp, water level, rainfall	Real-time + historical	Flood monitoring
[84]	IoT soil nodes	GSI	Underground	Soil moisture, shear strength, rain severity	Same	Landslide/earthquake
[99]	CDNN	Sensors + NOAA, NEXRAD	Urban dams	WF, WL, RS, humidity	Real-time + big data	Flood monitoring
[67]	IoT gateway	NOAA + flood/climate records	Multiple	Rainfall, WL, soil moisture, temp, humidity, etc.	Real-time + historical	Flood monitoring
[74]	UAV-based IoT	Local drones	Outdoor LOS	Frames/sec	Aerial images	Earthquake
[75]	IoT gateway	Predictions	Underground	Predictions	Local data	Earthquake
[76]	Feed processor	NOAA	Coastal	Location, depth, magnitude	Tsunami data	Earthquake
[92]	WSN	Sensors	Nuclear facility	Radiation, meteo, ops params	Radiation data	Nuclear monitoring
[93]	IoT sensors	Sensors	Surroundings	Radiation intensity	Radiation data	Radiation warning
[77]	IoT accel. nodes	Smartphones	Indoor NLOS	PGA, activity	Accel. data	Earthquake
[78]	Remote sensing	OSM, Wikimapia, Google	Indoor	Affected areas	GIS data	Earthquake
[79]	Tmote Sky	JMA, Hi-net	ID/OD	Location, magnitude	Seismic velocity	Earthquake
[80]	Accel. nodes	NIED	UG	PGA	Accel. data	Earthquake
[81]	MEMS	STEAD	Noisy env.	P-wave arrival	Waveform	Earthquake
[82]	Raspberry Pi	Local obs.	Mesh network	Local quake	Waveform	Earthquake
[83]	Accel. sensors	NIED, USGS	UG	PGA	Accel. data	Earthquake
[85]	MEMS	NIED	UG	Accel., SNR	Accel. data	Earthquake
[86]	SSN/SOSA	Local data	UW	Volcano-tectonic, blasts	Volcanic data	Earthquake
[87]	Arduino Cortex	MEMS accel. data	UG	Detection accuracy, latency	Accel. data	Earthquake
[88]	Seismometer	IRIS, NIED	UG	Quake data	GPS + weak motion	Earthquake
[89]	Smartphones	NIED, USGS	S-D env.	Quake data	Accel. data	Earthquake

4.1 Gateway node and event identification

The gateway node, serving as the edge device of a network, performs a critical role in disaster detection. It connects various installed sensors and devices to a central system for data collection, processing, and transmission. It collects real-time data from the sensor nodes either using a proactive routing or reactive polling. In the proactive routing, sensor nodes push data periodically, whereas in reactive polling, the gateway requests data on demand. This dual-mode operation offers flexibility in data acquisition, especially in mission-critical applications where real-time responsiveness is crucial [59, 114].

Once the recorded data is received, the gateways compare the readings against predefined safety threshold figures based on historical patterns and domain knowledge. If the collected figures violate (exceed or fall below) these thresholds, a disaster or pre-disaster event is declared. Safety threshold logic is often enhanced using machine learning models that are trained on historical disaster datasets to improve threshold-based anomaly detection. The communication between WSN and installed actuators is facilitated via short-range wireless communication technologies such as Wi-Fi, Zigbee, or Bluetooth, ensuring low latency and energy-efficient, robust operations [2]. On the other hand, long-range technologies, including LoRaWAN or NB-IoT are increasingly being adopted to extend connectivity in distant or inaccessible areas [2, 115–119].

4.2 Disaster response and actuation

Upon identifying a potential disaster event, the IoT-enabled system initiates a response protocol including real-time communication, resource allocation, and rescue operations. The response could be an automated actuation involving execution of Instant countermeasures without human intervention, such as activating sprinklers in fire-prone zones, releasing floodgates in river basins, shutting down gas pipelines in case of leakage, directing Vulnerable populations to safe routes or evacuation paths [20, 120].

These activities are governed by rule-based systems or AI algorithms embedded within the gateways. Another type of response involves human intervention, sending alerts to relevant authorities via SMS, email, mobile applications, or web dashboards. These emergency alerts often include geolocation, severity levels, and contextual metadata. The use of GSM/GPRS modules empowers communication even in distant areas with limited internet access. Advanced system architectures also integrate edge computing frameworks to diminish reliance on centralized cloud servers [121]. By processing data locally, these systems ensure faster response and enhanced resilience in network outages. GPS-enabled sensors monitor relief resources, whereas drones are used for aerial assessment, and wearable devices help to monitor responders and victims [122, 123].

4.3 Post-disaster analysis and decision making

In post-disaster analysis, recorded data is carefully examined to understand the disaster event impact, evaluate the efficiency of mitigation measures, and enhance future response strategies. Recorded data from the gateway nodes is kept in the cloud or on-premises servers for long-term analytics. Big Data platforms, predictive modeling, and visualization dashboards are advanced analytics tools employed to extract effective conclusions and informed decision-making [60, 124, 125]. These analytics help study patterns in disaster occurrence and propagation, efficacy of automated and manual interventions, optimization of resource allocation, and modification of risk prediction models for future events. These informed inferences not only advance post-disaster recovery planning but also contribute to defining proactive risk reduction strategies for the future [20].

4.4 Industrial IoT (IIoT) for high-risk environments

Industrial IoT (IIoT) employs the principles of IoT in high-risk environments, including nuclear power plants, oil refineries, and chemical industries. IIoT systems integrate advanced sensors, AI-driven models, and secure communication protocols to monitor risky environmental conditions and automate precautionary measures [126, 127]. For instance, in a nuclear facility, radioactive gas detectors continuously monitor air quality, Water level regulators prevent flooding in reactor chambers, employee-worn devices track location and critical signals, enabling rapid emergency response, and cloud-connected gateways relay real-time alerts to remote command centers [95, 128]. In critical setups, IIoT systems can activate autonomous preventive actions such as initiating cooling procedures or evacuating workers via automated alarm systems. Additionally, machine learning-based predictive maintenance models help detect equipment degradation before damage occurs, minimizing downtime and preventing cascading failures [127, 129–131].

5 Integration of big data and AI for disaster management

To further advance disaster management systems, IoT systems are being integrated with edge computing, machine learning & AI, digital twins, blockchain, and connectivity. Edge computing enables local processing and diminishes reliance on centralized cloud infrastructure, whereas Machine Learning & AI enhance anomaly detection, pattern recognition, and predictive modeling [132, 133]. Digital Twins provide virtual replicas of physical environments, enabling simulation-based training and situation planning [134]. Furthermore, blockchain confirms data integrity, auditability, and secure data privacy among all authorities, whereas 5G Connectivity offers ultra-low latency and high-bandwidth communication for instant coordination [124].

5.1 IoT and cloud integration to enhance the analytics layer in disaster management

In an IoT-based disaster management network, the cloud is integrated in the analytics layer, performing as a promising platform for storing, processing, and analyzing large volumes of real-time sensor data recorded from remote and disaster-prone environments. As stated, raw sensor data, including temperature, humidity, water levels, rainfall intensity, seismic activity, radiation intensity, or gas concentrations, is transmitted from the gateway node to the

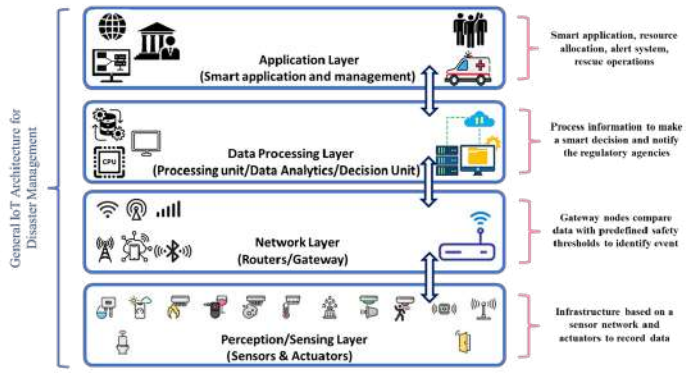

Figure 7. The general model for an IoT-enabled disaster management system

cloud through web services for long-term storage and insightful analysis for informed decision-making. The scalable cloud infrastructure facilitates the retention of massive historical datasets and the application of cutting-edge machine learning (ML) algorithms for predictive analytics, safety threshold monitoring, and understanding disaster patterns. These capabilities revolutionized future disaster preparedness, risk mitigation, and response strategies [135, 136].

A frequent issue faced in disaster management systems is their reliance on Wireless Sensor Networks (WSNs) installed in off-site and inaccessible locations, such as forests, seas, river basins, coastal areas, nuclear plants, and industrial facilities. These WSNs are usually battery-operated, which makes them extremely susceptible to energy depletion due to continuous computational and communication overheads. Excessive data transmission and processing significantly decrease the operational lifespan of these devices, resulting in potential network breakdowns, high inaccuracy rates, and in severe scenarios even the loss of critical early warning capabilities [136, 137]. Therefore, it's a key challenge to optimize energy consumption and maintain system performance to make WSN deployment sustainable.

Cloud integration offers a practical solution to these issues by offloading various computationally intensive tasks, including ML-model training, data collection, and complex analytics, to the cloud. This diminishes the burden on sensor nodes and prolongs their battery lifespan. Moreover, by introducing an edge computing layer together with the IoT architecture and the cloud, it remarkably enhances efficacy. Edge nodes, being intermediate processors, perform primary filtering, feature extraction, or data compression before transferring relevant data to the cloud [117, 138, 139].

5.2 Integration of IoT with various modern technologies for disaster management Applications

The rapid development of technology has substantially contributed to the development of new strategies to enhance disaster resilience and reduce associated hazards. Revolutionary advances in Information and Communication Technology (ICT) have shifted disaster prevention, mitigation, response, and recovery efforts. The digital transformation driven by IoT, together with Big Data analytics and Artificial Intelligence (AI), has revolutionized all four phases of disaster management, including prevention, preparedness, response, and recovery. Furthermore, disaster management networks are enhanced through the integration of a variety of supplementary technologies, such as 5G networks, blockchain, social media networks, crowdsourcing, and the deployment of UAVs and robots [138].

5.2.1 Big data

Crisis analytics encompasses utilizing data analysis methods to understand, prepare for, respond to, and recover from crises. It involves various stages, from detecting potential threats to assessing the efficacy of crisis management strategies. Crisis analytics involves processing and interpreting large-scale data of disaster events. By thoroughly examining the large amounts of data recorded via sensors and user activity, emergency management organizations enhance their situational awareness and make well-informed decisions during disaster events. In particular, analyzing social media posts and stories helps determine trends, identify misinformation, and comprehend the nature and origin of shared information during emergencies and crises [140, 141]. Correspondingly, mobile phone data has been demonstrated to be useful in tracking vulnerable populations during hazardous events such as floods, earthquakes, landslides, etc, offering real-time situational awareness [142, 143]. These analytical methods can also be applied to data obtained from IoT-integrated technologies, including drones, robots, and sensors, which are crucial for monitoring environmental variables in disaster-prone locations [125].

5.2.2 Artificial intelligence

Remarkable advancements in Artificial Intelligence (AI) and machine learning have unlocked new frontiers for effective classification, anomaly detection, and predictive modeling in disaster events. These technologies are promising platforms for forecasting natural risks such as earthquakes, floods, forest fires, and expediting post-disaster response and recovery activities [138].

Machine learning algorithms are effectively employed to automate crucial tasks such as satellite image examination, allowing instant map generation by categorizing and eliminating non-essential features, i.e., roads and buildings in aerial images has proposed an AI-integrated system using cost-effective solutions and open-source tools such as PHP, MySQL, and cloud-based web interfaces to improve weather prediction accuracy within Tanzania's meteorological agency [144]. This approach proves that effective AI deployment does not always entail expensive infrastructure [145].

Additionally, AI performs large-scale data processing, manages high volumes of emergency calls, facilitates social media sentiment analysis, and conducts predictive analytics using historical data to anticipate disaster outcomes. Optima Protect is a tool that utilizes processed data from emergency systems to optimize ambulance routing during crises [146–148]. Thus, when integrated with real-time dashboards, these systems enable emergency departments to deliver timely and coordinated responses [149].

Author Contributions

Muhammad Talal: Conceptualization, Methodology, Authored the initial manuscript draft. **Naghma Ajmal**: Data curation, Software. **Shahrukh**: Visualization, Investigation. **Abdul Rehman**:Critical Review,Writing Assistance. **Muhammad Mamoon**: Validation, Reviewing and Editing.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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