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A Review on Low-Latency AI-Based Architectures for Real-Time Disaster Prediction Systems

Nidhi Raghav1
Dr Manish Ranjan Pandey2
Research Scholar, Department of Computer Science and Applications, IFTM University, Moradabad, India1
Associate Professor, Department of Computer Applications, IFTM University, Moradabad, India2
nidhi.mbd002@gmail.com1
manish_pandey@iftmuniversity.ac.in2

Abstract—Natural disasters pose persistent threats to human life, infrastructure, economic stability, and public safety. Conventional disaster prediction systems often depend on centralized cloud infrastructures, which can introduce communication overhead and processing delays that limit their effectiveness in time-critical situations. Recent advances in Artificial Intelligence (AI), Internet of Things (IoT), and edge computing have created opportunities to develop more responsive disaster prediction systems by enabling data collection and processing closer to the source. This study presents a structured review of AI-based disaster prediction approaches, with particular emphasis on low-latency computing architectures for real-time applications. Published studies are categorized according to disaster type, AI techniques, sensing technologies, and deployment architectures, including cloud, fog, edge, and hybrid computing environments. The review identifies several important research gaps, including limited real-world deployment, inconsistent evaluation of latency and real-time performance, computational and resource constraints, and insufficient integration with emerging communication technologies. Based on these findings, the study proposes a conceptual low-latency architecture integrating IoT-based sensing, edge intelligence, fog coordination, and cloud-assisted learning to support timely disaster prediction and response. The study further highlights future research directions involving lightweight AI models, federated learning, adaptive resource management, and advanced communication technologies. Overall, the findings provide a foundation for developing scalable, efficient, and latency-aware AI-based frameworks for real-time disaster prediction.

Index Terms—Artificial Intelligence, Disaster Prediction, Edge Computing, IoT, Low Latency, Real-Time Systems

I. INTRODUCTION

Natural disasters, including floods, earthquakes, landslides, wildfires, and extreme weather events, can cause substantial damage to human life, infrastructure, and the environment. Effective disaster management therefore depends not only on the ability to predict hazardous events but also on the ability to generate and communicate predictions within a useful time frame. In time-critical situations, a prediction that arrives too late may have limited value for emergency response. This makes timeliness and low latency important considerations alongside prediction accuracy in the design of intelligent disaster prediction systems.

Traditional disaster prediction systems have largely relied on centralized computing and cloud-based infrastructures for data storage, analysis, and model execution. Cloud platforms provide considerable computational and storage capabilities; however, transferring continuously generated environmental data from remote sensing devices to centralized servers can introduce communication overhead and dependence on network connectivity. These limitations become particularly important in emergency situations, where rapid processing and timely decision-making are essential. The emergence of edge and fog computing has consequently created opportunities to move selected computational tasks closer to data sources and reduce dependence on centralized processing [1], [2], [3].

At the same time, advances in Artificial Intelligence (AI) have transformed the way disaster-related data can be analyzed. Machine learning and deep learning techniques can identify complex patterns in environmental observations and support prediction across different disaster scenarios. AI has consequently been increasingly investigated for disaster prediction, monitoring, response, and recovery applications [4]. However, improvements in predictive capability do not necessarily guarantee timely system responses. Computational complexity, data-transfer requirements, and the location at which AI models are executed can significantly influence the overall response time of a disaster prediction system.

The development of the Internet of Things (IoT) has further expanded the availability of real-time environmental data. Sensors, monitoring stations, cameras, drones, and other connected devices can continuously collect information such as rainfall, temperature, humidity, water level, wind speed, and seismic activity. Combining these data sources with AI models can support continuous environmental monitoring and early identification of potentially hazardous conditions [5], [6]. Nevertheless, processing large volumes of heterogeneous data through a centralized infrastructure can create additional communication and computational overhead.

To address these limitations, edge intelligence and distributed computing have received increasing attention. Edge computing enables selected processing and AI inference tasks to be performed closer to the location where data are generated, potentially reducing communication requirements and improving responsiveness [1], [7]. Fog computing further extends this approach by providing an intermediate computing layer between edge devices and centralized cloud infrastructure, supporting distributed resource management and processing [3], [8]. Research on edge intelligence has also emphasized the architectural challenges associated with deploying AI capabilities across distributed and resource-constrained environments [9].

Despite these developments, the existing literature remains fragmented across AI-based prediction, IoT sensing, edge/fog computing, and resource-efficient AI. Many disaster prediction studies primarily emphasize prediction accuracy, whereas edge-computing studies tend to focus on latency, resource

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management, and distributed processing. Similarly, research on Edge AI addresses efficient inference near data sources but is not always specifically designed around the requirements of disaster prediction and early-warning systems. Consequently, relatively limited attention has been given to architectures that jointly consider prediction accuracy, latency, computational complexity, communication overhead, energy consumption, and reliability.

Another important limitation is the lack of consistent latency-oriented evaluation across existing systems. Different studies employ different datasets, computing platforms, network configurations, and performance measures, making it difficult to directly compare their real-time capabilities. Communication delay, processing time, inference time, and end-to-end response time should therefore be considered when evaluating whether an AI-based disaster prediction system is genuinely suitable for time-critical applications. Edge AI and communication-efficient computing research provides a foundation for such latency-aware analysis [9], [10].

Furthermore, the literature indicates challenges related to resource constraints and practical deployment. High-capacity AI models can provide strong predictive performance but may require substantial computational and memory resources, limiting their suitability for lightweight edge devices. Conversely, highly lightweight models may reduce computational requirements but can involve trade-offs in predictive capability. This creates a need for architectures that can dynamically balance model performance, computational requirements, communication overhead, and response latency according to the characteristics of the deployment environment.

Against this background, this study presents a systematic review of AI-based disaster prediction systems with particular emphasis on low-latency architectures. Existing research is examined according to disaster applications, AI techniques, sensing technologies, and deployment architectures. The study further compares cloud, edge, fog, and hybrid computing approaches from the perspective of real-time processing, latency, scalability, and computational efficiency. The review identifies key limitations and research gaps and uses these findings to formulate requirements for a more integrated disaster prediction architecture.

Based on the identified gaps, a conceptual low-latency AI-based architecture is proposed that integrates IoT-enabled environmental sensing, edge processing, fog coordination, cloud intelligence, and an alert and response mechanism. The architecture follows a hierarchical processing strategy in which time-sensitive operations can be performed closer to the data source, while computationally intensive tasks can be selectively handled by fog or cloud resources. This design is intended to provide a foundation for balancing prediction performance with latency, computational efficiency, communication overhead, and scalability.

The major contribution of this study is therefore not the development of another standalone prediction model, but the integration of AI-based prediction with a latency-aware distributed computing architecture. By considering prediction accuracy and system-level factors together, the study provides a structured research direction for developing more responsive and practically deployable disaster prediction and early-warning systems.

II. KEY CONTRIBUTIONS OF THE STUDY

This review makes several contributions to the understanding of AI-based, low-latency disaster prediction systems. First, it brings together research on the application of artificial intelligence to disaster prediction and management, covering different hazard scenarios and highlighting the progression from conventional prediction approaches toward AI-enabled and distributed systems [4]. Second, the reviewed literature is organized according to disaster applications, AI techniques, sensing technologies, and deployment architectures, providing a structured view of how machine learning, deep learning, IoT, edge computing, fog computing, and cloud infrastructure are being used in this domain [9], [11].

A further contribution of the study is its examination of low-latency computing architectures for time-sensitive disaster applications. The review considers the role of mobile edge computing, fog computing, and edge intelligence in moving computational tasks closer to data sources and reducing unnecessary communication with centralized infrastructure [1], [3], [7]. It also examines the integration of IoT-enabled sensing with AI-based prediction, emphasizing the importance of continuously generated environmental data for applications such as flood forecasting and disaster monitoring [5], [6].

In addition, the study identifies important research gaps and practical challenges in the existing literature. These include computational and resource constraints at the edge, limited real-world deployment, communication overhead, heterogeneous infrastructure, and the absence of consistent approaches for evaluating latency and real-time performance [8], [10]. The review also highlights the need to consider system-level factors such as response time, computational requirements, scalability, and reliability alongside prediction accuracy when assessing disaster prediction architectures.

Finally, based on the findings of the review, the study proposes a conceptual low-latency AI-based architecture that integrates IoT data collection, edge processing, fog coordination, cloud intelligence, and an alert and response mechanism. The proposed framework provides a foundation for distributing computational tasks according to their urgency and resource requirements, while retaining cloud resources for large-scale storage, model training, and historical analysis. The study concludes by outlining future research directions involving lightweight AI models, distributed and federated learning, adaptive resource management, advanced communication technologies, multi-disaster prediction, and real-world evaluation. Overall, these contributions provide a structured basis for developing more responsive, scalable, and practically deployable AI-based disaster prediction systems.

III. METHODOLOGY

This study follows a systematic review-based methodology to analyze and evaluate existing AI-based disaster prediction systems with a focus on low-latency architectures. The methodology includes literature collection, study classification, comparative analysis, and identification of research gaps for developing an efficient disaster prediction framework.

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A. Literature Collection

Relevant research papers were collected from reputed databases such as:

- IEEE Xplore
- ScienceDirect
- SpringerLink
- Google Scholar

The selected studies mainly focus on AI, IoT, cloud computing, fog computing, and edge-based disaster prediction systems.

B. Study Selection Criteria

The research papers were selected based on the following criteria:

Papers published between 2017 and 2025

Studies related to AI-based disaster prediction

Research focusing on low-latency or real-time systems

Articles involving cloud, fog, edge, or hybrid architectures

Irrelevant and duplicate studies were excluded from the review.

C. Classification of Studies

The selected studies were categorized based on:

Type of disaster

AI techniques used

Computing architecture

Performance parameters such as latency and accuracy

This classification helped in identifying trends, strengths, and limitations in existing systems.

D. Performance Evaluation

The collected studies were compared using important performance metrics including:

Latency

Prediction accuracy

Response time

Scalability

Energy efficiency

The overall latency of the system is represented as:

L = T (data) + T (processing) + T (communication)

where:

T (data) = Data transmission delay

T (processing) = Processing time

T (communication)= Communication delay

E. Comparative Analysis and Gap Identification

A comparative analysis of cloud, fog, edge, and hybrid architectures was performed to evaluate their effectiveness in real-time disaster prediction. Based on this analysis, major research gaps and limitations in existing systems were identified.

F. Proposed Framework Development

Finally, a low-latency AI-based architecture integrating IoT sensors, edge processing, fog coordination, and cloud intelligence was proposed to improve real-time disaster prediction and response capabilities.

STEPS WE FOLLOWED TO DEVELOP THE ARCHITECTURE

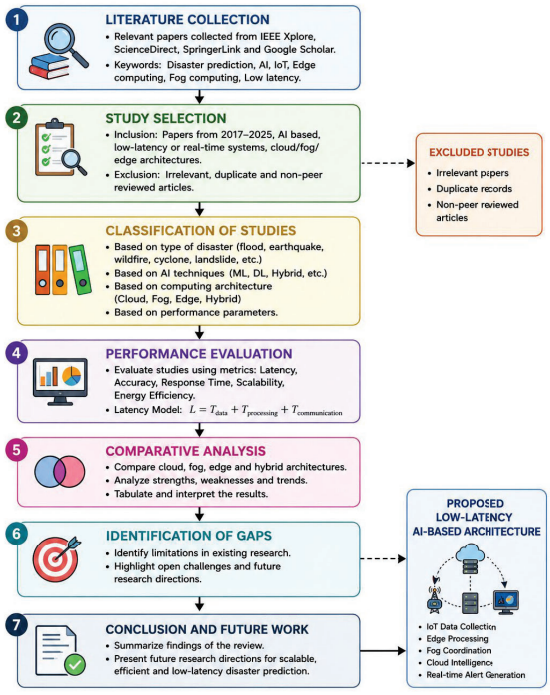


Fig. 2. Methodology Workflow of the Proposed Study

Fig.1. Methodology workflow of the Proposed Study.

IV. EXISTING STUDIES

Disaster prediction has traditionally depended on statistical forecasting, historical records, and centralized computing systems. These approaches have provided useful support for understanding disaster patterns and estimating future risks. However, disaster situations often change rapidly, and decisions may need to be made within seconds or minutes. In such circumstances, depending entirely on centralized processing can create delays because data generated by monitoring devices must first travel to a remote server before it can be analysed. This limitation has encouraged researchers to explore more intelligent and distributed approaches for disaster prediction and response.

The development of artificial intelligence (AI) has brought significant changes to disaster management research. Machine learning and deep learning methods are increasingly being used to identify patterns in complex environmental data and improve prediction capabilities. [4] reviewed the use of AI across different stages of disaster management and showed that intelligent techniques can support prediction, response, and recovery activities. Similarly, [16] developed a hybrid model for predicting damage to power transmission lines during typhoon events. Their study demonstrates how combining predictive techniques can provide useful support for disaster warning and infrastructure protection. More recent research has also examined the application of deep learning and trustworthy AI to natural disaster management, indicating the growing importance of intelligent methods in this field [12], [13].

At the same time, the Internet of Things (IoT) has made it possible to collect environmental information continuously through distributed sensing devices. This capability is particularly useful in disaster-prone environments, where

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parameters such as rainfall, water level, temperature, and other environmental conditions can change quickly. [6] demonstrated the use of IoT and edge intelligence for predicting flooding processes in a smart-city environment. Their work highlights the value of processing information closer to the point at which it is generated. Similarly, [5] examined the use of AI, machine learning, IoT, cloud computing, and other emerging technologies for flash-flood prediction. These studies suggest that effective disaster prediction increasingly depends not only on the prediction algorithm itself but also on how quickly and efficiently data can be collected and processed.

The increasing volume of real-time sensor data has also exposed a major limitation of conventional cloud-based architectures: latency. In a centralized model, sensor data generally needs to be transmitted to a remote cloud platform for computation. Network congestion, transmission distance, and server-side processing can increase the time required to generate a prediction. Edge computing provides an alternative by placing computational resources closer to data sources. [2] described edge computing as an approach that brings computation and services closer to users and data-producing devices. [1] examined mobile edge computing from the communication perspective, while Mach and Becvar (2017) investigated computation offloading strategies for edge environments. [14] further discussed multi-access edge computing as an architecture capable of bringing computing resources closer to network users. These developments are particularly relevant to disaster-management applications in which delayed predictions may reduce the usefulness of an early warning.

Fog computing provides another distributed layer between edge devices and centralized cloud infrastructure. [3] reviewed fog computing and related edge paradigms and discussed their role in supporting distributed applications. In addition to reducing the dependence on remote cloud processing, such architectures can distribute computational tasks according to the capabilities and requirements of individual devices. However, effective resource allocation remains an important concern because edge and fog environments normally contain devices with different processing capacities, energy limitations, and communication conditions [8].

The combination of AI and edge computing has subsequently led to the development of edge intelligence, where AI-related processing is performed closer to the location where data are produced. [10] examined communication-efficient edge AI and highlighted the importance of reducing communication requirements in distributed AI systems. Chen and Ran (2019) discussed the challenges involved in deploying deep learning models within edge environments, particularly where computational resources are limited. [20] investigated edge-based acceleration of deep neural network inference, demonstrating the potential of edge AI for applications requiring faster processing. [9] also examined edge intelligence architectures and identified challenges related to computation, communication, resource management, and AI deployment. Together, these studies establish the technical foundation for moving intelligent processing from centralized cloud platforms toward distributed edge environments.

Another important direction is the use of distributed learning techniques. [19] presented an in-edge AI approach based on federated learning, showing how intelligence can be distributed across edge environments without relying entirely on centralized processing. Such approaches can be useful in disaster-monitoring scenarios where large numbers of geographically distributed devices generate data continuously. At the same time, resource management remains critical because disaster-monitoring devices may operate under limited computational and energy budgets. Efficient management of these resources is therefore necessary when AI models are deployed at the edge [8].

Recent research indicates that the combination of AI, IoT, and edge technologies is also becoming increasingly relevant to climate resilience and smart-city applications. [5] highlighted the convergence of AI, machine learning, IoT, cloud computing, and related technologies in flash-flood prediction. [26] discussed edge AI in smart-city environments and identified both opportunities and challenges associated with deploying intelligence closer to data sources. From a broader climate perspective, [22] examined how AI can contribute to improving resilience to climate change. More recently, [18] explored the use of edge computing for urban flood disaster prevention, control, and rescue. These studies reflect a broader movement toward intelligent and distributed infrastructures capable of supporting faster responses to environmental and disaster-related events.

Despite the progress reported in existing studies, several challenges remain unresolved. A considerable portion of the existing research focuses on a particular disaster type, such as floods or typhoons, making it difficult to determine how effectively the proposed approaches can be generalized to different disaster scenarios. In addition, high prediction accuracy does not necessarily imply that a system is suitable for real-time deployment. A model may produce accurate predictions while still requiring considerable processing time or communication overhead. Therefore, end-to-end latency, computational cost, energy consumption, and response time need to be considered alongside prediction accuracy. Differences in datasets, hardware configurations, communication networks, and evaluation measures also make direct comparison between existing systems difficult.

Another challenge concerns practical deployment. AI models designed in laboratory environments may not perform in the same manner when deployed on resource-constrained edge devices in real disaster environments. Variations in sensor quality, network availability, processing capacity, and energy resources can affect system performance. Consequently, there is a need for architectures that consider these practical constraints while maintaining reliable and timely predictions.

Overall, the literature shows a gradual transition from centralized disaster prediction systems toward AI-enabled, IoT-supported, and edge-based architectures. AI provides the capability to identify complex patterns in disaster-related data, IoT enables continuous data collection, and edge and fog computing provide opportunities to process information closer to its source. However, the existing literature still leaves a gap in the development of a scalable and practical architecture that jointly considers prediction accuracy, low latency, energy

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efficiency, computational constraints, and real-time deployment. Addressing this gap can contribute to the development of more responsive disaster prediction systems capable of supporting timely decision-making during critical situations.

V. RESEARCH GAPS

Most existing studies focus mainly on prediction accuracy rather than real-time latency and response time.

Deep learning models often require high computational resources, making real-time deployment difficult on edge devices.

Many disaster prediction systems still rely heavily on centralized cloud computing, which increases communication delay.

Standardized metrics for evaluating latency and real-time performance are still lacking.

Most existing frameworks are designed for a single type of disaster and lack multi-disaster prediction capability.

Limited real-world implementation and testing reduce the practical applicability of many proposed systems.

Issues related to data quality, interoperability, and energy consumption are still insufficiently addressed.

Emerging technologies such as federated learning, 5G, and lightweight AI models remain underexplored in disaster prediction systems.

Many AI models operate as black-box systems, reducing explainability and user trust in critical situations.

There is still a need for scalable, low-latency, and adaptive architectures for efficient real-time disaster management.

TABLE I. Comparative Analysis of Existing Studies

Ref.	Author(s) & Year	Technique	Application	Key Contribution	Limitation	Low-Latency Relevance
[4]	Sun et al. (2020)	AI/ML/DL	Disaster management	Reviewed AI applications in disaster management	No specific architecture	Indirect
[16]	Hou et al. (2020)	Hybrid prediction	Typhoon damage	Improved damage-warning prediction	Disaster-specific	Limited
[6]	Chen et al. (2022)	IoT + Edge AI	Flood prediction	Supports real-time flood prediction	Flood-focused	High
[25]	Mishra et al. (2022)	Machine learning	Disaster management	ML-based disaster prediction	Limited validation	Limited
[17]	Aboualola et al. (2023)	Edge technologies	Disaster management	Reviewed edge-based disaster solutions	No specific implementation	High
[5]	Al-Rawas et al. (2024)	AI + IoT + Cloud	Flood prediction	Reviewed integrated flood-prediction technologies	Cloud dependency	Moderate
[12]	Akhyar et al. (2024)	Deep learning	Natural disasters	Reviewed deep-AI applications	Review-based	Indirect
[13]	Albahri et al. (2024)	Trustworthy AI	Natural disasters	Examined reliable AI applications	Limited latency focus	Indirect
[1]	Mao et al. (2017)	Mobile Edge Computing	Real-time applications	Reduces communication delay	Not disaster-specific	High
[7]	Mach & Becvar (2017)	Computation offloading	Edge computing	Improves workload distribution	General framework	High
[14]	Taleb et al. (2017)	MEC	5G/Edge systems	Supports low-latency services	Not disaster-specific	High
[15]	Chiang & Zhang (2016)	Fog + IoT	IoT systems	Enables distributed processing	No disaster-specific evaluation	High
[3]	Yousefpour et al. (2019)	Fog computing	Distributed systems	Provides fog/edge architecture	Security/resource challenges	High
[8]	Hong & Varghese (2019)	Resource management	Fog/Edge	Improves resource utilization	General application	High
[11]	Chen & Ran (2019)	DL + Edge	Intelligent systems	Examined DL deployment at edge	High computational demand	High
[10]	Shi et al. (2020)	Communication-efficient Edge AI	Edge systems	Reduces communication overhead	Not disaster-specific	High
[9]	Xu et al. (2020)	Edge intelligence	IoT/Edge	Discussed edge-AI architectures	Generalized study	High
[19]	Wang et al. (2019)	Federated learning	Edge AI	Improves distributed AI efficiency	Deployment complexity	High
[20]	Li et al. (2020)	DNN acceleration	Edge AI	Accelerates edge inference	Hardware dependency	High
[2]	Satyanarayanan (2017)	Edge computing	Distributed systems	Moves computation closer to data	Conceptual study	High
[23]	Elbamby et al. (2018)	Low-latency computing	Ultra-low-latency systems	Addresses latency and reliability	Not disaster-specific	High
[21]	Wang et al. (2017)	Mobile Edge Networks	Edge computing	Integrates computing and communication	General framework	High
[26]	Velaga et al. (2025)	Edge AI	Smart cities	Examined edge-AI opportunities	Limited disaster focus	High
[22]	Ayadi et al. (2025)	AI	Climate resilience	Examined AI for climate resilience	Limited latency focus	Indirect
[18]	Li et al. (2026)	Edge computing	Urban flood management	Applied edge computing to flood management	Infrastructure requirements	High

VI. INTERPRETATION AND ANALYSIS

The comparison presented in Table 1 shows a gradual shift in disaster prediction research from conventional and centralized approaches toward AI-enabled and distributed computing architectures. Earlier research established the importance of computational and communication resources for processing disaster-related information, while subsequent studies increasingly explored edge and fog environments for applications requiring timely responses. Edge computing provides an alternative to relying entirely on remote cloud infrastructure by bringing computation closer to data sources and users [2]. This transition is particularly relevant to disaster-management applications, where timely processing can support faster warning and decision-making.

The literature also demonstrates the growing use of artificial intelligence for disaster prediction and management. Machine learning, deep learning, and hybrid prediction techniques have been explored to analyze complex disaster-related data and improve prediction capabilities. [4] provided a comprehensive review of AI applications across disaster mitigation, preparedness, response, and recovery. Similarly, [16] investigated a hybrid prediction model for damage warning during typhoon disasters. More recent studies have expanded the application of deep learning and trustworthy AI to natural-disaster management [12], [13]. These studies demonstrate the increasing role of AI in disaster-related applications, although review-oriented research does not necessarily provide a unified architecture for real-time deployment.

IoT has further strengthened disaster-monitoring capabilities by enabling continuous collection of environmental information through distributed sensing devices. [6] combined IoT with edge intelligence for flooding-process prediction in a smart-city environment. Their study demonstrates the potential of processing information closer to its source for flood prediction. Similarly, [5] examined the integration of AI, machine learning, IoT, cloud computing, and other emerging technologies for flash-flood prediction. These studies indicate that real-time sensing can provide valuable inputs to prediction models; however, the collected information must also be processed sufficiently quickly to support timely decisions.

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From an architectural perspective, the literature shows increasing interest in edge and fog computing for latency-sensitive applications. Mobile edge computing brings computational resources closer to users and can reduce dependence on distant processing infrastructure [1]. Computation offloading provides mechanisms for distributing workloads between end devices and edge resources [7], while multi-access edge computing supports computing services closer to network users [14]. Fog computing similarly enables distributed processing between IoT devices, edge resources, and cloud infrastructure [3], [15]. Although these studies are not specifically focused on disaster prediction, they provide an important technical foundation for systems in which rapid processing is required.

The integration of AI with edge computing has further increased the potential for real-time intelligent applications. [10] examined communication-efficient edge AI and discussed techniques for reducing communication overhead during AI training and inference. [9] discussed architectures, challenges, and applications associated with edge intelligence, while Chen and Ran (2019) examined the challenges of deploying deep-learning models in edge environments. [20] investigated the acceleration of deep neural-network inference through edge computing, highlighting the potential of edge-based processing for computationally demanding AI applications.

Resource management is another important issue identified from the reviewed studies. Edge and fog environments generally contain heterogeneous devices with different computational, storage, communication, and energy capabilities. Hong and Varghese (2019) examined resource-management requirements in fog and edge environments, emphasizing the importance of efficient allocation of available resources. [21] also discussed the convergence of computing, caching, and communication in mobile edge networks. These findings are relevant to disaster prediction because practical real-time systems may need to process large amounts of sensor data while operating under constrained edge resources.

Recent research further demonstrates the growing relevance of edge technologies to disaster and smart-city applications. [17] reviewed edge technologies for disaster management, while [26] examined the foundations and challenges of edge AI in smart-city environments. [5] focused on emerging technologies for flash-flood prediction, whereas [18] investigated edge computing for urban flood disaster prevention, control, and rescue. At a broader level, [22] examined the contribution of AI to climate resilience. Together, these studies indicate a growing movement toward combining AI with distributed computing technologies for more responsive disaster-management systems.

Despite these developments, Table 1 highlights several research gaps. First, many existing studies focus on a particular disaster type, such as floods or typhoons, which may restrict their applicability to multiple disaster scenarios. Second, several studies emphasize prediction capability or architectural concepts without providing consistent evaluation of end-to-end latency under realistic deployment conditions. Third, practical edge-based AI systems must address computational limitations, communication overhead, energy consumption, and deployment complexity. These factors can directly influence the ability of a system to generate timely predictions.

Another limitation is the absence of a consistent basis for comparing latency and performance across different studies. Variations in datasets, hardware configurations, communication environments, AI models, and evaluation metrics make direct comparison difficult. Therefore, prediction accuracy alone is not sufficient to determine whether a disaster prediction system is suitable for real-time deployment. A practical system should consider prediction performance together with response time, communication overhead, computational requirements, and resource efficiency.

Overall, the reviewed literature demonstrates a clear progression from AI-based prediction and IoT-enabled sensing toward edge-enabled intelligent disaster-management systems. Existing studies provide important foundations in AI-based prediction, real-time sensing, edge and fog computing, communication-efficient AI, and resource management. However, there remains a need for an integrated and scalable architecture that jointly considers low latency, prediction performance, resource efficiency, and real-time deployment across multiple disaster scenarios. This gap motivates the development of a low-latency AI-based architecture capable of processing disaster-related data closer to its source and supporting timely prediction and decision-making.

VI-A. PERFORMANCE METRICS FOR LOW-LATENCY DISASTER SYSTEMS

Modern disaster prediction systems require standardized evaluation metrics to ensure fair comparison across different architectures. The key performance indicators used in this study are defined as follows:

- Latency (L): Total delay between data acquisition and prediction output
- Response Time (RT): Time taken to generate actionable alerts
- Throughput (T): Number of processed events per second
- Scalability (S): Ability to handle increasing data loads
- Energy Consumption (E): Computational energy required per prediction

The total system latency is expressed as:

$$L = T(\text{data transmission}) + T(\text{processing}) + T(\text{communication})$$

$$\text{Accuracy} = \text{Correct Predictions} \times 100 / \text{Total Predictions}$$

This formulation enables a structured evaluation of latency across cloud, fog, and edge-based architectures.

Table 2: Latency Comparison Across Architectures

Architecture	Average Latency	Processing Location	Energy Usage	Suitability
Cloud	High	Centralized	High	Batch Processing
Fog	Medium	Distributed	Moderate	Near Real-Time
Edge	Low	Local Devices	Low	Real-Time Systems
Hybrid	Medium-Low	Mixed	Optimized	Balanced Systems

VI-B. TRADE-OFF ANALYSIS: ACCURACY VS LATENCY

A key challenge in AI-based disaster prediction systems is balancing prediction accuracy with system responsiveness.

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Deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks provide high prediction accuracy due to their ability to capture complex spatial and temporal patterns. However, these models require significant computational resources, resulting in increased latency.

In contrast, lightweight machine learning models deployed at the edge offer faster inference but may compromise prediction accuracy. Hybrid architectures that combine edge-based inference with cloud-assisted training provide an effective trade-off between performance and latency.

This trade-off highlights the need for adaptive systems that dynamically balance accuracy and response time based on application requirements.

VII. LIMITATIONS IN EXISTING AI-BASED MODELS

Although recent studies have demonstrated considerable progress in applying artificial intelligence (AI), the Internet of Things (IoT), and edge computing to disaster prediction, several challenges still need to be addressed before these technologies can consistently support low-latency, real-time applications.

One of the major challenges is the dependence on centralized computing and cloud-based infrastructure. When large volumes of data collected from distributed sensors are transmitted to remote servers for processing, communication and processing delays can affect the timeliness of disaster-related decisions. Edge and fog computing have therefore gained attention as alternatives that bring computational resources closer to data sources and users [2], [3], [15]. However, integrating these distributed resources into a reliable disaster prediction architecture remains challenging.

Another important limitation is the computational complexity of AI models. Deep-learning models can require substantial computational power, memory, and energy, which can make their deployment difficult on resource-constrained edge devices. Chen and Ran (2019) discussed the challenges associated with deploying deep-learning models in edge environments, while [20] investigated approaches for accelerating deep neural-network inference through edge computing. These studies indicate that achieving fast inference requires an appropriate balance between model complexity and available edge resources.

The reviewed literature also indicates a limited ability to generalize across different disaster scenarios. Several studies focus on specific hazards, such as typhoon-related damage or flood prediction [6], [16]. Although such specialized models can be effective for their intended applications, their applicability to other disaster types, geographical conditions, and environmental settings may be limited. Developing adaptable architectures that can support multiple disaster scenarios therefore remains an important research requirement.

Real-world deployment and scalability represent another significant challenge. Studies examining edge technologies for disaster management have identified several practical issues associated with deployment, including heterogeneous devices, infrastructure requirements, connectivity, and resource management [8], [17]. Recent work on edge computing for urban flood disaster management further demonstrates the potential of distributed processing while highlighting the practical requirements associated with deploying such systems in real environments [18].

Another important research gap concerns the evaluation of latency. Edge computing is intended to reduce communication and processing delays by moving computation closer to data sources; however, studies often employ different hardware configurations, datasets, network conditions, and performance measures [1], [7], [10]. As a result, direct comparison of latency across different disaster prediction architectures remains difficult. A consistent evaluation framework incorporating parameters such as communication delay, processing time, inference time, and end-to-end response time would provide a more meaningful assessment of real-time performance.

Data quality and reliability are also important considerations in IoT-enabled disaster prediction systems. Continuous data collection from distributed sensing devices can introduce variations in data quality and availability. The integration of AI, IoT, and other emerging technologies for flood prediction emphasizes the importance of reliable and timely data for effective forecasting [5]. Therefore, practical disaster prediction architectures should incorporate appropriate data preprocessing, validation, and handling mechanisms before information is provided to AI models.

Security and privacy present additional challenges when AI and data processing are distributed across edge and IoT environments. Fog and edge computing research has identified security, resource management, and system heterogeneity as important issues that must be considered during deployment [3], [8]. Federated learning provides a potential approach for distributed AI by allowing participating devices to contribute to model training without requiring all training data to be transferred to a central location [19]. Nevertheless, the coordination and communication requirements of distributed learning introduce additional implementation challenges.

The integration of advanced communication technologies and distributed AI also remains an area requiring further investigation. Multi-access edge computing provides a foundation for bringing computational services closer to network users and supporting latency-sensitive applications [14]. Communication-efficient edge AI and federated learning further provide mechanisms for reducing communication requirements and enabling distributed intelligence [10], [19]. However, integrating these technologies into a unified disaster prediction framework while simultaneously addressing latency, computational limitations, reliability, security, and scalability remains challenging.

Overall, the existing literature provides strong foundations for AI-based prediction, IoT-enabled sensing, and edge-based processing. However, the studies reviewed indicate a need for a more integrated, scalable, adaptive, and low-latency architecture capable of supporting real-time disaster prediction across different scenarios. In particular, there is a need to jointly consider AI prediction performance, edge-based processing, communication efficiency, computational constraints, and end-to-end response time. Addressing these challenges provides the motivation for developing the proposed low-latency AI-based architecture for real-time disaster prediction.

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VIII. PROPOSED ARCHITECTURE

Based on the limitations identified in previous studies, this research proposes a conceptual architecture for low-latency, real-time disaster prediction. The proposed architecture combines IoT-based sensing with edge and fog computing, AI-based prediction, and cloud infrastructure. The primary objective is to process time-sensitive information closer to its source while retaining the computational and storage capabilities of cloud systems. This distributed approach is intended to reduce unnecessary data transmission, improve responsiveness, and support timely decision-making during disaster situations [1], [2], [3].

The proposed architecture is organized into five interconnected layers, as described below.

1. Data Collection Layer

The Data Collection Layer forms the foundation of the proposed architecture. It consists of IoT sensors and other data-generating devices, including weather stations, drones, surveillance cameras, satellite systems, and mobile devices. These sources can continuously provide information such as rainfall, temperature, humidity, wind speed, water level, and seismic activity, depending on the type of disaster being monitored. The availability of continuous and diverse data provides the input required for subsequent analysis and prediction. The integration of IoT with intelligent prediction systems has been explored particularly in flood and disaster-management applications [5], [6].

2. Edge Processing Layer

The Edge Processing Layer is responsible for handling time-sensitive data close to the point where it is generated. Instead of transmitting all raw data to a centralized cloud server, nearby edge nodes can perform initial data processing, filtering, anomaly detection, and AI-based inference. Lightweight models can be deployed at the edge when the available computational resources permit. Processing information locally can reduce unnecessary data transmission and potentially improve the responsiveness of time-critical applications [1], [7], [20].

This layer is particularly important for the proposed low-latency architecture because it allows urgent information to be processed without depending entirely on communication with remote cloud infrastructure. More computationally demanding tasks can subsequently be forwarded to the fog or cloud layers.

3. Fog Computing Layer

The Fog Computing Layer provides an intermediate computing environment between edge devices and the cloud. It can coordinate computational resources across multiple edge nodes and support functions such as workload distribution, resource management, temporary data handling, and coordination of AI-related tasks. Fog computing extends computational capabilities toward the network edge and is particularly relevant to IoT environments involving geographically distributed devices [3], [8], [15].

Within the proposed architecture, the fog layer can therefore support situations in which individual edge devices have insufficient resources to handle the complete processing workload. This hierarchical arrangement can help distribute computational tasks according to their processing requirements.

4. Cloud Intelligence Layer

The Cloud Intelligence Layer provides centralized resources for computationally intensive and long-term activities. These activities may include large-scale data storage, historical data analysis, model training, periodic model refinement, and long-term disaster trend analysis. Edge intelligence can work together with cloud infrastructure so that computationally demanding operations are not forced onto resource-constrained edge devices [9], [10].

The cloud can also support the development and updating of AI models using accumulated historical and newly acquired data. Updated models or relevant model parameters can subsequently be made available to edge or fog nodes for future inference. This creates a complementary relationship in which edge resources support rapid local decisions, while cloud resources support computationally intensive learning and long-term analysis.

5. Alert and Response Layer

The Alert and Response Layer represents the final stage of the proposed architecture. When the prediction system identifies a potentially hazardous condition, the resulting information can be communicated to relevant stakeholders, such as emergency-management authorities, response teams, healthcare services, and affected communities. Depending on the deployment environment, alerts may be delivered through mobile applications, SMS-based services, emergency communication networks, or other notification mechanisms.

The effectiveness of this layer depends not only on the accuracy of the prediction model but also on the timeliness of information delivery. Therefore, the proposed architecture treats prediction and communication as interconnected components of the overall disaster-management process. The broader literature on AI-enabled disaster management emphasizes the importance of intelligent prediction and timely information for disaster preparedness and response [4].

Overall Architecture

The five layers work together as a hierarchical and distributed processing framework. IoT devices first collect environmental information, after which edge nodes perform time-sensitive processing. The fog layer coordinates resources and handles intermediate workloads, while the cloud provides large-scale storage, training, and historical analysis. Finally, the alert and response layer communicates prediction outcomes to relevant users and authorities.

The central idea of the proposed architecture is to avoid sending every piece of collected data directly to a remote cloud server. Instead, processing is distributed according to the urgency and computational requirements of the task. This approach is consistent with the principles of edge intelligence, fog computing, and mobile edge computing, where computation is moved closer to data sources to support responsive applications [1], [9], [10].

Thus, the proposed architecture provides a conceptual foundation for developing a scalable, adaptive, and low-latency disaster prediction system that combines real-time sensing, distributed AI processing, resource coordination, cloud intelligence, and timely alert generation.

VIII-A. FLOWCHART OF ARCHITECTURE

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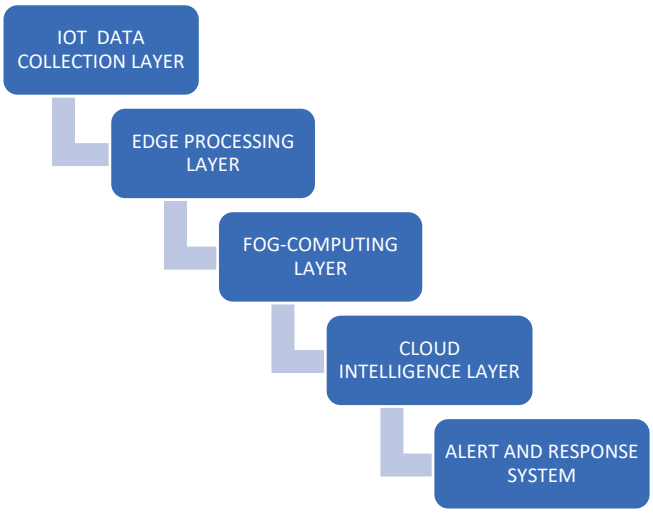


Fig. 1. Edge processing minimizes communication overhead by performing local inference.

VIII-B. ALGORITHM 1: LOW-LATENCY DISASTER PREDICTION WORKFLOW

Step 1: Collect real-time sensor data
Step 2: Preprocess data at edge layer
Step 3: Detect anomalies using AI model
Step 4: Forward critical data to fog layer
Step 5: Perform cloud-based optimization
Step 6: Generate emergency alerts

VIII-C. PROPOSED LOW LATENCY BASED ARCHITECTURE

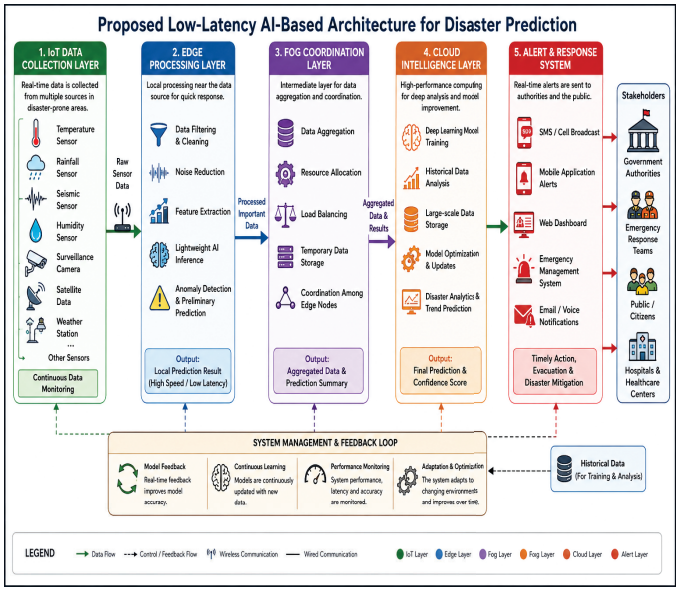


Fig. 2. Proposed Low-Latency AI-Based Disaster Prediction Architecture.

VIII-D. WORKING PRINCIPLE OF THE PROPOSED SYSTEM

The proposed low-latency disaster prediction system is designed to provide fast and intelligent disaster alerts by combining AI with IoT, edge computing, fog computing, and cloud technology. The system works in multiple stages to ensure real-time monitoring, quick data processing, and timely emergency response.

The process starts with the IoT Data Collection Layer, where different sensors continuously collect environmental data from disaster-prone areas. These sensors may include temperature sensors, rainfall sensors, humidity sensors, seismic sensors, cameras, and weather monitoring devices. The collected information helps in monitoring environmental changes that may indicate possible disaster situations.

Instead of sending all the raw data directly to the cloud, the proposed system first processes the data at the Edge Processing Layer. This layer is located close to the data source and performs tasks such as data filtering, preprocessing, and quick AI-based analysis. By processing important information locally, the system can detect abnormal conditions more quickly and reduce communication delay.

After initial processing, the important data is transferred to the Fog Coordination Layer. The fog layer acts as an intermediate layer that manages communication between edge devices and the cloud. It helps in data aggregation, resource management, temporary storage, and load balancing. This distributed processing improves system efficiency and reduces the burden on the cloud server.

The processed information is then forwarded to the Cloud Intelligence Layer, where advanced AI models perform deeper analysis using both historical and real-time data. The cloud layer is responsible for large-scale data storage, model training, and long-term analysis to improve prediction accuracy over time.

Once a potential disaster is detected, the system immediately generates alerts through the Alert and Response System. Notifications can be sent through SMS, mobile applications, web dashboards, or emergency management systems. These real-time alerts help authorities and affected people take quick action and reduce disaster impact.

One of the major advantages of the proposed system is its distributed architecture. Instead of depending completely on cloud computing, the system performs important processing at the edge and fog layers, which significantly reduces latency and improves response time. This makes the framework more suitable for real-time disaster prediction and emergency management applications.

The proposed architecture is also flexible and scalable, making it suitable for integration with future technologies such as 5G networks, federated learning, and lightweight AI models for smarter and faster disaster prediction systems.

Advantages of Proposed Architecture

- Reduces latency through edge-based processing
- Supports real-time disaster prediction
- Improves scalability through fog-cloud integration
- Enhances prediction accuracy using AI models
- Reduces bandwidth usage
- Enables faster emergency response mechanisms

This architecture addresses the major limitations found in existing systems and provides a scalable framework for future real-time disaster prediction applications.

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VIII-E. NOVEL CONTRIBUTIONS OF PROPOSED ARCHITECTURE

- The proposed architecture introduces several key improvements over existing systems:
- Incorporates a latency-aware processing pipeline
- Enables real-time prediction using edge intelligence
- Supports multi-disaster prediction capability
- Integrates edge–fog–cloud hierarchical processing
- Reduces bandwidth usage through local data filtering
- Improves scalability using distributed computing

VIII-F. PRACTICAL IMPLICATIONS

The proposed low-latency AI architecture can be applied in multiple real-world scenarios:

- Smart city disaster management systems
- Flood and earthquake early warning systems
- Agricultural risk monitoring
- Environmental hazard detection
- Emergency response and evacuation planning

These applications demonstrate the practical relevance and scalability of the proposed system in real-world environments.

VIII-G. LIMITATIONS OF THE PROPOSED STUDY

The proposed framework is conceptual and has not been validated through real-world implementation.

Experimental evaluation using live sensor data has not been performed.

The study mainly relies on comparative analysis of existing literature rather than practical deployment results.

Performance metrics such as latency and accuracy are discussed theoretically and not tested in real-time environments.

The framework does not consider hardware-specific constraints of edge and fog devices.

Security and privacy challenges in distributed disaster prediction systems are not explored in detail.

The proposed model is designed as a general architecture and may require customization for specific disaster scenarios.

Integration with emerging technologies such as 5G and federated learning is suggested but not experimentally evaluated.

These limitations provide opportunities for future research to further validate and improve the proposed low-latency disaster prediction framework.

IX. FUTURE WORK

The findings from the reviewed literature indicate several promising directions for advancing real-time disaster prediction. Future research should move beyond improving prediction accuracy alone and consider latency, computational efficiency, scalability, reliability, and practical deployment as equally important requirements. A major focus should be on developing AI-based systems that can provide timely predictions while operating under the resource and connectivity constraints commonly found in edge environments.

One important direction is the development of lightweight and computationally efficient AI models for edge deployment. Conventional deep-learning models can require substantial computational and memory resources, which may limit their use on resource-constrained devices. Future studies should therefore investigate model optimization techniques that reduce computational requirements while retaining acceptable prediction performance. Research on deep learning at the edge and accelerated neural-network inference provides a foundation for this direction [11], [20].

Another important area is the deeper integration of AI, IoT, and edge computing. IoT devices can continuously generate environmental information through sensors, weather stations, cameras, drones, and other monitoring sources. Combining these data streams with distributed AI processing can support more responsive disaster-monitoring and prediction systems. Existing research on IoT-enabled flood prediction and AI-based flood forecasting demonstrates the potential of such integration [5], [6]. Future architectures should focus on coordinating heterogeneous data sources while minimizing unnecessary communication with centralized infrastructure.

The use of advanced communication technologies is another promising research direction. Multi-access edge computing provides a framework for placing computational resources closer to end users, which can be valuable for applications with strict response-time requirements [14]. Similarly, mobile edge networks have been investigated for combining communication and computational resources at the network edge [21]. Future disaster-management systems could investigate how these technologies can support reliable communication and timely information exchange, particularly in situations where conventional communication infrastructure is disrupted.

Federated learning and distributed AI also provide opportunities for future development. Federated approaches can allow multiple edge devices or participating nodes to contribute to model training without requiring all local data to be transferred to a central server. [19] highlighted the potential of federated learning for intelligentizing mobile edge environments. Future research could investigate federated disaster prediction models that combine distributed environmental data while considering communication overhead, model convergence, privacy, and heterogeneous edge resources.

Efficient resource management and workload allocation will also be essential for practical deployment. Disaster environments can generate sudden increases in data volume and computational demand. Fog and edge computing can provide intermediate resources for distributing workloads among connected devices and computing nodes [3], [8]. Future systems should therefore investigate adaptive resource-allocation mechanisms that can respond dynamically to changing workloads, network conditions, and device availability.

Another significant research direction is the development of multi-hazard prediction frameworks. Existing research frequently concentrates on individual hazards, such as typhoons or floods [6], [16]. Although specialized models can provide effective predictions for particular events, a more flexible architecture could support multiple hazards, including floods,

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earthquakes, landslides, wildfires, and extreme weather events. Such systems would require adaptable AI models and mechanisms for handling different types of environmental data within a common computational framework.

Greater attention should also be given to real-world implementation and field evaluation. Reviews of edge technologies for disaster management indicate the potential of distributed computing approaches, but practical deployment involves challenges related to infrastructure, device heterogeneity, connectivity, resource availability, and system scalability [17]. Future research should therefore include pilot implementations and field-based experiments to evaluate system behaviour under realistic environmental and network conditions rather than relying only on simulation or laboratory-based evaluation.

A further research requirement is the establishment of consistent performance-evaluation criteria. Studies of edge intelligence and communication-efficient AI use different experimental configurations and performance measures, making direct comparison between systems difficult [9], [10]. Future research should consider a common evaluation framework incorporating end-to-end latency, data-transfer delay, AI inference time, prediction accuracy, computational resource consumption, energy efficiency, reliability, and response time. Such metrics would provide a more comprehensive assessment of whether a disaster prediction system is genuinely suitable for real-time deployment.

Finally, future research should consider security, privacy, and reliability as integral components of the architecture rather than treating them as separate concerns. Distributed edge and IoT environments involve numerous connected devices and communication points, creating additional requirements for secure data exchange and reliable operation [3], [8]. Integrating appropriate security and privacy mechanisms with low-latency AI processing will be important for ensuring that future disaster prediction systems remain dependable during critical situations.

Overall, future research should move toward integrated, scalable, adaptive, and low-latency disaster prediction architectures that combine AI, IoT, edge/fog computing, distributed learning, and advanced communication technologies. The key challenge is not simply to develop more accurate prediction models, but to create systems capable of delivering accurate predictions within a sufficiently short response time under realistic operating conditions. Addressing these issues can contribute to more effective early-warning systems and strengthen the practical role of AI in disaster preparedness and response.

X. CONCLUSION

This study reviewed recent developments in AI-based disaster prediction systems, with particular emphasis on technologies that support real-time and low-latency decision-making. The literature demonstrates that artificial intelligence has significantly enhanced the capability of disaster prediction systems by improving the analysis of large and complex environmental datasets. At the same time, the review highlights that reliance on centralized cloud-based infrastructures can introduce communication and processing delays, which may reduce the effectiveness of disaster response in time-critical situations [1], [2].

The analysis further indicates that distributed computing paradigms, including edge computing and fog computing, offer promising solutions for addressing latency-related challenges. By processing data closer to its source, these technologies can reduce communication overhead, improve responsiveness, and support faster decision-making during emergency events [3], [7]. Nevertheless, several challenges remain, including efficient resource management, deployment complexity, interoperability among heterogeneous devices, energy consumption, and the limited availability of large-scale real-world implementations [8], [17].

Based on the identified research gaps, this study proposed a conceptual low-latency architecture that integrates IoT-enabled sensing, edge intelligence, fog-based coordination, cloud-supported learning, and alert-generation mechanisms. The proposed framework is designed to support distributed processing, reduce unnecessary data transmission, and facilitate timely disaster prediction and response. By combining the strengths of AI, IoT, edge computing, and cloud intelligence, the architecture provides a foundation for developing more responsive and scalable disaster-management systems.

The review also highlights several opportunities for future research. These include the development of lightweight AI models for resource-constrained edge devices, the adoption of federated and distributed learning approaches, the integration of advanced communication technologies, and the design of multi-hazard prediction frameworks capable of supporting diverse disaster scenarios. Furthermore, future studies should prioritize real-world deployment and establish standardized performance metrics for evaluating latency, prediction accuracy, resource utilization, and system reliability.

In conclusion, the convergence of artificial intelligence, IoT, edge computing, fog computing, and cloud technologies presents significant opportunities for improving disaster prediction and preparedness. Developing scalable, adaptive, secure, and low-latency architectures will be essential for enabling timely predictions and supporting effective disaster-management strategies in increasingly complex and dynamic environments.

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