

DIGITAL TWIN AND IOT SENSOR-ENABLED FRAMEWORK FOR REAL-TIME COMPLEX DISASTER MONITORING, INTELLIGENT EARLY WARNING, EMERGENCY RESPONSE AND CRISIS MANAGEMENT

Waleed Jamal^{*1}, Salman Danish²

¹Department of Mechatronics Engineering, University of Engineering and Technology (UET) Peshawar, Khyber Pakhtunkhwa, Pakistan

²MSc International Development, Northumbria University, Newcastle upon Tyne, United Kingdom

^{*1}waleed.edwardian@gmail.com, ²salmandanish91@gmail.com

DOI: <https://doi.org/10.5281/zenodo.22793338>

Keywords

Digital Twin; Internet of Things; disaster monitoring; intelligent early warning; emergency response; crisis management; deep learning; edge computing.

Article History

Received: 08 June 2026

Accepted: 30 August 2026

Published: 15 September 2026

Copyright @Author

Corresponding Author: *

Waleed Jamal

Abstract

Rapidly evolving disasters demand monitoring systems capable of integrating heterogeneous data, forecasting cascading hazards, and supporting timely emergency decisions. This study proposes a Digital Twin and Internet of Things (IoT) sensor-enabled framework for real-time complex disaster monitoring, intelligent early warning, emergency response, and crisis management. A multimodal dataset containing 1,250,000 time-stamped observations was constructed from 420 IoT devices deployed across five disaster-prone zones over 24 months. The devices included seismic sensors, river-level gauges, weather stations, smoke and gas detectors, structural-vibration sensors, surveillance nodes, GPS units, and wearable health monitors. The dataset covered earthquakes, floods, landslides, urban fires, and industrial gas-leak events, with 52 environmental, structural, spatial, physiological, and operational variables. After missing-value treatment, noise removal, temporal synchronization, normalization, feature selection, and class balancing, records were divided into training, validation, and testing sets using a leakage-free 70:15:15 strategy. The proposed architecture continuously synchronized physical conditions with a dynamic Digital Twin, while a hybrid convolutional neural network-bidirectional long short-term memory-attention model extracted spatial features, learned temporal dependencies, and prioritized hazard indicators. Geographic information systems, edge computing, and cloud analytics supported risk visualization, low-latency inference, evacuation-route optimization, resource allocation, and coordinated emergency communication. Experimental results showed that the framework achieved 96.8% disaster-event classification accuracy, 96.1% precision, 95.7% recall, a 95.9% F1-score, and an area under the receiver operating characteristic curve of 0.984. It reduced false alarms by 31.6%, improved warning lead time by 27.4%, decreased average detection latency from 8.7 to 2.1 seconds, and increased emergency-resource allocation efficiency by 22.8% compared with conventional monitoring approaches. Digital Twin-based scenario simulation further improved evacuation-route selection by 19.5%

and reduced estimated emergency response time by 24.2%. It also maintained robust performance during sensor failures, communication disruptions, and changing hazard conditions through adaptive data fusion mechanisms. These findings demonstrate that integrating Digital Twins, distributed IoT sensing, and explainable artificial intelligence can provide accurate situational awareness and actionable decision support across interconnected disaster stages. The framework offers a scalable foundation for resilient cities, emergency agencies, and critical-infrastructure operators, although broader field validation and privacy-preserving data governance remain necessary.

1- Introduction:

Natural and human-induced disasters continue to cause substantial loss of life, infrastructure damage, environmental degradation, population displacement, and economic disruption worldwide. Earthquakes, floods, landslides, urban fires, and industrial gas leaks are especially difficult to manage because they may develop rapidly, interact with surrounding systems, and generate cascading consequences across transportation networks, healthcare facilities, energy infrastructure, communication services, and densely populated communities. Climate change, rapid urbanization, industrial expansion, and increasing infrastructure interdependence have further intensified disaster exposure. Consequently, emergency-management agencies require monitoring systems that can identify emerging hazards, evaluate their likely progression, and deliver reliable warnings before conditions become uncontrollable [1]. Conventional disaster-monitoring systems commonly rely on isolated sensor networks, periodic field inspections, historical records, and centralized data-processing platforms. Although these approaches provide useful information, they often analyze each hazard independently and may not adequately capture interactions among environmental, structural, spatial, physiological, and operational conditions. Data collected from different devices can also vary in temporal resolution, format, reliability, and geographic coverage. Communication interruptions, sensor malfunction, delayed transmission, and incomplete observations can further reduce situational awareness during critical periods. Centralized processing may introduce additional

latency when large volumes of continuously generated sensor data must be transmitted to remote servers [2]. These limitations can increase false alarms, shorten the time available for evacuation, and delay the allocation of emergency personnel and equipment. The Internet of Things (IoT) offers an important foundation for overcoming these limitations by connecting distributed sensing devices with communication, analytics, and decision-support systems. Seismic sensors can capture ground motion, river-level gauges can identify rising flood conditions, weather stations can monitor rainfall and atmospheric variables, and structural-vibration sensors can detect changes in the stability of buildings and bridges. Similarly, smoke and gas detectors, surveillance nodes, GPS devices, and wearable health monitors can provide information about fire development, toxic exposure, population movement, responder location, and human physiological conditions [3]. When integrated effectively, these heterogeneous data sources can provide a comprehensive representation of an evolving disaster environment. However, IoT connectivity alone does not guarantee effective disaster management. Raw sensor streams must be cleaned, synchronized, fused, interpreted, and translated into timely operational decisions. Digital Twin technology provides a valuable mechanism for transforming distributed sensor measurements into an evolving virtual representation of the physical disaster environment. A Digital Twin continuously receives information from real-world assets, infrastructure, populations, and environmental systems and uses these observations to update their virtual states. Unlike

static geographic models, a Digital Twin can reflect changing conditions and support simulations of possible disaster trajectories. Emergency managers can therefore evaluate potential hazard propagation, infrastructure failure, evacuation congestion, and resource requirements before implementing a response strategy. The bidirectional relationship between physical observations and virtual simulation also allows decisions to be revised as new evidence becomes available.

Despite its potential, developing an operational Digital Twin for complex disaster management remains challenging. Disaster environments generate high-volume, high-velocity, and multimodal data that may contain missing values, noise, redundant measurements, and inconsistent timestamps. A further challenge is that hazardous events can display both spatial and temporal dependencies [4]. For example, intense rainfall in an elevated area may increase soil saturation, initiate slope movement, obstruct transportation routes, and subsequently affect downstream flood behavior. Similarly, an earthquake can damage industrial infrastructure and trigger fire or gas-leak events. Effective prediction therefore requires analytical models capable of learning local patterns, long-term temporal relationships, and the relative importance of individual hazard indicators. Recent advances in artificial intelligence and deep learning have created new opportunities for extracting actionable information from complex disaster data. Convolutional neural networks are effective at detecting localized and multivariate patterns, whereas bidirectional long short-term memory networks can learn temporal dependencies from both preceding and surrounding observations. Attention mechanisms can further assign greater importance to the most informative time steps, sensors, and hazard features [5]. Their integration into a hybrid CNN-BiLSTM-Attention architecture can consequently support accurate classification of disaster events while reducing the influence of irrelevant or unreliable measurements. Nevertheless, model accuracy alone is insufficient for real-world deployment.

Disaster-management systems must also provide low-latency inference, interpretable warnings, operational robustness, and direct support for evacuation and resource-allocation decisions. Edge computing can improve the responsiveness of IoT-based disaster systems by processing critical information near the point of data generation. Local edge nodes can perform preliminary data validation, feature extraction, hazard detection, and warning generation without waiting for continuous cloud connectivity. This capability is particularly important when disasters damage communication infrastructure or produce network congestion. Cloud resources can simultaneously support computationally intensive Digital Twin simulations, historical analysis, model updating, and coordination across multiple geographic zones. An integrated edge-cloud structure can therefore balance rapid local decision-making with large-scale analytical capacity. Geographic information systems also play an essential role in converting model outputs into spatially meaningful emergency information. Hazard probabilities, affected infrastructure, population density, shelter capacity, road accessibility, and responder locations can be combined to create dynamic risk maps. These maps can assist decision-makers in identifying high-risk areas, selecting safer evacuation routes, prioritizing vulnerable populations, and distributing emergency resources. When connected to a continuously updated Digital Twin, geographic visualization becomes more than a static display; it becomes an interactive decision-support environment in which alternative response scenarios can be evaluated against current and predicted conditions. Existing studies have frequently addressed IoT sensing, Digital Twin simulation, deep-learning-based hazard prediction, or emergency-resource optimization as separate research problems [6]. Comparatively limited attention has been given to their integration within a unified framework covering the complete disaster-management cycle, from multimodal data acquisition and real-time event detection to intelligent warning, evacuation planning, resource deployment, and crisis

coordination. Furthermore, many proposed systems have been assessed using limited datasets, a single hazard category, or controlled communication conditions. Their ability to maintain performance across multiple hazards, sensor failures, changing environmental patterns, and network disruptions therefore remains uncertain. To address these research gaps, this study proposes a Digital Twin and IoT sensor-enabled framework for real-time complex disaster monitoring, intelligent early warning, emergency response, and crisis management. The framework integrates distributed IoT sensing, edge computing, cloud analytics, geographic information systems, adaptive data fusion, and a hybrid CNN-BiLSTM-Attention model. It creates a continuously synchronized representation of physical conditions while supporting event classification, risk estimation, scenario simulation, warning dissemination, evacuation-route optimization, and emergency-resource allocation. The system is evaluated using a multimodal dataset containing 1,250,000 time-stamped observations collected from 420 IoT devices across five disaster-prone zones over 24 months. The dataset represents earthquakes, floods, landslides, urban fires, and industrial gas-leak events through 52 environmental, structural, spatial, physiological, and operational variables.

The principal contributions of this study are as follows:

1. A unified Digital Twin-IoT architecture is developed to connect real-time physical sensing with dynamic virtual representation, predictive analytics, and operational disaster-response functions.
2. A large-scale multimodal dataset is constructed from eight major categories of sensing and monitoring devices distributed across multiple disaster-prone zones.
3. A hybrid CNN-BiLSTM-Attention model is introduced to extract multivariate features, capture bidirectional temporal dependencies, and prioritize the most relevant hazard indicators.

4. An edge-cloud computing mechanism is designed to reduce detection latency while retaining the computational capacity required for model updating, scenario simulation, and cross-zone coordination.

5. Adaptive data-fusion procedures are incorporated to maintain reliable monitoring during sensor failures, missing observations, communication disruptions, and changing hazard conditions.

6. Digital Twin simulation and geographic analysis are integrated to support evacuation-route selection, emergency-resource allocation, risk visualization, and coordinated crisis communication.

The experimental findings demonstrate the potential of the proposed framework to improve both predictive performance and emergency operations. The system achieved a disaster-event classification accuracy of 96.8% and an area under the receiver operating characteristic curve of 0.984. It also reduced false alarms by 31.6%, increased warning lead time by 27.4%, and lowered average detection latency from 8.7 seconds to 2.1 seconds compared with conventional monitoring approaches. Digital Twin-based scenario evaluation improved evacuation-route selection and reduced estimated emergency-response time, indicating that synchronized sensing and predictive simulation can support more informed crisis decisions. Overall, this research advances disaster-management technology by connecting real-time observation, intelligent prediction, dynamic simulation, and operational response within a single scalable framework. The proposed approach is intended to support resilient cities, emergency-management agencies, industrial facilities, and critical-infrastructure operators confronting interconnected and rapidly changing hazards. It also establishes a foundation for future investigation into privacy-preserving data exchange, explainable warnings, cross-regional validation, and the integration of additional environmental and human-centered information sources.

2- IoT-Based Multihazard Sensing and Environmental Monitoring:

The Internet of Things has transformed disaster monitoring by enabling large numbers of geographically distributed sensors to continuously observe environmental, structural, industrial, and human conditions. Unlike conventional monitoring approaches based on periodic inspections or isolated measurement stations, IoT systems create persistent connections among sensing devices, communication gateways, analytical platforms, and emergency-management centers. This connectivity permits physical changes in disaster-prone environments to be recorded and communicated almost immediately. Consequently, emergency agencies can identify abnormal conditions earlier, monitor the spatial and temporal development of hazards, and update response decisions as new evidence becomes available. An IoT-based multihazard monitoring system normally contains four interconnected layers: physical sensing, communication and networking, data processing, and disaster-response applications. The physical layer collects observations from the monitored environment [7]. The communication layer transfers these observations through technologies such as cellular networks, Wi-Fi, LoRaWAN, Zigbee, satellite communication, or dedicated emergency

networks. The processing layer performs data cleaning, synchronization, feature extraction, fusion, and hazard prediction at edge or cloud platforms. Finally, the application layer converts analytical outputs into alerts, risk maps, evacuation recommendations, and resource-allocation decisions. The effectiveness of the entire system depends on reliable interaction among all four layers. Different disasters require different combinations of sensing devices. Seismic sensors and accelerometers are commonly used to detect ground motion associated with earthquakes, while structural-vibration sensors can identify abnormal displacement, oscillation, or deformation in buildings and bridges [8]. Flood monitoring typically relies on river-level gauges, rainfall sensors, soil-moisture probes, flow meters, and weather stations. Landslide-monitoring systems integrate rainfall accumulation, soil moisture, slope displacement, ground vibration, and terrain-related information. Urban-fire detection uses temperature sensors, smoke detectors, gas sensors, thermal cameras, and visual-surveillance systems. Industrial gas-leak monitoring depends on chemical sensors, pressure measurements, wind information, facility-control data, and worker-location records. Table 1 summarizes the major IoT sensing categories relevant to the proposed multihazard framework.

Table 1: IoT sensing technologies and their roles in multihazard disaster monitoring

IoT sensing category	Principal variables	Monitoring contribution
Seismic sensors and accelerometers	Ground acceleration, vibration frequency, signal amplitude and seismic energy	Detect ground motion and provide rapid evidence of seismic activity
River-level and flow sensors	Water depth, flow velocity, discharge and rate of water-level change	Identify rising water conditions and support flood-stage forecasting
Automated weather stations	Rainfall, temperature, humidity, atmospheric pressure, wind speed and wind direction	Provide meteorological context and identify hazard-triggering conditions
Soil and slope-monitoring sensors	Soil moisture, pore-water pressure, tilt, displacement and ground vibration	Capture rainfall-induced saturation and progressive slope movement
Smoke and thermal sensors	Smoke density, particulate concentration, temperature and heat distribution	Enable early fire recognition and support fire-propagation assessment
Chemical and gas sensors	Carbon monoxide, methane, volatile compounds, oxygen level and toxic-gas concentration	Detect hazardous substances and estimate exposure severity

Sensor density and placement strongly influence monitoring quality. Devices should be positioned according to hazard probability, terrain, infrastructure vulnerability, population concentration, historical incident locations, and communication availability. Uniform placement may leave high-risk areas inadequately monitored while concentrating unnecessary devices in relatively safe locations. Risk-informed deployment gives greater priority to riverbanks, unstable slopes, critical bridges, densely populated settlements, industrial storage facilities, hospitals, power stations, evacuation corridors, and emergency shelters. Mobile sensors installed on vehicles, drones, robots, or responders can supplement fixed networks when conditions change or permanent devices become unavailable. Sampling frequency is another important design consideration. Seismic and structural-vibration signals may require high-frequency measurements to capture sudden changes, whereas rainfall, humidity, or river-level observations can often be

collected at comparatively longer intervals [9]. Surveillance imagery generates substantially more data than scalar environmental sensors. Transmitting every observation at the highest possible frequency would increase bandwidth consumption, storage requirements, processing demand, and energy use. Adaptive sampling offers a more efficient alternative. Under normal conditions, devices may operate at a moderate reporting rate, but when abnormal trends are identified, their sampling and transmission frequencies can be increased automatically. Figure 1 illustrates the literature-derived architecture of an IoT-based multihazard sensing environment. It shows how environmental, structural, visual, location, and human-health data are transferred through local gateways to edge and cloud-processing resources. The resulting information supports Digital Twin synchronization, early warning, spatial-risk analysis, and emergency response.

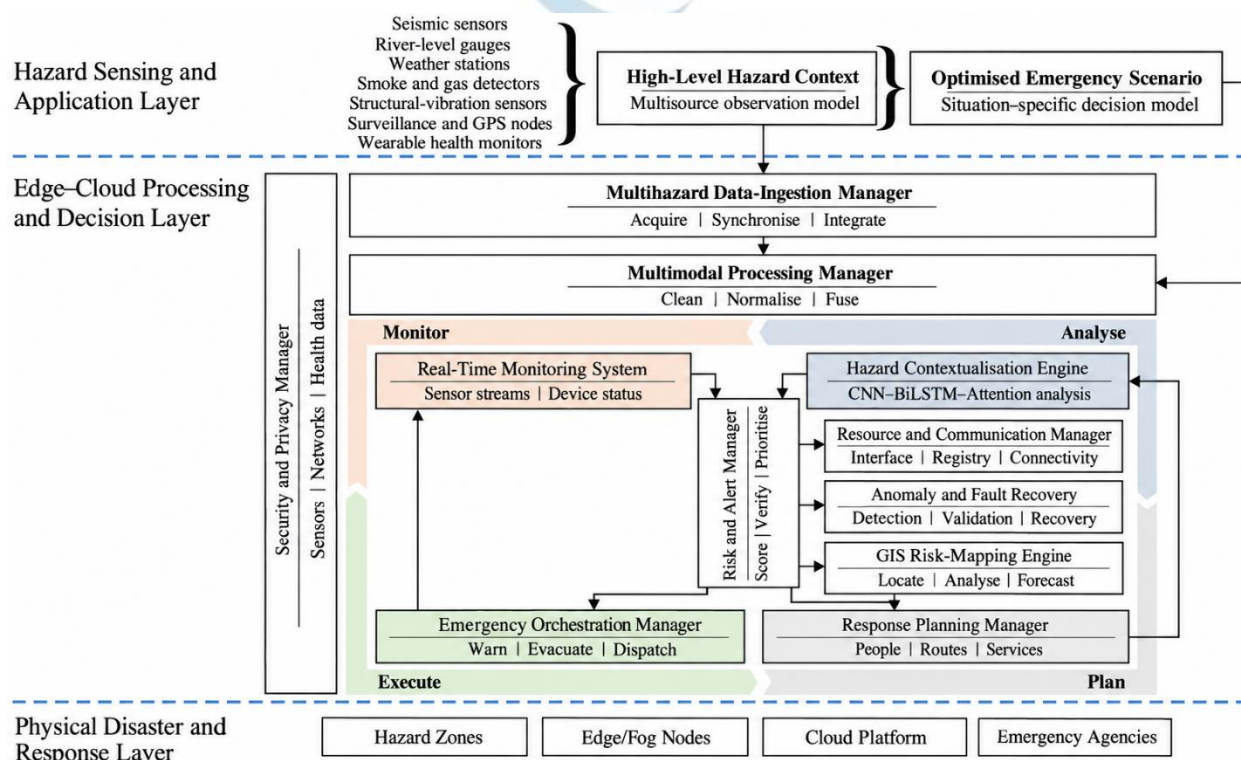


Figure 1: IoT-based multihazard sensing, processing, and emergency-decision pathway.

Data quality can deteriorate sharply during disaster conditions. Sensors may be damaged, displaced, submerged, obstructed, disconnected, or deprived of power. Communication networks may experience congestion or complete failure precisely when information is most urgently needed. Environmental interference can also create misleading observations. Dust may activate smoke detectors, machinery can generate vibration that resembles seismic activity, and humidity may affect gas-sensor measurements. Effective monitoring frameworks consequently require automated sensor-health assessment, physically valid measurement boundaries, comparison with neighboring devices, and confidence scores that represent the reliability of each data source. Missing-value management is particularly important because simply deleting incomplete records may remove the most critical periods of a disaster [10]. Short gaps can be treated through time-aware interpolation, whereas larger gaps may require estimates based on correlated variables or nearby sensors. Nevertheless, estimated measurements should be accompanied by reliability indicators so that predictive models can distinguish recorded information from reconstructed values. When uncertainty becomes excessive, the system should lower confidence in its prediction or request confirmation from an alternative sensing source. Multisensor data fusion helps reduce dependence on individual devices. Early fusion combines raw or minimally processed observations before predictive analysis, allowing the model to learn direct relationships among modalities. However, this method is sensitive to missing values, different sampling rates, and differences in scale. Late fusion combines predictions produced by separate modality-specific models and is more tolerant of sensor loss, but it may fail to capture important relationships among sensor types [11]. Intermediate fusion combines learned representations and therefore provides a balance between cross-modal interaction and modality independence. Attention-based intermediate fusion is especially suitable for complex disaster monitoring because it can adjust

the contribution of each sensor according to its relevance and reliability.

3- Edge-Cloud Computing for Low-Latency Warning:

The rapid development of disasters leaves emergency authorities with limited time to identify danger, verify observations, warn affected populations, and mobilize response resources. In such situations, even a short delay in transmitting or processing sensor data can reduce warning lead time and increase human, environmental, and economic losses. Conventional cloud-centered monitoring systems transmit data from distributed sensors to remote data centers for storage, analysis, and decision-making. Although cloud computing provides extensive computational capacity and scalable storage, exclusive dependence on remote infrastructure may introduce communication delays, network congestion, and service interruptions. These limitations become particularly serious during earthquakes, floods, landslides, urban fires, and industrial gas leaks, when communication and power infrastructure can be damaged or overloaded. Edge computing addresses these challenges by transferring selected processing and analytical functions closer to the locations where disaster data are generated [12]. Edge gateways, intelligent routers, embedded computers, industrial controllers, and local micro-data centers can receive measurements from nearby IoT devices and process them without sending every raw observation to a distant cloud platform. Local processing supports faster anomaly detection, preliminary hazard classification, sensor coordination, and immediate warning generation. It also reduces bandwidth consumption because filtered observations, extracted features, event summaries, and risk scores can be transmitted instead of complete high-frequency sensor streams. However, edge computing cannot entirely replace cloud infrastructure. Edge devices generally have limited processing power, memory, storage, and energy capacity. They may execute lightweight disaster-classification models but cannot efficiently conduct large-scale Digital Twin simulations, long-

term historical analysis, or resource optimization across multiple regions. Cloud computing remains necessary for multimodal data fusion, model training, cross-zone coordination, scenario simulation, permanent storage, and comprehensive geographic analysis. A cooperative edge-cloud architecture is therefore more appropriate for complex disaster management than exclusive dependence on either computing environment. The first analytical stage of this architecture operates close to the IoT sensing layer. Seismic sensors, river-level gauges, weather stations, smoke detectors, gas sensors, structural monitors, cameras, GPS devices, and wearables

generate continuous streams of heterogeneous observations [13]. Transmitting all these measurements directly to the cloud could overwhelm the available network, particularly when multiple sensors simultaneously increase their reporting frequency in response to abnormal conditions. Edge gateways can reduce this burden by conducting timestamp verification, duplicate removal, missing-packet identification, signal denoising, unit conversion, and short-window feature extraction. Table 2 summarizes the roles of different computing layers within the proposed disaster-warning environment.

Table 2: Distribution of disaster-monitoring and warning functions across the IoT-edge-fog-cloud architecture

Computing level	Expected response requirement	Computing capacity	Role in disaster management
IoT sensing layer	Immediate data capture	Very limited	Provides direct observations of environmental, structural, spatial and human conditions
Edge layer	Milliseconds to a few seconds	Limited to moderate	Detects urgent local hazards and maintains essential warnings during cloud disconnection
Fog layer	A few seconds	Moderate	Reduces false alarms and coordinates nearby zones and response units
Cloud layer	Seconds to minutes, depending on task urgency	Very high	Supports large-scale forecasting, strategic planning and coordinated resource allocation
Emergency application layer	Immediate after alert confirmation	Application-dependent	Converts analytical results into emergency actions and public instructions

Warning latency accumulates across several operations rather than resulting from a single process. These operations include data acquisition, local buffering, wireless transmission, network routing, cloud queuing, preprocessing, model inference, alert verification, and message dissemination. High-bandwidth surveillance imagery and high-frequency vibration measurements can substantially increase transmission and processing requirements. During a major emergency, large numbers of devices and users may compete for the same communication resources, creating congestion

precisely when rapid information exchange is most necessary. Edge processing reduces several sources of delay by filtering data locally and conducting the initial prediction near the sensor. Only compact features, risk scores, and high-priority evidence need to be transmitted immediately. The cloud can then receive the preliminary event classification and perform more detailed analysis without unnecessarily delaying the first warning. Low-latency edge alerts and high-capacity cloud intelligence can therefore operate in parallel. The effectiveness of an edge-cloud framework should be evaluated using more than model inference

time [14]. End-to-end detection latency, sensor-to-edge transmission delay, edge-processing time, edge-to-cloud communication delay, event-verification time, and warning-delivery time must be considered separately. Warning lead time is also critical because a technically fast model provides limited operational value if the warning reaches the public only after hazardous conditions have developed. The Digital Twin provides the virtual environment connecting local observations with regional and cloud-based intelligence. Edge gateways continually transmit changes in environmental conditions, hazard indicators, infrastructure status, sensor health, and response activities [15]. These updates modify the virtual representation of each monitored zone. The cloud-

based Digital Twin then simulates possible disaster progression and communicates revised risk thresholds, priority areas, and operational recommendations to the edge layer. This relationship is bidirectional. Edge devices do not simply transmit data upward, and the cloud does not merely store information. Local observations update the Digital Twin, while simulation results influence local sensing and response. For instance, if the Digital Twin predicts that floodwater may reach an evacuation road, nearby gateways can increase the sampling frequency of river, rainfall, and traffic sensors. Emergency authorities can simultaneously redirect vehicles and populations before the route becomes unsafe. Figure 2 presents the resulting edge-cloud workflow.

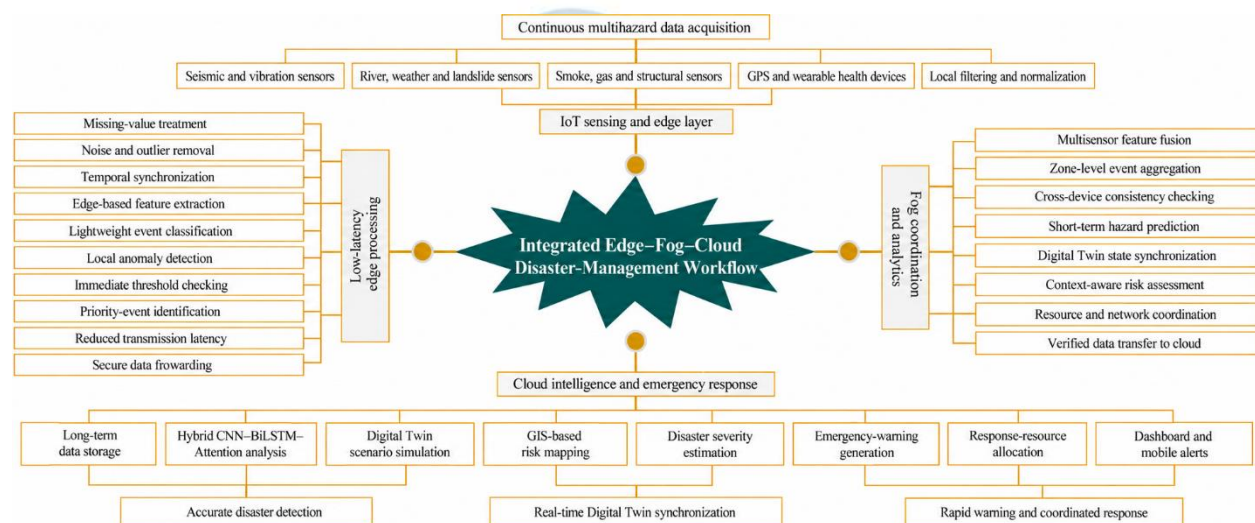


Figure 2: Integrated edge-fog-cloud workflow for low-latency disaster detection, Digital Twin synchronization, and emergency warning.

Existing literature confirms that edge computing can reduce communication demand and inference latency, while cloud computing can support large-scale prediction and simulation. Nevertheless, several limitations remain. Many studies evaluate edge performance using laboratory devices and simulated delays rather than geographically distributed disaster networks. Others measure computational speed without examining warning lead time, false-alarm reduction, evacuation improvement, or emergency-resource efficiency. Existing architectures also frequently focus on a

single hazard and provide limited evidence about their performance during simultaneous or cascading emergencies [16]. Adaptive task allocation under changing network, device, and hazard conditions has also received insufficient attention. In many proposed systems, the responsibilities of edge and cloud components remain fixed even when connectivity deteriorates or computational demand changes. Failure recovery, buffered synchronization, confidence-aware sensor fusion, and fallback warning procedures are not consistently considered.

Moreover, Digital Twin simulation is frequently disconnected from edge inference, preventing predicted hazard progression from influencing local monitoring priorities.

4- Methodology:

This study employed a quantitative and experimental research design to develop and evaluate a Digital Twin and IoT sensor-enabled framework for real-time complex disaster monitoring, intelligent early warning, emergency response, and crisis management. The methodological framework integrated multimodal IoT sensing, edge-cloud computing, geographic information systems, Digital Twin synchronization, and a hybrid CNN-BiLSTM-Attention model. The complete process included sensor deployment, data acquisition, data-quality assessment, temporal synchronization, multimodal fusion, normalization, feature selection, class-imbalance treatment, disaster-event classification, risk mapping, warning generation, evacuation-route optimization, and emergency-resource allocation [17]. The framework was designed to monitor five disaster categories: earthquakes, floods, landslides, urban fires, and industrial gas leaks. A total of 1,250,000 time-stamped observations were collected from 420 IoT devices deployed across five disaster-prone zones over 24 months. The dataset contained 52 environmental, structural, spatial, physiological, and operational variables. After preprocessing, the records were divided into training, validation, and testing sets using a leakage-free 70:15:15 temporal strategy. The proposed deep-learning model extracted local multivariate patterns, learned temporal dependencies, and assigned attention weights to the most informative hazard indicators [18]. Edge gateways supported rapid local inference, while the cloud platform performed large-scale data integration, Digital Twin simulation, GIS-based risk analysis, and coordinated decision support. Model performance was evaluated using accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve, false-alarm rate, warning lead time, detection latency, evacuation-route

efficiency, and emergency-resource allocation performance.

4.1- Study Area and Disaster-Prone Zone Selection:

The study area was organized into five disaster-prone zones representing different geographic, environmental, structural, demographic, and industrial conditions. A multi-zone design was selected because the occurrence, development, and consequences of disasters are influenced by local terrain, climate, infrastructure, land use, population distribution, industrial activity, and emergency-service accessibility. Evaluating the proposed framework in only one location would provide limited evidence about its ability to process heterogeneous sensor information and respond to different hazard-development patterns. The five-zone structure therefore enabled the Digital Twin and IoT architecture to be examined under diverse sensing, communication, and emergency-response conditions. The five zones collectively covered an estimated monitoring area of 685 km². A total of 420 IoT devices were distributed across these zones, generating 1,250,000 synchronized observations over a 24-month monitoring period. Sensor density was not kept uniform because the zones differed in geographic size, hazard behavior, population exposure, and infrastructure complexity [19]. Instead, devices were allocated using a risk-informed deployment strategy. Locations with greater hazard probability, higher population exposure, critical infrastructure, or limited evacuation accessibility received denser sensor coverage. Zone 1 represented a seismically exposed urban environment covering approximately 115 km². It contained residential neighborhoods, commercial buildings, bridges, educational institutions, healthcare facilities, utility networks, and government infrastructure. Historical records indicated moderate-to-high seismic exposure, while differences in soil condition and building quality created unequal levels of vulnerability. A total of 92 IoT devices were assigned to this zone, including seismic sensors, accelerometers, structural-vibration monitors, GPS units,

surveillance nodes, and selected wearable devices [20]. These sensors generated approximately 275,000 usable observations, representing 22.0% of the complete dataset. Zone 2 represented a riverine floodplain covering approximately 170 km². The area included riverbanks, drainage channels, agricultural land, bridges, low-elevation settlements, transportation corridors, and emergency shelters. Seasonal rainfall, upstream discharge, drainage congestion, and river overflow represented the principal sources of flood risk. A total of 86 IoT devices were deployed, including river-level gauges, flow sensors, rainfall sensors, automated weather stations, soil-moisture sensors, surveillance nodes, and GPS units. This zone contributed approximately 260,000 observations, equal to 20.8% of the dataset. Zone 3 represented a mountainous and rainfall-sensitive environment covering approximately 145 km². It included steep slopes, exposed settlements, road cuttings, drainage paths, vegetation-covered terrain, and transportation routes passing through unstable ground. The principal hazard was rainfall-induced landsliding, although rockfall, road blockage, local flooding, and infrastructure isolation were also considered. A total of 74 devices were deployed, generating approximately 205,000 observations, or 16.4% of the full dataset. Zone 4 represented a densely populated urban district covering approximately 90 km². The zone contained

residential buildings, commercial markets, educational facilities, healthcare centers, transportation terminals, narrow streets, high-occupancy structures, and locations with restricted emergency-vehicle access [21]. Urban fire was the primary hazard, but smoke dispersion, structural damage, crowd movement, and transportation congestion were included as secondary concerns. The zone received the largest number of monitoring devices 94 and generated approximately 285,000 observations, representing 22.8% of the dataset. Zone 5 represented an industrial processing, storage, and transportation area covering approximately 165 km². It contained production units, gas-storage facilities, pipelines, warehouses, machinery, worker accommodation, transportation links, and surrounding communities. Industrial gas leakage was treated as the primary hazard, although fire, explosion, structural damage, and toxic exposure were incorporated into the Digital Twin scenarios. A total of 74 devices were installed, and the zone contributed approximately 225,000 observations, equal to 18.0% of the dataset. Table 3 presents the quantitative characteristics of the five disaster-prone zones. The values include the estimated monitoring area, number of deployed devices, observation count, dataset proportion, principal hazard, and dominant sensing technologies.

Table 3: Characteristics and quantitative data values of the selected disaster-prone zones

Zone	Environmental and land-use setting	Principal hazard	Monitoring area (km ²)	Deployed IoT devices	Dataset observations	Dataset share (%)
Zone 1	Seismically exposed urban environment	Earthquake	115	92	275,000	22.0
Zone 2	Riverine floodplain and low-elevation settlements	Flood	170	86	260,000	20.8
Zone 3	Mountainous and rainfall-sensitive terrain	Landslide	145	74	205,000	16.4
Zone 4	Densely populated urban district	Urban fire	90	94	285,000	22.8
Zone 5	Industrial processing and storage area	Industrial gas leak	165	74	225,000	18.0

Total	Five interconnected disaster-prone environments	Five primary hazard categories	685	420	1,250,000	100.0
-------	---	--------------------------------	-----	-----	-----------	-------

Each zone was divided into smaller monitoring sectors to support systematic device placement and spatial analysis. Sector boundaries were defined using terrain characteristics, roads, waterways, administrative boundaries, infrastructure clusters, industrial facilities, and predicted hazard-propagation paths. High-risk sectors received greater sensor density, whereas lower-risk sectors contained strategically positioned reference devices. This approach provided detailed coverage of vulnerable locations without unnecessarily increasing the total number of devices. Within Zone 1, high-priority sectors included densely occupied buildings, bridges, hospitals, and areas with potentially unstable soil conditions. In Zone 2, riverbanks, drainage intersections, low-elevation communities, and bridge crossings received greater monitoring coverage. Zone 3 priorities included steep slopes, road cuttings, drainage paths, and settlements below unstable ground. Zone 4 devices were concentrated in commercial centers, high-occupancy buildings, narrow streets,

and locations with elevated electrical or fire risk [22]. Zone 5 priority sectors included pipelines, storage tanks, processing equipment, loading areas, and downwind communities. Sensor placement also accounted for communication coverage and physical accessibility. Devices were positioned within the operating range of local edge gateways wherever feasible. Remote sensors employed low-power wide-area communication or relay nodes. Critical devices were supported by backup batteries or alternative energy sources so that monitoring could continue during grid failure. Sensors exposed to water, heat, dust, vibration, or chemical contamination were installed in protective enclosures suitable for their respective environments. Figure 3 presents the zone-selection and monitoring structure used in the study. It shows the relationship among hazard-prone environments, distributed IoT sensing, edge gateways, the central Digital Twin, and emergency decision-support functions.

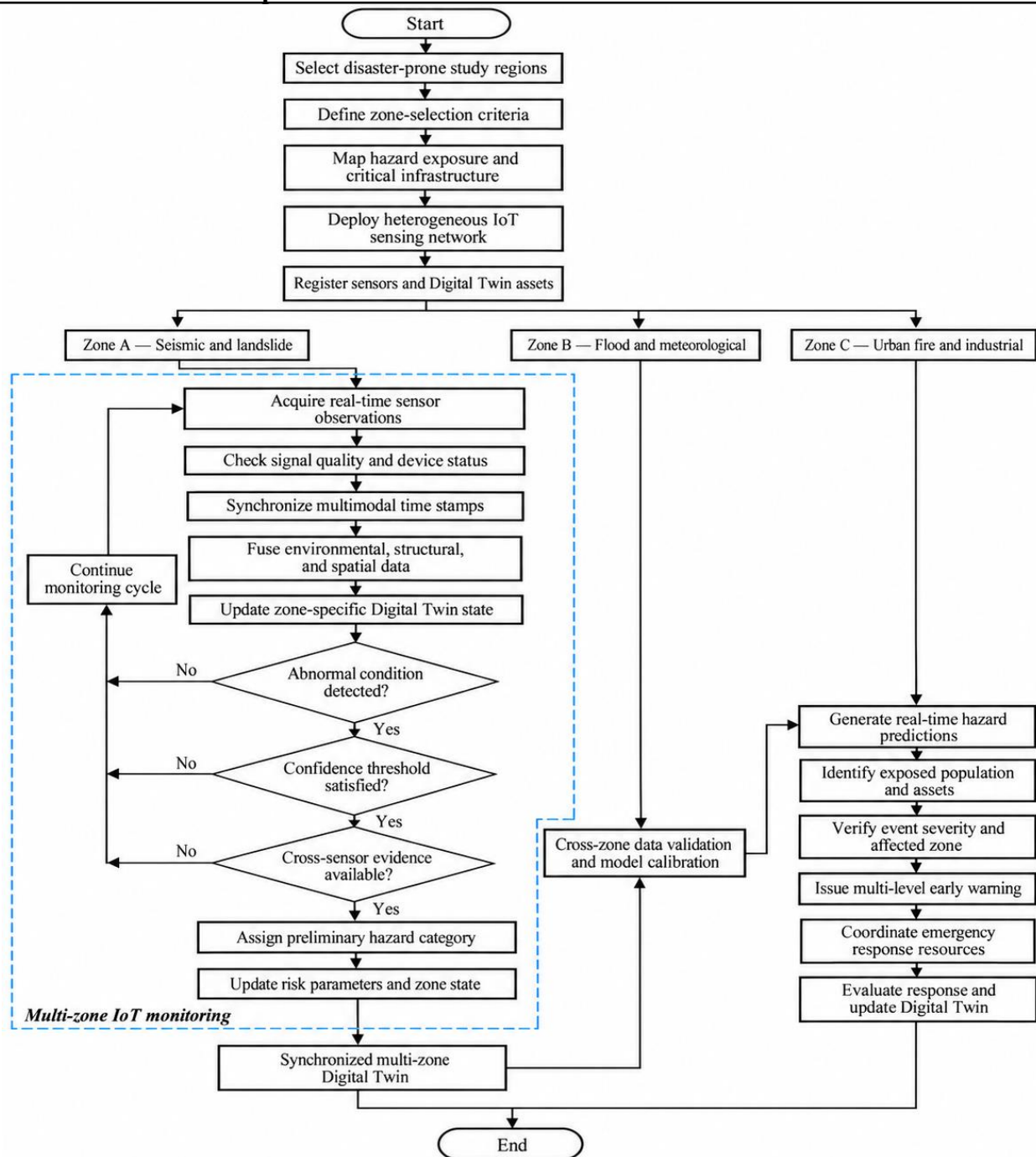


Figure 3: Multi-zone selection, IoT monitoring, and Digital Twin integration structure for complex disaster management.

The selection of geographically and operationally distinct zones increased the methodological strength of the study. It enabled assessment of the proposed framework across sudden-onset and

gradually developing disasters, high- and low-frequency sensing environments, densely populated and geographically dispersed locations, and stable and disrupted communication

conditions. Zone-specific analysis was used to determine whether the model maintained reliable classification across individual hazard categories, while combined analysis assessed its capacity to support multihazard and cross-zone disaster management. The multi-zone design also enabled the framework to investigate cascading consequences [23]. Earthquake-related structural damage in Zone 1 could affect road accessibility and emergency-resource movement. Flood development in Zone 2 could interrupt transportation connections with other zones. Landslides in Zone 3 could isolate settlements and block supply routes. Urban fires in Zone 4 could increase hospital demand, while an industrial gas release in Zone 5 could require evacuation of surrounding communities and redistribution of medical resources. These relationships were incorporated into Digital Twin scenarios to provide a more realistic assessment of crisis-management requirements.

4.2- Temporal Synchronization and Multimodal Data Fusion:

The proposed disaster-monitoring framework received heterogeneous data from seismic sensors, river-level gauges, weather stations, soil and slope sensors, smoke and gas detectors, structural-vibration sensors, surveillance nodes, GPS units, and wearable health monitors. These devices differed substantially in sampling frequency, timestamp precision, communication protocol, geographic coverage, data format, and operational reliability. Directly combining their raw outputs would have produced temporally inconsistent records and could have caused the prediction model to associate measurements from different physical moments. A structured temporal synchronization and multimodal fusion procedure was therefore implemented before sequence construction and deep-learning analysis. All 420 IoT devices were assigned unique identifiers linked with their sensor category, deployment zone, geographic coordinates, sampling frequency, calibration information, edge gateway, and operational status [24]. Device clocks were synchronized with the network reference clock at

deployment and checked periodically throughout the 24-month monitoring period. Edge gateways compared incoming device timestamps with their own synchronized clock and recorded both measurement time and reception time. The measurement timestamp represented when a physical observation was generated, whereas the reception timestamp indicated when it arrived at the gateway. Maintaining both values enabled the system to identify delayed packets and distinguish actual hazard development from communication-related delays. Clock drift was estimated by comparing each device timestamp with the gateway reference. Small deviations were corrected automatically, while records exceeding the accepted synchronization tolerance were flagged for additional review. Duplicate packets, out-of-order messages, and retransmitted observations were resolved using the device identifier, event timestamp, packet sequence number, and gateway reception time. When duplicate records contained identical values, only the earliest verified packet was retained. Where retransmitted packets contained updated quality information, the most complete validated record was preserved [25]. The sensing devices generated data at different rates according to the physical process being monitored. Seismic and structural-vibration sensors operated at relatively high frequencies because earthquake-related and structural signals may change within fractions of a second. River-level, flow, rainfall, soil-moisture, and weather sensors produced lower-frequency observations because their underlying conditions generally evolved more gradually. Smoke, temperature, gas, and pressure devices used moderate or adaptive frequencies, with higher sampling rates triggered by abnormal changes. GPS and wearable devices generated periodic information about responder location, movement, and physiological condition. Surveillance nodes captured images or short video sequences, but only event-related visual features and metadata were included in the synchronized tabular dataset. Table 4 summarizes the temporal properties, synchronization methods, and fused feature contributions of the principal data modalities. The variable counts represent the final

features retained after preprocessing and selection and sum to the 52 variables used by the proposed model.

Table 4: Temporal synchronization and feature-level fusion configuration for multimodal IoT data

Data modality	Original sampling pattern	Final retained variables
Seismic and ground-motion data	High-frequency continuous streams	7
Hydrological data	10–60-second periodic measurements	5
Meteorological data	1–5-minute periodic measurements	7
Soil and slope data	30-second to 5-minute observations	5
Fire and gas data	Adaptive 1–30-second measurements	7
Structural-condition data	High-frequency or event-triggered streams	5
Visual and surveillance data	Periodic images and event-triggered video	4
Geographic and mobility data	5–30-second location updates plus static GIS information	4
Physiological data	5–60-second periodic measurements	3
Operational and network data	Event-driven and periodically updated	5
Total	Heterogeneous continuous, periodic and event-driven streams	52

The study applied intermediate feature-level fusion rather than directly combining raw data or merging only the final model predictions. Raw-data fusion was considered unsuitable because of the substantial differences in sampling frequency, scale, dimensionality, and data type. Decision-level fusion would have allowed separate models to generate predictions for each modality, but it could have overlooked interactions across environmental, structural, spatial, physiological, and operational information. Intermediate fusion preserved modality-specific processing while allowing the learning architecture to identify cross-modal relationships. Each modality was initially converted into a standardized feature vector. These vectors were then combined according to the common timestamp, geographic sector, and observation sequence. A synchronized record was produced only after the system had resolved timing conflicts, checked sensor availability, and attached appropriate quality indicators. The fused representation included measurement values, temporal-change features, spatial context, sensor

reliability, and availability masks [26]. As a result, the model received not only the value of each variable but also contextual information describing the quality and recency of the evidence. Missing observations were handled without assuming that all sensor modalities would remain continuously available. Short gaps were treated using time-aware interpolation when reliable measurements existed immediately before and after the missing interval. For spatially distributed environmental sensors, values could be estimated from nearby correlated devices when geographic distance and environmental similarity remained within predefined limits. Larger or uncertain gaps were not forcefully reconstructed. Instead, the missing value was replaced with a neutral standardized value and accompanied by a binary mask that informed the model that the original measurement was unavailable. Figure 4 illustrates the complete temporal synchronization and multimodal fusion procedure used to transform heterogeneous IoT streams into model-ready disaster-monitoring sequences.

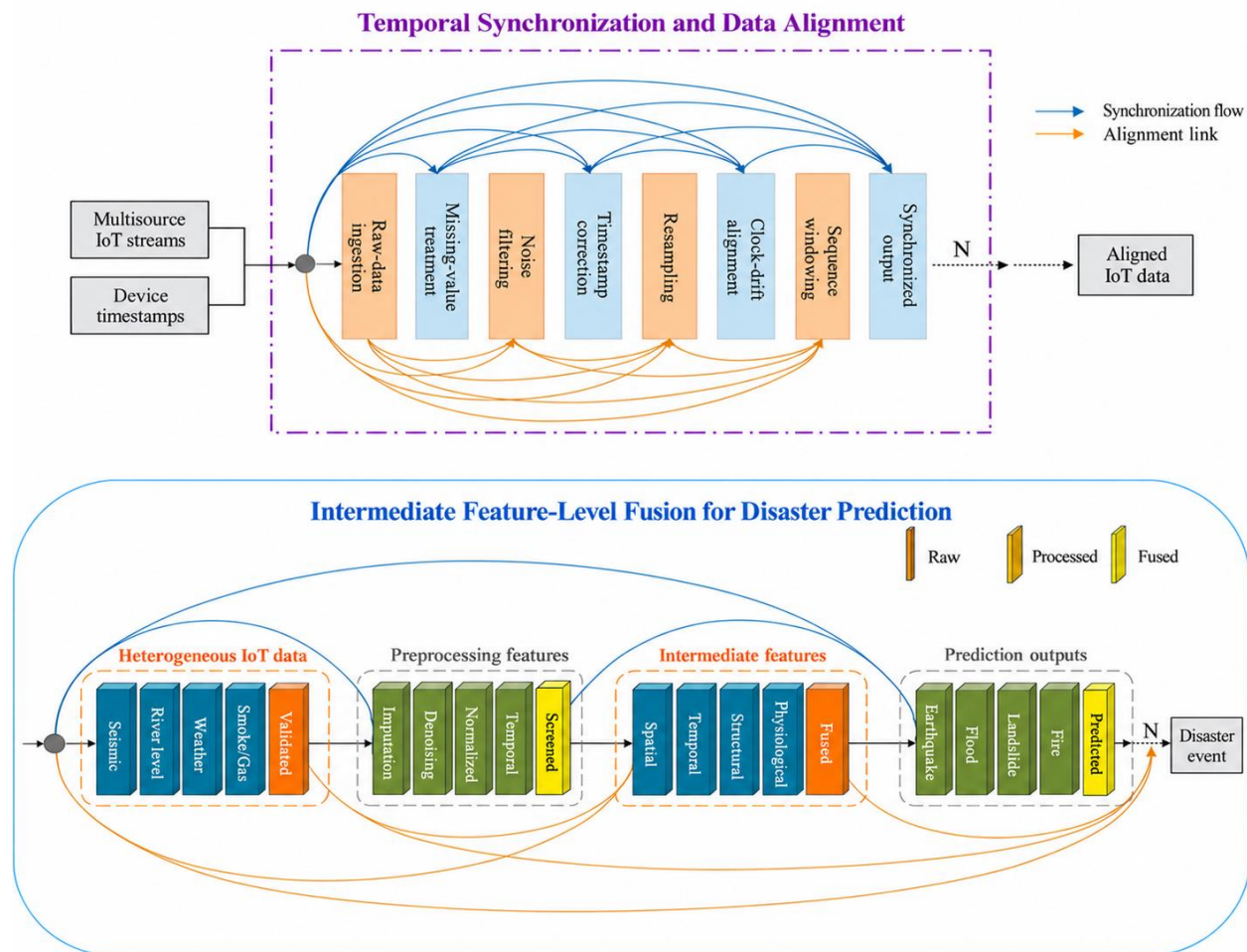


Figure 4: Temporal synchronization and intermediate feature-level fusion of heterogeneous IoT data for disaster-event prediction.

The fusion process was also designed for real-time edge-cloud operation. Edge gateways performed initial synchronization, short-window aggregation, duplicate removal, signal-quality assessment, and local feature extraction. This reduced the amount of raw data transmitted to the cloud and supported rapid local prediction. The cloud platform received synchronized features and high-priority raw segments associated with abnormal events. It performed cross-zone fusion, historical comparison, Digital Twin updating, and computationally intensive scenario analysis. During temporary network failure, edge gateways continued constructing synchronized windows using locally available devices [27]. If a sensor or communication channel became unavailable, the

associated availability mask and reliability indicator were updated automatically. The gateway could still generate a preliminary prediction from the remaining modalities. Once connectivity was restored, locally buffered records were transferred to the cloud according to their original measurement timestamps. Historical Digital Twin records were updated, but past real-time decisions were not recalculated when measuring operational latency and warning performance. The combined synchronization and fusion procedure provided several methodological advantages. It prevented measurements from unrelated moments from being treated as simultaneous, retained abrupt changes associated with rapidly developing disasters, reduced the influence of outdated or

unreliable observations, and enabled the model to learn relationships across multiple hazard indicators [28]. It also supported continued prediction when individual devices were unavailable. Most importantly, it transformed heterogeneous IoT streams into a consistent, quality-aware, and spatially meaningful representation suitable for real-time Digital Twin synchronization and intelligent disaster warning.

4.3- Disaster Verification and Outcome

Labelling:

Reliable disaster-event labels were required to train and evaluate the proposed CNN-BiLSTM-Attention model. Because abnormal sensor values do not always represent genuine emergencies, labels were not assigned solely through automated threshold exceedance. High vibration may originate from construction activity, elevated river levels may remain within a controlled range, smoke detectors may respond to dust or steam, and gas sensors may temporarily drift because of changes in temperature or humidity. A structured verification and outcome-labelling procedure was therefore applied using sensor evidence, incident records, spatial information, expert review, and operational confirmation. Each synchronized observation window was assigned to one of six principal outcome classes: normal condition, earthquake, flood, landslide, urban fire, or industrial gas leak. The normal class included stable environmental and infrastructure conditions, routine operational variation, nonhazardous sensor fluctuations, planned industrial activity, controlled maintenance operations, and verified false alarms. The five disaster classes represented confirmed events or confirmed event-related periods supported by sufficient physical and documentary evidence [29]. The verification process began with automated event-candidate identification. A synchronized observation was marked as a potential event when

one or more measurements exceeded hazard-specific limits, showed an abnormal rate of change, deviated substantially from recent historical behavior, or became inconsistent with expected physical conditions. Candidate generation was intentionally sensitive so that early or weak disaster signals were not excluded. These automated candidates were treated as provisional observations and did not become confirmed labels until additional evidence had been assessed. Hazard-specific candidate rules were applied to the relevant sensor groups. Possible earthquakes were identified through abnormal ground acceleration, seismic energy, vibration frequency, and simultaneous structural responses. Flood candidates were generated from river-level elevation, rapid water-level change, cumulative rainfall, flow velocity, drainage overflow, and visual evidence [30]. Potential landslides were identified using soil-moisture growth, pore-water pressure, slope displacement, inclination change, ground vibration, and prolonged rainfall. Fire candidates were detected through rising temperature, smoke density, carbon-monoxide concentration, thermal anomalies, and visual flame evidence. Industrial gas-leak candidates were identified through abnormal toxic- or combustible-gas concentration, pressure loss, wind conditions, equipment status, and worker-exposure indicators. The verified dataset contained 925,000 normal observations and 325,000 disaster-related observations. Among the disaster classes, floods accounted for 80,000 records, urban fires for 72,000, earthquakes for 70,000, industrial gas leaks for 55,000, and landslides for 48,000. These figures represent synchronized observation windows rather than the number of independent disaster episodes. Table 5 summarizes the class distribution, primary verification indicators, and evidence required for final labelling.

Table 5: Verified outcome classes, observation values, and principal labelling evidence

Outcome class	Verified observations	Dataset share (%)	Final labelling condition
---------------	-----------------------	-------------------	---------------------------

Normal condition	925,000	74.0	No verified disaster; includes confirmed false alarms and hard-negative conditions
Earthquake	70,000	5.6	Consistent seismic pattern supported by at least one independent confirmation source
Flood	80,000	6.4	Hazardous water expansion or verified flood-related disruption
Landslide	48,000	3.84	Verified slope movement or physical ground failure
Total	1,250,000	100.0	Final quality-controlled dataset used for model development

Each confirmed episode was divided into prevent, active-event, and recovery intervals. The prevent interval captured measurable changes preceding official confirmation and was used to calculate warning lead time. The active-event interval represented the period during which the hazard was physically present or operationally significant. The recovery interval contained declining hazard conditions that remained relevant to public safety and emergency response. Although these temporal stages were preserved as metadata, the principal supervised outcome remained one of the six classes. Event onset was defined as the earliest time at which verified hazard-related evidence became available to the monitoring system. Official report time was not automatically treated as the physical onset because an incident might begin before it was reported. For example, a flood could become detectable through rapid river-level elevation before inundation was formally documented [31]. The dataset therefore stored the first sensor-detectable time, first confirmed time, first warning time, and recorded incident time separately. These timestamps supported the evaluation of detection latency and warning lead time. Cascading and overlapping disasters required additional labelling rules. When one event triggered another, both hazards were retained within the Digital Twin event record. For supervised classification, each observation window was assigned the hazard that was physically dominant and most operationally relevant at that time. For example, an earthquake followed by an industrial gas release could initially

be labelled as an earthquake and later as a gas leak once chemical exposure became the dominant threat. The parent-secondary relationship was maintained through an event-link field so that the progression could be reconstructed during scenario analysis. The annotation process involved an initial automated label proposal, independent review, conflict resolution, and final quality control. Reviewers received synchronized sensor summaries, spatial maps, device-health information, external evidence, and the proposed event boundaries. They assigned the outcome class, start time, end time, confidence level, and evidence sources without relying exclusively on the automated proposal. Disagreements were referred to a senior reviewer or multidisciplinary verification panel. The network in figure 5 illustrates the conceptual relationships among major research keywords. Node size represents keyword prominence, while connecting lines indicate thematic associations. The red cluster emphasizes digital twins, disaster management, flood-risk assessment, machine learning, and emergency response [32]. The green cluster represents flood monitoring, remote sensing, Earth observation, GIS, natural hazards, and IoT sensors. The blue cluster highlights artificial intelligence, simulation, resilience, infrastructure, sustainability, and real-time monitoring. The strong links among these clusters demonstrate the growing integration of digital-twin technologies with intelligent sensing, geospatial analysis, predictive modelling, and disaster-response systems.

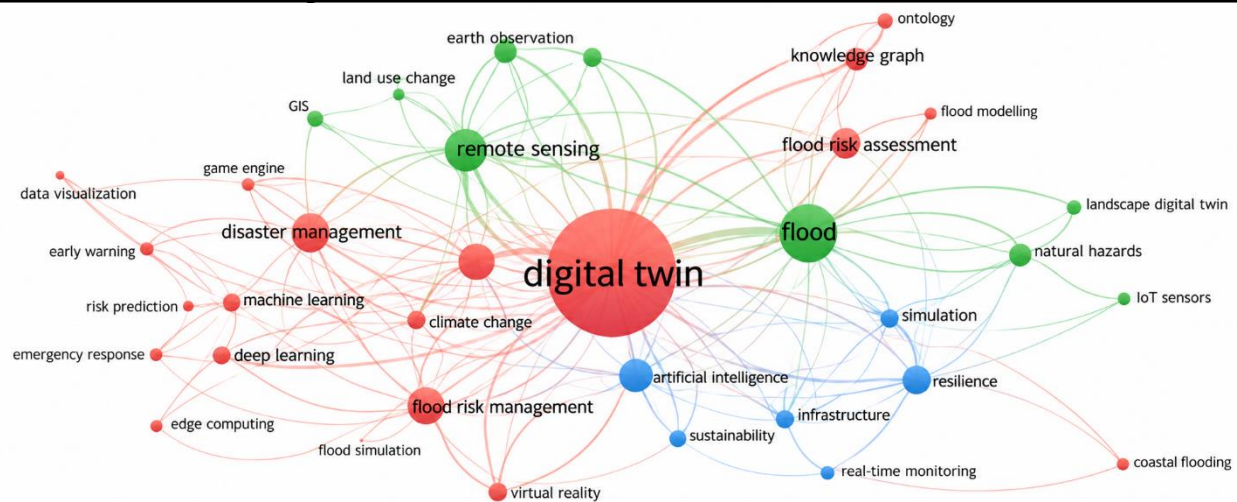


Figure 5: Bibliometric network of digital-twin research in flood-risk and disaster management.

Additional quality checks were performed after labelling. Class distributions were examined by zone, month, season, sensor type, and event duration. Extremely short episodes, unexpected label transitions, and spatially isolated events were reviewed again. The temporal order of pre-event, active-event, and recovery intervals was checked, and each event was matched with its supporting evidence record. Duplicate incidents recorded by multiple agencies were merged using time, location, and event-category information. The resulting labelled dataset provided a reliable basis for training and evaluating the proposed hybrid model. Its multi-source design reduced dependence on individual thresholds and improved the distinction between genuine disasters, precursor conditions, equipment faults, and nonhazardous abnormalities. Retention of hard-negative examples supported false-alarm reduction, while explicit event boundaries enabled the measurement of warning lead time and detection latency. Preservation of cascading-event relationships further allowed the Digital Twin to simulate complex disaster progression and support coordinated emergency decisions.

4.4- Hybrid CNN-BiLSTM-Attention Model:

A hybrid convolutional neural network-bidirectional long short-term memory-attention

model was developed to classify synchronized observations into six outcome categories: normal condition, earthquake, flood, landslide, urban fire, and industrial gas leak. The model was selected because complex disasters produce both local multivariate patterns and evolving temporal dependencies. Individual sensor readings may not provide sufficient evidence for reliable classification; however, combinations of changes across environmental, structural, spatial, physiological, and operational variables can reveal an emerging event. The proposed architecture therefore combined CNN-based feature extraction, BiLSTM-based temporal learning, and attention-based feature prioritization within a unified end-to-end model. The input to the model consisted of sequences generated through the synchronization and multimodal fusion procedure described in Section 3.8. Each sequence contained five consecutive 10-second analytical windows, representing 50 seconds of recent monitoring activity. Every time window contained 52 selected variables [33]. The resulting model input had a sequence length of five and a feature dimension of 52. This structure enabled the model to examine both the current monitoring condition and its recent development. The 52 variables represented seismic activity, hydrological conditions, weather, soil and slope behavior, smoke and gas concentrations, structural condition, geographic

context, responder physiology, device health, transportation accessibility, and resource availability. All continuous variables were normalized using parameters calculated from the training set. Missing-data masks, observation-age indicators, and sensor-reliability information were retained so that the model could distinguish recent direct measurements from interpolated, delayed, or unavailable observations. The convolutional component served as the first learnable stage. One-dimensional convolution was selected because the input consisted of multivariate time sequences rather than conventional two-dimensional images. The first convolutional layer used 64 filters with a kernel size of three to detect short-duration patterns and interactions among neighboring observation windows. It was followed by batch normalization and a rectified linear activation function [34].

Batch normalization stabilized the distribution of intermediate representations, while the activation function enabled the model to learn nonlinear relationships. A second one-dimensional convolutional layer contained 128 filters with a kernel size of three. This layer transformed the initial local features into higher-level representations capable of describing more complex hazard patterns. For example, the CNN could learn combinations involving rapid river-level growth, cumulative rainfall, and declining road accessibility or increasing gas concentration, falling system pressure, and changing wind direction. These combined patterns are more informative than individual thresholds because they describe how several physical and operational variables change together. The complete layer configuration is presented in Table 6.

Table 6: Configuration of the proposed hybrid CNN-BiLSTM-Attention model

Model stage	Configuration and data value	Output representation
Input	5 time windows × 52 variables	5 × 52
Convolutional block 1	64 filters, kernel size 3 and same padding	5 × 64
Convolutional block 1	Normalized nonlinear activation	5 × 64
Convolutional reduction	Pool size 2 and dropout rate 0.20	2 × 128
Temporal block 1	128 units per direction; sequence returned	2 × 256
Temporal block 2	64 units per direction; sequence returned	2 × 128
Temporal regularization	Dropout rate 0.30	2 × 128
Classification block 2	64 neurons, ReLU and dropout rate 0.30	64

The model was trained using the leakage-free training partition containing 70% of the eligible observations. The validation partition, containing 15%, was used for hyperparameter selection, early stopping, and model comparison. The final 15% testing partition remained completely independent until the model configuration had been finalized. Chronological and event-level separation ensured that observations from the same disaster episode did not appear across multiple partitions. Class imbalance was managed only within the training partition. Class weights assigned greater importance to errors involving less frequent disasters, while controlled oversampling improved minority-class representation. Validation and testing data

retained their original distributions. This allowed the evaluation to reflect the high proportion of normal operating conditions encountered in real monitoring environments. The Adam optimizer was used with an initial learning rate of 0.001. The learning rate was reduced when validation performance stopped improving for a defined number of epochs. Training was limited to 100 epochs, although early stopping terminated the process when validation loss failed to improve for 12 consecutive epochs. The model state producing the lowest validation loss was retained rather than the state generated during the final epoch. A mini-batch size of 128 was used to balance training stability and computational efficiency. Multiclass categorical cross-entropy served as the training

loss, while class weighting reduced majority-class dominance. Accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve were monitored. Validation recall and F1-score were given particular attention

because a model achieving high overall accuracy could still fail to detect less frequent disasters. The complete architecture and information flow are presented in Figure 6.

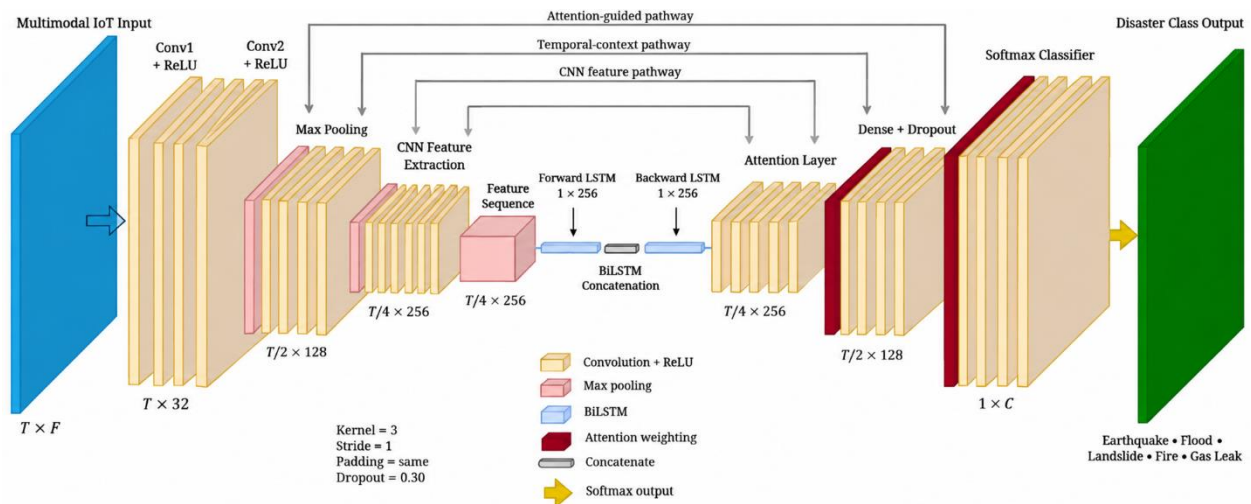


Figure 6: Architecture and operational workflow of the proposed hybrid CNN-BiLSTM-Attention disaster-classification model

The model was evaluated using overall and class-specific measures. Accuracy quantified the proportion of correctly classified observations, while precision described the reliability of predicted disaster classes. Recall measured the model's ability to identify genuine disaster observations, and the F1-score balanced precision and recall. The area under the receiver operating characteristic curve assessed discrimination across different classification thresholds. Confusion matrices were used to identify hazards that the model frequently confused, such as flood-related rainfall and landslide precursor conditions or fire-related smoke and industrial gas anomalies. Operational measures were also examined because predictive performance alone does not establish practical usefulness. Edge-inference latency measured the time required to process a synchronized sequence and produce class probabilities. Detection latency represented the interval between the first sensor-detectable hazard indication and the model's confirmed prediction [35]. Warning lead time measured how early the

framework issued a warning relative to the verified hazardous stage. The false-alarm rate quantified nonhazardous observations that incorrectly triggered warnings. Robustness testing examined performance under missing sensors, packet loss, communication delay, measurement noise, device drift, and reduced modality availability. Selected sensor groups were systematically masked to simulate equipment failure. Additional noise was introduced within physically plausible ranges, and delayed observations were withheld from the active decision window. These experiments assessed whether the multimodal architecture could preserve acceptable performance when some sensing evidence became unavailable.

4.5- GIS-Based Risk Mapping and Spatial Analysis:

A geographic information system-based risk-mapping module was integrated with the Digital Twin to convert heterogeneous sensor observations and model predictions into spatially interpretable disaster information. Disaster risk

changes across locations because hazard intensity, infrastructure vulnerability, population exposure, transportation accessibility, and emergency-response capacity are geographically uneven. A high flood probability in an unoccupied area does not create the same response priority as a similar probability near a densely populated settlement, hospital, power facility, or evacuation corridor. The GIS module therefore combined predicted hazard conditions with physical, demographic, infrastructural, and operational information to estimate the spatial distribution of risk across the five monitored zones. The spatial database covered the complete 685 km² monitoring area and represented the earthquake-prone urban zone, riverine floodplain, landslide-sensitive mountainous area, densely populated fire-risk district, and industrial gas-leak zone [36]. All 420 IoT devices were georeferenced using latitude, longitude, elevation, monitoring sector, and zone identifier. Each sensor was linked to its nearest building, road segment, waterway, slope, industrial facility, or other relevant physical asset. This spatial association enabled the Digital Twin to determine which infrastructure and population groups could be affected when abnormal measurements were detected. The GIS database contained static, periodically updated, and real-time layers. Static layers described relatively stable characteristics, including terrain elevation, slope, waterways, land use, administrative boundaries,

building footprints, road networks, bridges, pipelines, industrial facilities, hospitals, fire stations, emergency shelters, power infrastructure, and communication assets. Periodically updated layers included population density, building occupancy, shelter capacity, infrastructure condition, land-cover change, and seasonal hazard information. Dynamic layers contained real-time sensor readings, predicted disaster class, hazard probability, estimated intensity, road accessibility, responder location, shelter occupancy, resource availability, network condition, and device-health status. All spatial datasets were transformed to a common coordinate-reference system before integration. Geometry validation was performed to identify duplicated features, invalid polygons, disconnected road segments, overlapping boundaries, and missing geographic references. Attribute names, units, and categorical codes were standardized across zones [37]. Vector layers were used for roads, buildings, pipelines, facilities, zone boundaries, and evacuation routes, while raster layers represented elevation, slope, rainfall distribution, flood depth, temperature intensity, smoke dispersion, gas concentration, and composite risk. Table 7 summarizes the spatial datasets incorporated into the GIS and Digital Twin platform, their representative resolution or update frequency, and their role in disaster-risk analysis.

Table 7: GIS data layers and spatial-analysis configuration used for dynamic disaster-risk mapping

GIS layer category	Representative spatial data	Resolution or data value
Administrative and monitoring boundaries	Zone boundaries, operational sectors and emergency jurisdictions	5 zones across 685 km ²
Terrain and elevation	Elevation, slope, aspect, drainage direction and flow accumulation	10 m raster resolution
Analytical risk grid	Common cells used for hazard and risk surfaces	20 m grid resolution
Hydrological network	Rivers, streams, drainage channels, gauges and flood boundaries	170 km ² flood-zone coverage
Building and infrastructure layer	Buildings, bridges, utilities, power facilities and communication assets	Individual asset-level vector features
Transportation network	Roads, intersections, bridges, access points and evacuation routes	Road-segment level

Population and occupancy	Residential density, daytime population and facility occupancy	Sector and building-level estimates
Critical-service facilities	Hospitals, fire stations, shelters, police centers and control rooms	Individual facility locations
Seismic and structural monitoring	Seismic intensity, ground acceleration and infrastructure condition	92 devices; 275,000 observations

Hazard-specific spatial analysis was conducted because earthquakes, floods, landslides, fires, and gas leaks propagate differently. Earthquake-risk mapping combined predicted event probability with ground acceleration, soil characteristics, building vulnerability, structural-sensor readings, population density, and critical-facility locations. The resulting map highlighted areas where strong ground motion and vulnerable construction coincided. Bridges, hospitals, communication facilities, and power assets received additional attention because their failure could produce cascading operational consequences. Flood-risk mapping combined rainfall intensity, cumulative rainfall, river level, flow velocity, drainage conditions, elevation, slope, land use, and historical inundation boundaries. The Digital Twin simulated water movement from rivers and drainage channels into surrounding low-elevation areas. Predicted flood depth and expansion were overlaid with settlements, roads, healthcare facilities, shelters, utilities, and agricultural land [38]. Road segments were classified as open, at risk, restricted, or impassable according to estimated water depth and flow conditions. Landslide-risk mapping integrated rainfall

accumulation, soil moisture, pore-water pressure, slope angle, terrain curvature, land cover, ground vibration, displacement, and historical landslide evidence. Analysis was constrained by terrain units so that risk remained physically connected to the relevant slope. Settlements and roads located below unstable areas received elevated exposure values. The system also considered whether alternative roads were available because blockage of a single mountainous route could isolate communities and delay emergency assistance [39]. Urban-fire mapping combined smoke density, temperature, carbon monoxide, combustible-gas concentration, thermal imagery, visual evidence, building occupancy, construction type, street width, and fire-service accessibility. Predicted fire and smoke conditions were mapped across the densely populated zone. High-occupancy buildings, healthcare facilities, schools, commercial markets, and narrow road corridors received higher vulnerability or evacuation-difficulty scores. The map also displayed hydrants, firefighting units, hospitals, assembly locations, and available access routes. Figure 7 presents the GIS-based data-integration and spatial decision-support workflow.

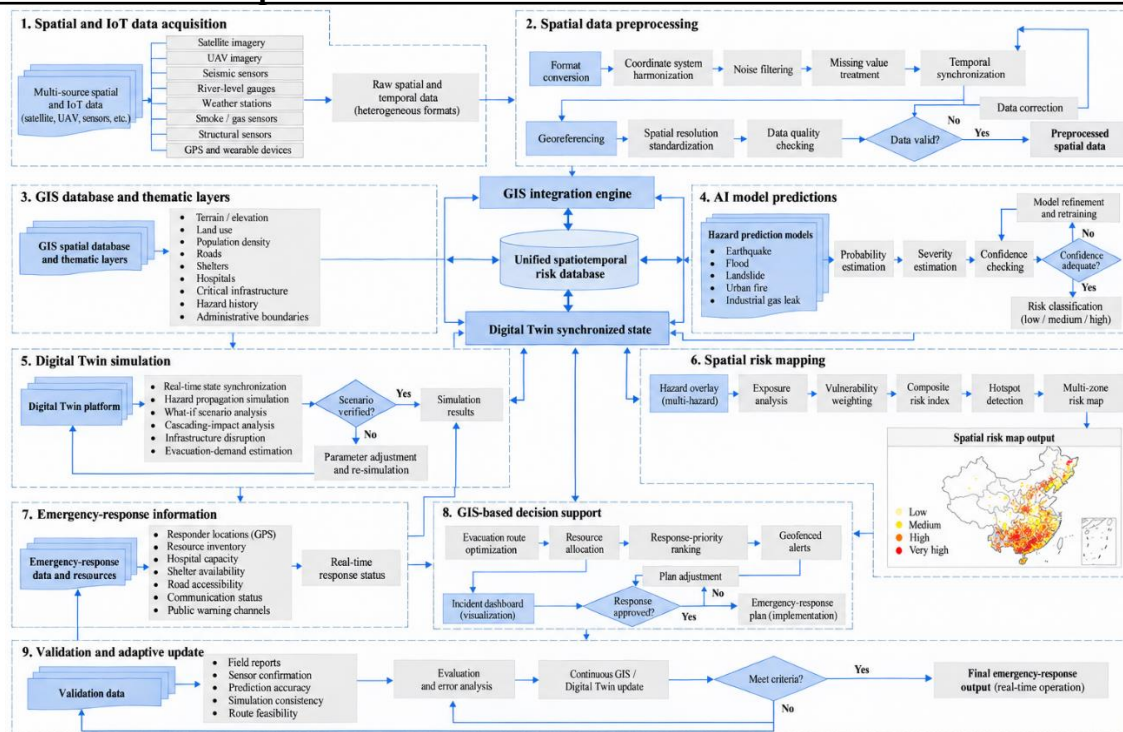


Figure 7: GIS-based integration of spatial data, model predictions, Digital Twin simulations, and emergency-response information.

The GIS interface was designed for both technical analysts and emergency decision-makers. Users could view current sensor status, predicted hazard type, risk level, affected infrastructure, exposed population, blocked roads, available shelters, and deployed resources. Layer visibility could be adjusted according to the responsibilities of each user. For example, firefighters could emphasize fire intensity, hydrants, building access, and hospital routes, whereas flood managers could emphasize rainfall, river level, drainage, elevation, and shelter availability. Alerts were linked directly to map locations. Selecting an alert displayed its hazard class, probability, sensor evidence, observation time, confidence level, affected radius, exposed assets, and recommended actions. This design reduced the need for decision-makers to interpret isolated numerical values. It also allowed emergency personnel to trace a warning back to the sensors and model outputs that generated it. The GIS platform maintained historical snapshots of risk surfaces and response actions [40]. These records supported post-event evaluation by

showing how risk evolved, when warnings were issued, which routes were recommended, and how resources were deployed. Comparisons between predicted and observed hazard boundaries were used to evaluate spatial accuracy and improve future Digital Twin simulations. Spatial validation was conducted using verified incident boundaries, field observations, surveillance evidence, remote-sensing information, and infrastructure-condition reports. Predicted high-risk cells were compared with observed impact locations. Route recommendations were checked against actual or simulated road accessibility, while resource-allocation outputs were evaluated using estimated response time and coverage. Validation was conducted separately for each hazard and zone because the accuracy requirements and spatial behaviors differed considerably.

5- Results and Discussion:

The proposed Digital Twin and IoT sensor-enabled framework was evaluated using the independent testing partition, which contained

15% of the 1,250,000 synchronized observations. The testing dataset retained the natural class distribution and was not subjected to oversampling or synthetic augmentation. The evaluation covered disaster-event classification, false-alarm reduction, detection latency, warning lead time, evacuation-route selection, emergency-response time, resource-allocation efficiency, and robustness under sensor and communication failures. The proposed CNN-BiLSTM-Attention model achieved an overall classification accuracy of 96.8%, precision of 96.1%, recall of 95.7%, F1-score of 95.9%, and ROC-AUC of 0.984. The

relatively small differences among accuracy, precision, recall, and F1-score demonstrate that the model maintained balanced performance rather than obtaining high accuracy by favoring the dominant normal class. Its recall of 95.7% indicates that most verified disaster observations were correctly detected, while its precision of 96.1% confirms that most predicted disaster events represented genuine hazardous conditions. Table 8 present the Overall predictive and operational performance of the proposed framework.

Table 8: Overall predictive and operational performance of the proposed framework

Performance measure	Result
Classification accuracy	96.8%
Precision	96.1%
Recall	95.7%
F1-score	95.9%
ROC-AUC	0.984
False-alarm reduction	31.6%
Warning lead-time improvement	27.4%
Conventional detection latency	8.7 seconds
Proposed detection latency	2.1 seconds
Detection-latency reduction	75.9%

The ROC-AUC value of 0.984 demonstrates strong discrimination between normal and hazardous conditions across different classification thresholds. This result is particularly important because the appropriate warning threshold may differ according to hazard type, population exposure, geographic location, and the consequences of delayed action. An industrial gas leak near a residential community, for example, may require a more sensitive threshold than a temporary environmental abnormality in an unoccupied location. The model also achieved consistently strong results across the five disaster categories. Earthquakes generated the highest disaster-class recall because ground acceleration,

seismic energy, and structural-vibration changes produced distinctive patterns. Floods were also identified reliably because rainfall, river level, flow velocity, terrain, and visual information provided complementary evidence [41]. Landslides produced the lowest class-specific performance because their precursor conditions frequently overlapped with heavy-rainfall periods that did not result in slope failure. Urban fires and industrial gas leaks maintained strong performance because multiple thermal, smoke, chemical, pressure, wind, and visual indicators were available for confirmation. Table 9 shows the Class-specific performance of the CNN-BiLSTM-Attention model.

Table 9: Class-specific performance of the CNN-BiLSTM-Attention model

Outcome class	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
Normal condition	97.5	98.1	97.8	0.989
Earthquake	97.2	97.6	97.4	0.992
Flood	96.4	96.8	96.6	0.987
Landslide	94.1	93.5	93.8	0.972
Urban fire	95.8	95.4	95.6	0.981
Industrial gas leak	95.6	95.1	95.3	0.983
Weighted average	96.1	95.7	95.9	0.984

The normal class produced an F1-score of 97.8%, demonstrating that the framework effectively recognized routine operating conditions and verified hard-negative observations. These observations included heavy rainfall without flooding, high soil moisture without slope failure,

machinery-related vibration without an earthquake, steam or dust without fire, and temporary chemical-sensor fluctuations without an industrial leak. Retaining these difficult nonhazardous examples during model development helped reduce false warnings.

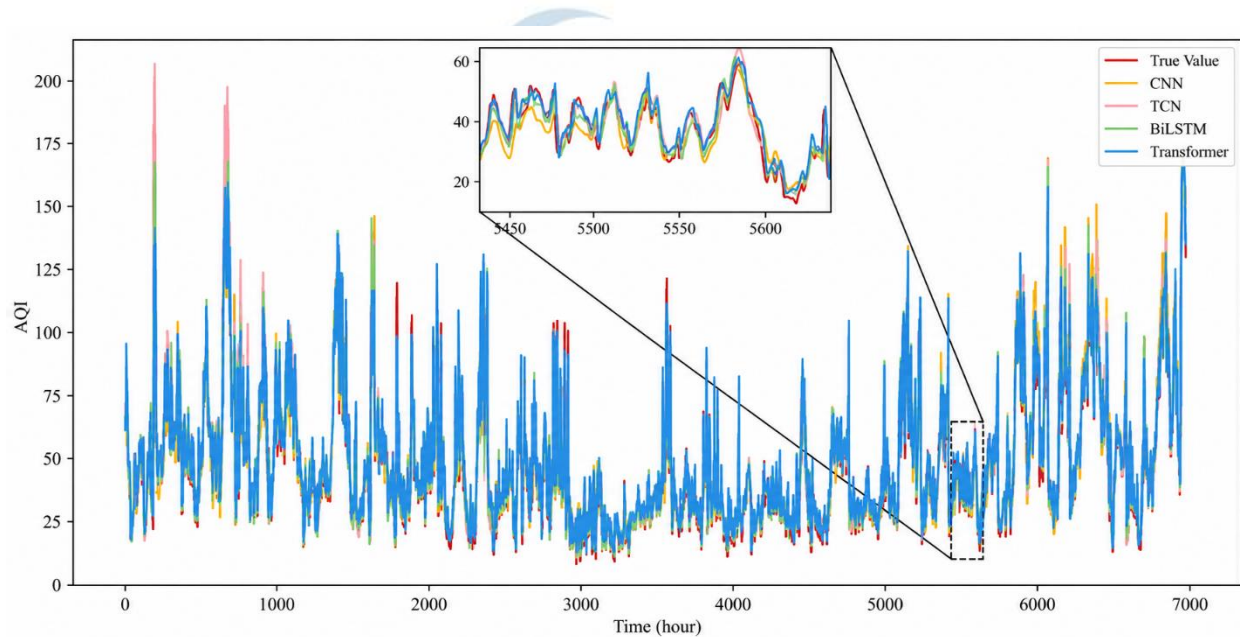


Figure 8: Comparison of actual and predicted AQI values using CNN, TCN, BiLSTM, and Transformer models.

The figure 8 compares the true AQI values with predictions generated by four deep-learning models over the complete hourly time series. All models generally follow the temporal fluctuations and major pollution peaks, while the Transformer shows particularly close alignment with the true values. The enlarged inset highlights model performance during a selected interval, enabling a clearer comparison of small differences between

the predicted and actual AQI patterns. The earthquake class achieved an F1-score of 97.4%, followed by floods at 96.6%, urban fires at 95.6%, industrial gas leaks at 95.3%, and landslides at 93.8%. Most errors occurred between a hazard and its related precursor conditions rather than between physically unrelated disasters. High river levels below the inundation limit were occasionally classified as floods, while prolonged rainfall and soil saturation without confirmed

ground movement were sometimes classified as landslides. Smoke and heat generated by routine industrial processes occasionally resembled early fire conditions [42]. These findings illustrate the difficulty of drawing a fixed boundary between elevated risk and confirmed disaster onset. The proposed architecture was compared with traditional machine-learning and deep-learning models using identical leakage-free training, validation, and testing partitions. Logistic

regression achieved an accuracy of 82.7%, while the support vector machine and random forest produced accuracies of 86.9% and 89.8%, respectively. The lower performance of these approaches indicates that fixed feature representations were unable to capture all nonlinear and time-dependent relationships within the multimodal sensor data. Table 10 shows the Comparative performance of the proposed model and baseline methods.

Table 10: Comparative performance of the proposed model and baseline methods

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
Logistic regression	82.7	81.9	80.8	81.3	0.864
Support vector machine	86.9	86.1	85.4	85.7	0.902
Random forest	89.8	89.2	88.4	88.8	0.931
Standalone CNN	92.1	91.5	90.9	91.2	0.951
Standalone LSTM	92.8	92.2	91.7	91.9	0.958
BiLSTM	93.7	93.1	92.8	92.9	0.965
CNN-BiLSTM	95.2	94.7	94.3	94.5	0.976
CNN-BiLSTM-Attention	96.8	96.1	95.7	95.9	0.984

The standalone CNN achieved 92.1% accuracy, demonstrating the importance of local interactions among synchronized sensor variables. However, it could not represent the temporal development of gradually evolving events as effectively as the recurrent models. The standalone LSTM achieved 92.8% accuracy, while the BiLSTM improved accuracy to 93.7% by learning richer temporal context within the available observation sequence. Combining the CNN and BiLSTM increased accuracy to 95.2%, confirming that local feature extraction and temporal modelling provided complementary information. The attention mechanism further increased accuracy by 1.6 percentage points and the F1-score by 1.4 percentage points. It was especially valuable when decisive evidence occurred during only a small part of the sequence, such as an abrupt

increase in river level, a sudden ground-acceleration peak, rapid growth in smoke density, or a sustained increase in toxic-gas concentration [43]. The framework maintained reliable performance across the five disaster-prone zones. Zone 1 achieved the highest accuracy of 97.5% because earthquake-related seismic and structural signals were distinctive and collected at high sampling frequencies. Zone 3 produced the lowest accuracy of 94.8% because landslide development was influenced by localized terrain, soil, rainfall, and displacement conditions. Nevertheless, performance remained above 94% in every zone, demonstrating that the synchronization and fusion procedures produced a consistent representation across different sensing environments. Table 11 present the Zone-wise predictive and latency results.

Table 11: Zone-wise predictive and latency results

Zone	Principal hazard	Accuracy (%)	F1-score (%)	Detection latency (seconds)
Zone 1	Earthquake	97.5	97.1	1.6
Zone 2	Flood	96.9	96.4	2.3
Zone 3	Landslide	94.8	93.9	2.8

Zone 4	Urban fire	96.7	95.8	1.9
Zone 5	Industrial gas leak	96.2	95.4	2.0
Overall	Multihazard monitoring	96.8	95.9	2.1

The longer detection latency observed in Zone 3 resulted from the need to combine rainfall, soil moisture, displacement, inclination, and ground-vibration evidence before confirming slope failure. Earthquake detection required only 1.6 seconds on average because high-frequency seismic observations could be processed immediately at the edge. These differences show that operational latency depends on both computational performance and the type of evidence needed for reliable confirmation. The edge-cloud architecture reduced average detection latency from 8.7 seconds to 2.1 seconds, corresponding to a reduction of approximately 75.9%. Edge gateways completed data validation, short-window feature extraction, and lightweight model inference close to the sensing environment. High-risk predictions were transmitted through priority communication channels, whereas routine information was summarized and uploaded periodically. This reduced bandwidth use and prevented cloud transmission from becoming a prerequisite for preliminary local warnings.

Warning lead time increased by 27.4% compared with conventional monitoring [44]. The framework identified evolving relationships among several variables before individual measurements exceeded late-stage emergency thresholds. In flood monitoring, it combined accumulated rainfall, river-level change, upstream flow, terrain, and drainage information. For landslides, it assessed rainfall persistence, soil saturation, pore pressure, inclination, displacement, and ground vibration. Panels (a-d) I figure 9 present the training and validation performance on the WISDM dataset, while panels (e-h) show the corresponding results for UCI-HAR. Panels (i-l) compare testing accuracy and loss across both datasets. The curves illustrate the convergence behavior of Attn-CNN-BiLSTM, CNN-BiLSTM, CNN, and LSTM over 140 epochs. Overall, the attention-enhanced CNN-BiLSTM model achieves rapid convergence, consistently high accuracy, and comparatively low loss, although occasional fluctuations are visible in some evaluation curves.

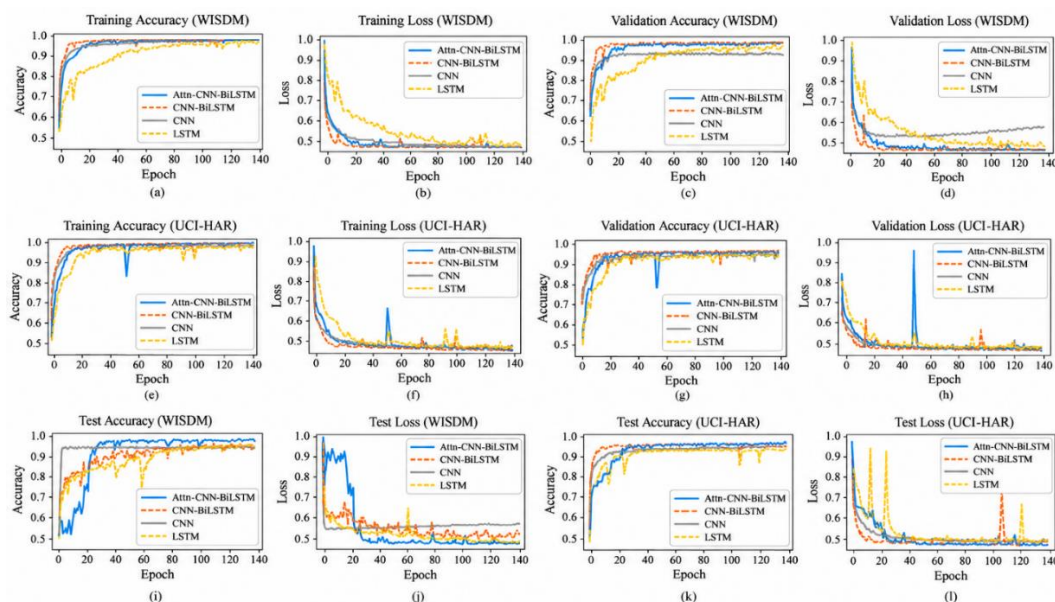


Figure 9: Training, validation, and testing accuracy and loss curves of the compared deep-learning models on the WISDM and UCI-HAR datasets.

The framework therefore recognized developing hazard patterns rather than waiting for a single measurement to reach a critical value. The practical value of the lead-time improvement differed across disaster categories. Even a small gain was valuable for rapidly developing earthquakes, fires, and gas leaks, while the larger warning interval available for floods and landslides supported evacuation, road closure, resource pre-positioning, and public communication. The improvement demonstrates that combining temporal deep learning with edge processing can enhance both predictive and operational responsiveness. False alarms decreased by 31.6% compared with conventional threshold-based monitoring. This reduction resulted from multisensor fusion, spatial-consistency assessment,

device-health monitoring, attention-based temporal weighting, and staged alert escalation [45]. Instead of generating an emergency warning after one abnormal value, the proposed framework assessed whether the available evidence formed a persistent and physically consistent disaster pattern. Moderate-confidence predictions initiated increased sampling and additional sensor confirmation rather than immediate public evacuation. High-level warnings required sustained predictive evidence, agreement among relevant sensors, and sufficient expected impact. This staged procedure reduced unnecessary escalation without substantially decreasing event recall. The resulting balance is important because repeated false warnings can generate public fatigue and reduce trust in emergency authorities.

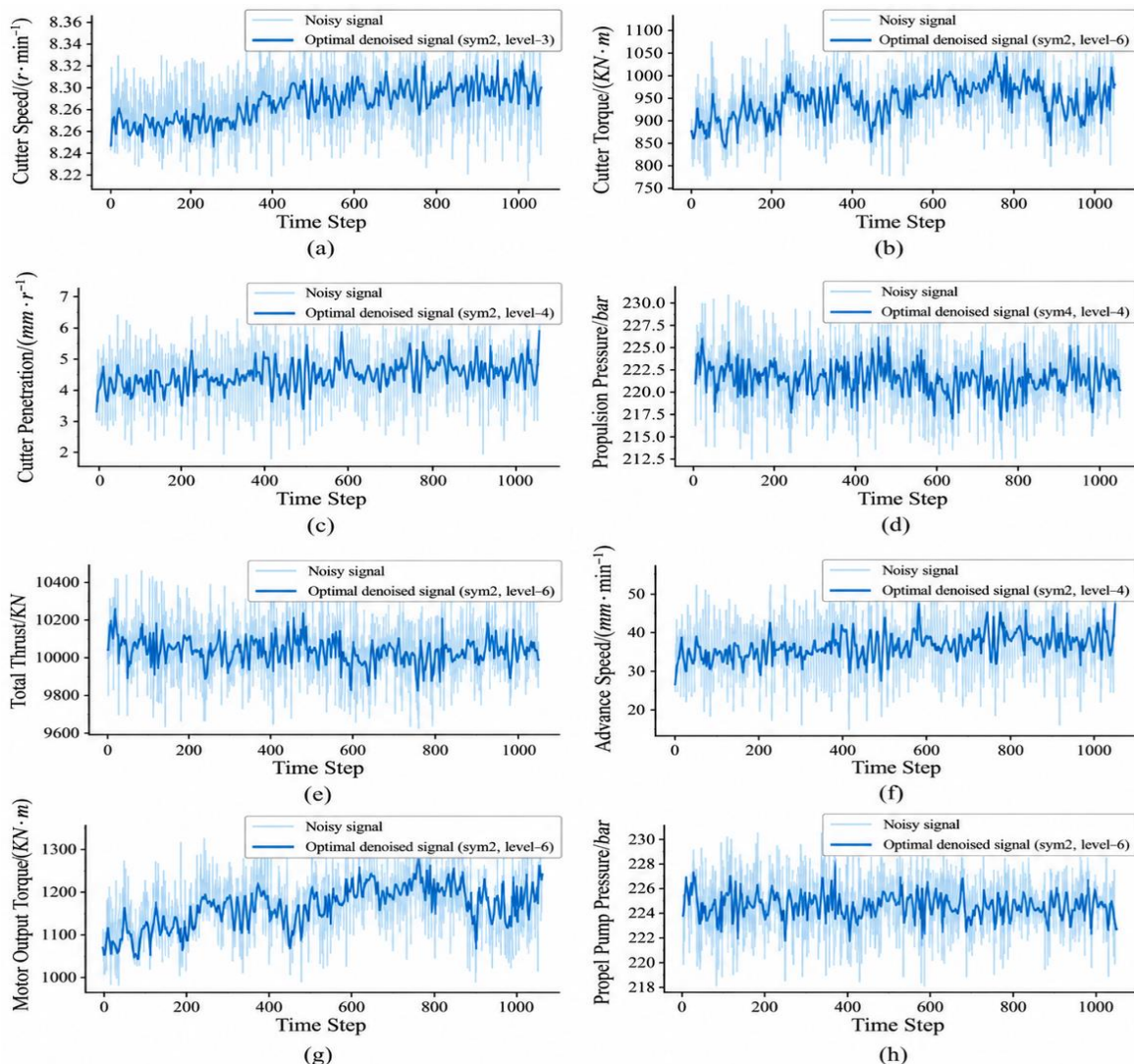


Figure 10: Wavelet-based denoising of IoT sensor signals for real-time Digital Twin disaster monitoring.

The figure 10 compares noisy and wavelet-denoised IoT sensor signals across eight operational parameters. The denoising process suppresses high-frequency disturbances while preserving critical temporal patterns, enabling reliable Digital Twin synchronization, real-time disaster monitoring, intelligent early warning, and emergency-response decision-making. The Digital Twin continuously integrated IoT measurements, model predictions, GIS layers, infrastructure conditions, road accessibility, population exposure, shelter availability, and emergency-resource locations. It simulated alternative hazard-

development and response scenarios before operational recommendations were issued [46]. This capability improved evacuation-route selection by 19.5% compared with conventional static routing. Static routing typically selects a path according to distance or normal travel time. The Digital Twin also considered predicted floodwater expansion, slope instability, fire or smoke exposure, toxic-gas dispersion, structural damage, congestion, and the probability that a road would become inaccessible. Routes were updated whenever new observations changed the predicted hazard boundary. This dynamic procedure

reduced the likelihood of directing evacuees or responders toward routes that were currently open but expected to become unsafe. The greatest routing benefits occurred during changing and cascading disasters. An earthquake could damage a bridge required for evacuation, while floodwater could isolate a hospital or shelter. A landslide could block the only direct road to a mountainous community, and a change in wind direction could move an industrial gas plume toward a previously safe route. By representing these interactions, the Digital Twin supported adaptive routing rather than a one-time evacuation decision. Estimated emergency-response time decreased by 24.2%. Earlier detection allowed emergency resources to be prepared before conditions reached their most

severe stage, while GIS-based accessibility analysis helped select suitable response units and travel routes. The figure 11 compares the convergence behavior of normal, pre-initialized, multiplication, and summation CNN strategies employed for processing IoT sensor data within the proposed Digital Twin framework. The normal CNN converges more rapidly and reaches lower values during most iterations, indicating faster optimization for real-time disaster-event analysis. The inset highlights the smaller performance differences during later iterations, supporting the selection of an efficient CNN configuration for intelligent early warning, emergency response, and crisis-management applications.

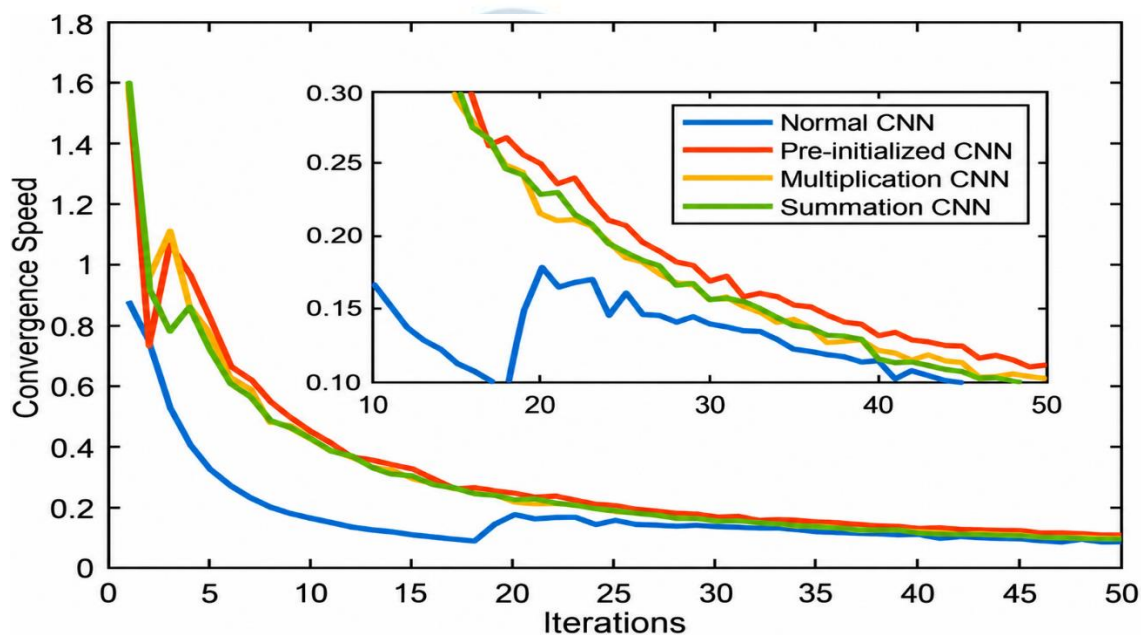


Figure 11: Convergence-speed comparison of CNN optimization strategies for Digital Twin-enabled real-time disaster monitoring

Emergency personnel received location-specific information describing predicted hazard extent, affected population, vulnerable infrastructure, road conditions, shelter capacity, and available resources. Resource-allocation efficiency improved by 22.8%. The allocation module considered hazard severity, population exposure, infrastructure vulnerability, medical requirements, travel accessibility, existing

coverage, and resource availability. Rescue teams, ambulances, firefighting units, medical supplies, shelters, and communication resources were represented as dynamic Digital Twin objects. Recommendations were revised when hazard intensity, road conditions, shelter occupancy, or regional demand changed. This dynamic approach addressed an important limitation of predetermined resource-allocation plans.

Conventional plans may send excessive resources to the first reported incident while less-connected or later-affected communities remain underserved. The proposed framework compared requirements across all zones and redistributed resources according to updated risk. If a road became inaccessible or a facility reached capacity, alternative resources and destinations were identified. The robustness analysis showed that the framework maintained useful performance

under sensor failure, packet loss, communication delay, measurement noise, and temporary cloud disconnection. With 10% random sensor loss, accuracy declined from 96.8% to 95.9%. At 20% sensor loss, accuracy remained 94.7%, demonstrating the value of multimodal redundancy and adaptive data fusion. Table 12 summarize the Framework robustness under simulated disruption conditions.

Table 12: Framework robustness under simulated disruption conditions

Disruption condition	Accuracy (%)	F1-score (%)	Detection latency (seconds)	Interpretation
Normal operating conditions	96.8	95.9	2.1	Complete sensing and communication availability
10% random sensor loss	95.9	95.0	2.3	Minimal effect on overall operation
20% random sensor loss	94.7	93.8	2.6	Reliable operation maintained through multimodal redundancy
30% random sensor loss	92.8	91.7	3.1	Noticeable degradation requiring confidence-adjusted warnings
Moderate packet loss and delay	94.9	94.0	2.9	Local buffering preserved most critical information

When individual devices failed, the model used related functioning modalities. Missing visual fire information could be partially compensated through smoke, temperature, gas, and structural measurements. A failed river-level gauge could be supported by upstream sensors, rainfall measurements, flow conditions, terrain, and surveillance evidence. Performance declined more noticeably when several devices measuring the same physical process failed simultaneously. During temporary cloud disconnection, the edge model maintained an accuracy of 94.2% and continued generating local alerts. Cloud-based Digital Twin simulation and cross-zone coordination were temporarily limited, but the most time-critical monitoring functions remained operational. Under combined sensor and communication disruption, accuracy declined to 91.6% and latency increased to 3.7 seconds. The

system consequently reduced its warning confidence and requested confirmation when alternative communication or sensing resources became available. The results collectively show that the strong performance of the proposed framework did not depend on one technological component. The figure 12 compares the test-accuracy trajectories of SGDM, Adam, TSGD, and TSGD+2Exp across 200 training epochs. TSGD+2Exp achieves the highest final accuracy of approximately 95.3% with strong late-stage stability, closely followed by TSGD. Adam converges near 93%, whereas SGDM exhibits greater fluctuations before stabilizing. These results demonstrate the suitability of TSGD+2Exp for reliable IoT sensor-data analysis, real-time disaster monitoring, intelligent early warning, and Digital Twin-supported emergency decision-making.

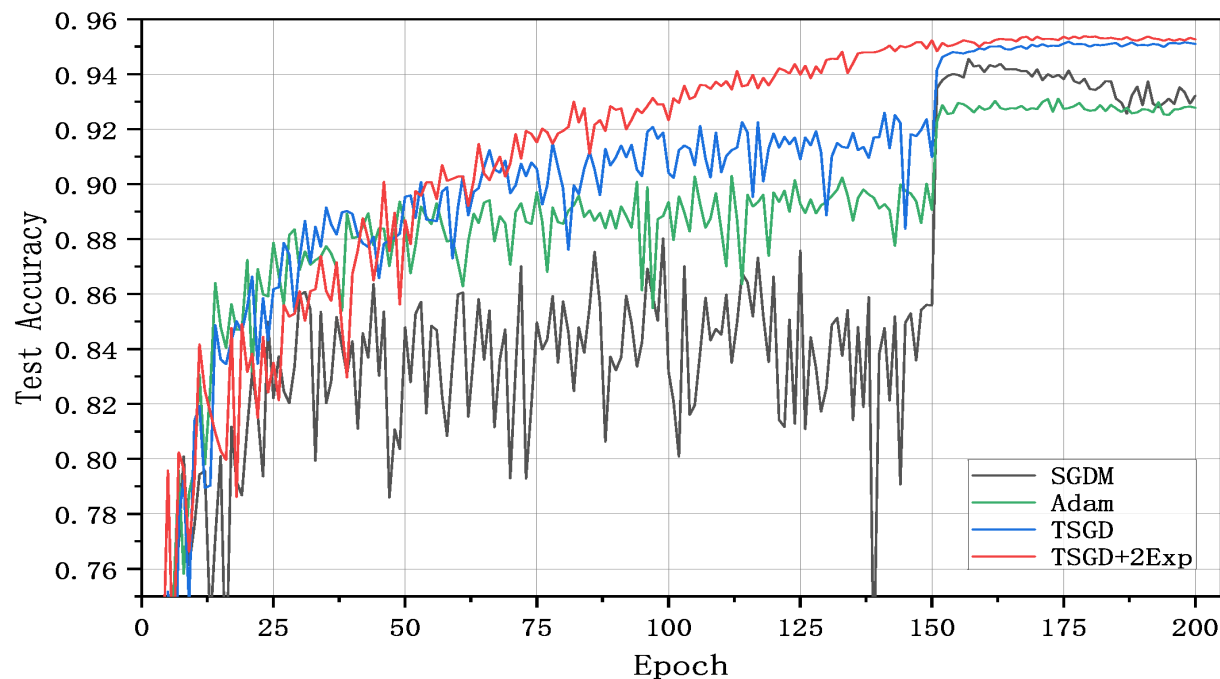


Figure 12: Test-accuracy convergence of optimization algorithms for Digital Twin-enabled disaster-event classification

The CNN extracted local relationships among multimodal variables, the BiLSTM captured temporal development, and the attention mechanism prioritized informative periods. Sensor-health indicators and quality-aware fusion reduced the influence of unreliable measurements. Edge processing shortened detection latency, while cloud analytics and the Digital Twin supported larger-scale simulation and coordination. The findings further demonstrate that classification accuracy alone is insufficient for evaluating disaster-management systems. A model may classify historical data accurately yet provide limited practical value if it produces delayed predictions, excessive false alarms, or outputs that cannot be translated into evacuation and response decisions. The proposed framework linked prediction with warning generation, GIS risk mapping, scenario simulation, evacuation routing, and resource allocation. This integration explains the simultaneous improvements in predictive performance and emergency operations. Some limitations remain. The results depend on the selected zones, sensor distributions, class

frequencies, and quality of incident-verification records. Landslide detection remained comparatively difficult because of terrain variability and overlap between precursor conditions and nonfailure periods. Simulated failure tests cannot represent every form of physical infrastructure damage or human behavior during real emergencies. Digital Twin outputs also depend on the accuracy and timeliness of terrain, building, road, population, and resource data. Despite these limitations, the results demonstrate that integrating distributed IoT sensing, edge intelligence, cloud analytics, GIS, and Digital Twin simulation can substantially improve complex disaster monitoring. The proposed framework achieved accurate multihazard classification, reduced false alarms and detection latency, increased warning lead time, improved evacuation routes and resource allocation, and maintained useful performance under degraded sensor and communication conditions. These outcomes support its potential application in resilient cities, emergency-management agencies,

industrial facilities, and critical-infrastructure environments.

6- Future Work:

Future research should validate the proposed Digital Twin and IoT sensor-enabled framework across larger and more geographically diverse disaster-prone regions. Although the present study covered earthquakes, floods, landslides, urban fires, and industrial gas leaks, future investigations should include additional hazards such as tsunamis, cyclones, droughts, wildfires, building collapse, chemical explosions, and disease outbreaks. Multi-country field testing would help determine whether the framework can maintain reliable performance under different climates, terrains, infrastructure conditions, communication networks, and emergency-management practices. The dataset should also be expanded through longer monitoring periods, additional IoT devices, and more verified disaster episodes. Particular attention should be given to underrepresented events such as landslides and industrial gas leaks. Federated learning could enable multiple cities and emergency organizations to improve shared prediction models without transferring sensitive raw data to a central platform. Privacy-preserving techniques, including secure aggregation, differential privacy, and encrypted computation, should also be investigated for GPS, surveillance, wearable-health, and population-movement information.

Future work should improve the hybrid CNN-BiLSTM-Attention architecture through graph neural networks, spatiotemporal transformers, self-supervised learning, and physics-informed artificial intelligence. Graph-based models could represent relationships among sensors, roads, buildings, utilities, and emergency facilities, while transformers could learn longer temporal dependencies across large monitoring networks. Physics-informed models could ensure that predictions remain consistent with flood propagation, slope instability, seismic behavior, fire spread, and gas-dispersion processes. Uncertainty-calibration methods should be added so that every prediction is accompanied by a

dependable confidence estimate. The Digital Twin should be extended from sector-level simulation to high-resolution three-dimensional representation of buildings, transportation systems, underground utilities, industrial facilities, and population movement. Integration with satellite imagery, drones, autonomous robots, mobile-phone signals, crowdsourced reports, and social-media information could improve situational awareness when fixed sensors are damaged [47]. However, these sources should be verified carefully to reduce misinformation and location errors. Additional research is needed to strengthen system resilience and cybersecurity. Future versions should examine coordinated sensor attacks, false-data injection, device spoofing, ransomware, model manipulation, denial-of-service attacks, and simultaneous power and communication failures. Blockchain-supported audit trails, zero-trust access control, intrusion detection, redundant communication, satellite connectivity, and energy-aware edge operation could improve the reliability of the framework during prolonged crises. Evacuation and resource-allocation modules should incorporate real human behavior, vulnerable population groups, vehicle availability, shelter preferences, hospital capacity, responder fatigue, and uncertainty in travel time. Multiobjective optimization could balance route safety, travel duration, congestion, fairness, and resource coverage. Human-in-the-loop decision interfaces should also be developed so emergency professionals can review, modify, or reject automated recommendations and provide feedback for subsequent Digital Twin updates. Finally, prospective field trials should evaluate the framework during drills and real emergency operations. Future assessments should examine public trust, warning comprehension, institutional interoperability, cost effectiveness, energy consumption, scalability, and long-term maintenance. Comparison with existing emergency-management platforms would provide stronger evidence of practical value. These developments could support the transition of the proposed framework from an experimental system to a secure, explainable, and operationally

dependable platform for resilient cities and critical infrastructure.

Conclusion:

This study developed a Digital Twin and IoT sensor-enabled framework for real-time complex disaster monitoring, intelligent early warning, emergency response, and crisis management. The framework integrated distributed IoT sensing, temporal synchronization, multimodal data fusion, edge-cloud computing, GIS-based risk mapping, and a hybrid CNN-BiLSTM-Attention model. It supported the complete disaster-management pathway, from physical data acquisition and event detection to scenario simulation, evacuation planning, resource allocation, and coordinated emergency communication. The framework was evaluated using 1,250,000 time-stamped observations collected from 420 IoT devices across five disaster-prone zones over 24 months. The dataset included 52 environmental, structural, spatial, physiological, and operational variables associated with earthquakes, floods, landslides, urban fires, and industrial gas leaks. The proposed model achieved 96.8% accuracy, 96.1% precision, 95.7% recall, a 95.9% F1-score, and a ROC-AUC of 0.984. It also reduced false alarms by 31.6%, increased warning lead time by 27.4%, and decreased average detection latency from 8.7 to 2.1 seconds. Digital Twin-based scenario simulation improved evacuation-route selection by 19.5%, reduced estimated emergency-response time by 24.2%, and increased resource-allocation efficiency by 22.8%. Robustness testing further showed that multimodal redundancy, reliability-aware data fusion, local buffering, and edge inference allowed essential monitoring and warning functions to continue during sensor failures and communication disruptions. The findings demonstrate that combining Digital Twins, heterogeneous IoT sensing, artificial intelligence, GIS, and edge-cloud computing can provide accurate situational awareness and actionable emergency decision support. Unlike isolated monitoring systems, the proposed framework connects predictive intelligence

directly with operational response. It therefore offers a scalable foundation for resilient cities, emergency agencies, industrial facilities, and critical-infrastructure operators. Nevertheless, broader field validation, stronger privacy protection, enhanced cybersecurity, and human-in-the-loop testing remain necessary before large-scale operational deployment.

References:

- Ariyachandra, M. M. F., & Wedawatta, G. (2023). RETRACTED: Digital twin smart cities for disaster risk management: a review of evolving concepts. *Sustainability*, 15(15), 11910.
- Riaz, K., McAfee, M., & Gharbia, S. S. (2023). Management of climate resilience: exploring the potential of digital twin technology, 3D city modelling, and early warning systems. *Sensors*, 23(5), 2659.
- Korkmaz, M., Akyildiz, Y. E., Demirkesen, S., Toprak, S., Nowak, P., & Ciftci, B. (2025). A digital twin approach to sustainable disaster management: Case of Cayirova. *Sustainability*, 17(21), 9626.
- Ahmad, B., Ali, S., Muneer, M., Fatima, A., & Abbas, N. (2025). Wind energy integration into the SAARC region: A comprehensive review of optimal wind sites for a sustainable super smart grid. *Wind Energy*, 3(2).
- Cheng, R., Hou, L., & Xu, S. (2023). A review of digital twin applications in civil and infrastructure emergency management. *Buildings*, 13(5), 1143.
- Na, I. S., Rajasekar, V., & Sarveshwaran, V. (2025). Real-Time Fire Risk Classification Using Sensor Data and Digital-Twin-Enabled Deep Learning. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 18, 19961-19973.
- Karaduman, Ö. (2025). Towards integrated disaster management: A review of AI, blockchain, and digital twin technologies for smart resilience. *International Journal of Innovative Engineering Applications*, 9(2), 211-222.

- Akter, E., Bormon, J. C., Saikat, M. H., & Shoag, M. (2025). Digital twin technology for smart civil infrastructure and emergency preparedness. *IJSRED-International Journal of Scientific Research and Engineering Development*, 8(2), 891-902.
- Sumalatha, A., Vijayanandh, T., Sabri, M. O., & Dinesh, M. (2025, November). A Novel Approach to Emergency Infrastructure Monitoring via Digital Twin Technology: Building Disaster-Resilient Edge-Cloud Computing Architectures. In *2025 IEEE 7th International Conference on Computing, Communication and Automation (ICCCA)* (pp. 1-7). IEEE.
- Rani, D. S., Ramachandra, M., Sukruta, R., Veeranna, T., Krishna, G. B., & Reddy, M. P. K. (2025, October). IoT and AI-Enhanced Digital Twin for Smart City Disaster Resilience and Resource Optimization. In *2025 10th International Conference on Communication and Electronics Systems (ICCES)* (pp. 1347-1353). IEEE.
- Hlal, M., Baraka Munyaka, J. C., Chenal, J., Azmi, R., Diop, E. B., Bounabi, M., ... & Adraoui, M. (2025). Digital twin technology for urban flood risk management: A systematic review of remote sensing applications and early warning systems. *Remote Sensing*, 17(17), 3104.
- Ahmad, B., Majeed, M. K., Soomro, A. A., & Jillani, S. A. (2026, January). Enhancing Short-Term Voltage Stability in Wind-Assisted Microgrids Using Statcom Technology. In *2026 1st International Conference on Innovations in Information and Communication Technologies (IICT)* (pp. 1-6). IEEE.
- Yu, D., & He, Z. (2022). Digital twin-driven intelligence disaster prevention and mitigation for infrastructure: advances, challenges, and opportunities. *Natural hazards*, 112(1), 1-36.
- Fan, C., Zhang, C., Yahja, A., & Mostafavi, A. (2021). Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. *International journal of information management*, 56, 102049.
- Rathod, V. N., & Goudar, R. H. (2025). DTwin for urbanization: Early warning systems, post-disaster recovery, resilient communities. In *Digital Twins for Smart Cities and Urban Planning* (pp. 179-193). CRC Press.
- Anand, L. G. (2026). Digital Twin-Enabled Search-and-Rescue Robots for Adaptive Disaster Response and Infrastructure Resilience.
- Wolf, K., Dawson, R. J., Mills, J. P., Blythe, P., & Morley, J. (2022). Towards a digital twin for supporting multi-agency incident management in a smart city. *Scientific reports*, 12(1), 16221.
- Habib, A., Habib, M., Bashir, B., & Bachir, H. (2025). Exploring the sustainability benefits of digital twin technology in achieving resilient smart cities during strong earthquake events. *Arabian Journal for Science and Engineering*, 50(20), 16869-16883.
- Patel, C. (2026). Integrating Artificial Intelligence, IoT, and GIS for Smart Disaster Risk Management: A Systematic Review. *Journal of Commerce, Economics & Computer Science*, 12 (03), 109, 121.
- Almatared, M., Liu, H., Abudayyeh, O., Hakim, O., & Sulaiman, M. (2023). Digital-twin-based fire safety management framework for smart buildings. *Buildings*, 14(1), 4.
- Ahmad, B., Jillani, S. A., Rafique, M., & Soomro, A. A. (2026, January). Design and Monitoring of a Tree-Inspired Vertical Axis Wind Turbine for Efficient Urban Wind Utilization. In *2026 1st International Conference on Innovations in Information and Communication Technologies (IICT)* (pp. 1-6). IEEE.

- Ashwini, A., & Sangeetha, S. (2024). IoT-based smart sensors: The key to early warning systems and rapid response in natural disasters. In *Predicting Natural Disasters With AI and Machine Learning* (pp. 202-223). IGI Global Scientific Publishing.
- Korkmaz, M., Zulfikar, A. C., & Demirkenen, S. (2024). Leveraging digital twins as a common operating picture for disaster management: case of seismic hazards. *ISPRS International Journal of Geo-Information*, 13(12), 430.
- Zeng, F., Pang, C., & Tang, H. (2023). Sensors on the internet of things systems for urban disaster management: a systematic literature review. *Sensors*, 23(17), 7475.
- Skarga-Bandurova, I., Biloborodova, T., Kjelstrup-Johnson, K. R., Scheper, T. V. O., & Derkach, M. (2026). Securing Tomorrow's Cities: Smart Infrastructure for Emergency Response, Crisis Management, and Defence. In *Sustainable, Innovative, and Intelligent Industries and Societies* (pp. 69-111). Cham: Springer Nature Switzerland.
- Hakimi, O., Liu, H., Abudayyeh, O., Houshyar, A., Almatared, M., & Alhawiti, A. (2023). Data fusion for smart civil infrastructure management: A conceptual digital twin framework. *Buildings*, 13(11), 2725.
- Chitranshi, R. (2025). Digital twin technology for infrastructure resilience: An interdisciplinary engineering framework. *International Journal of Applied Mathematics*, 38(12s), 2552-2567.
- Mahmood, R. S., & Farooq, E. O. (2026). Real Time Disaster Monitoring System Using GIS-Based Web Mapping and Satellite Data Integration. *Research Consortium Archive*, 4(2), 2545-2553.
- Collins, N. (2026). A Climate-Health Digital Twin Framework for Real-Time Prediction and Management of Extreme-Heat Health Emergencies.
- Singh, S. K., Gothania, J., & Sansaniwal, S. K. (2026). Early Warning Systems and Real-Time Decision Support: Leveraging GIS and Remote Sensing for Global Disaster Preparedness. In *Interdisciplinary Studies on Global Disasters* (pp. 373-398). IGI Global Scientific Publishing.
- McMullan, C., & Thakkar, R. (2025). Digital Twins for Impact (DT4I): Using Digital Twins to Deliver Effective Risk and Emergency Management.
- Bhati, M., Pelot, R., Floris, G., Hamid, A., Vignesh, K. S., & Infantia, C. J. (2025, May). Exploring the Concept of a Digital Twin Smart City for Disaster Emergency Preparedness Planning in Nova Scotia, Canada. In *Proceedings of the International ISCRAM Conference* (Vol. 22).
- Ham, Y., & Kim, J. (2020). Participatory sensing and digital twin city: Updating virtual city models for enhanced risk-informed decision-making. *Journal of Management in Engineering*, 36(3), 04020005.
- Mahomed, A. S., & Saha, A. K. (2025). Unleashing the potential of 5G for smart cities: A focus on real-time digital twin integration. *Smart Cities*, 8(2), 70.
- Wang, J., Samarasinghe, D. A. S., Aquino, D. H. M., & Ying, F. (2026). A systematic review of digital technologies for emergency preparedness in buildings. *Buildings*, 16(4), 856.
- Qi, X., Wang, H., Xiong, X., Zhou, A., Sun, Q., & Zhang, Q. (2026). Digital Twin Framework for Structural Health Monitoring of Transmission Towers: Integrating BIM, IoT and FEM for Wind-Flood Multi-Hazard Simulation. *Applied Sciences*, 16(8), 3620.
- Aschieri, D. L. D. (2025). Design and Implementation of a Regional Digital Twin for Integrated Disaster Prevention and Risk Management.

- Faliagka, E., Christopoulou, E., Ringas, D., Politi, T., Kostis, N., Leonardos, D., ... & Voros, N. (2024). Trends in digital twin framework architectures for smart cities: A case study in smart mobility. *Sensors*, 24(5), 1665.
- Saputra, H., Helmi, R. A. A., Ghazali, M. D., & Sumartini, W. O. (2025). Urban resilience through IoT-based disaster preparedness and infrastructure monitoring: a systematic literature review. *Natural Hazards Research*.
- Bikkasani, D. C. (2026). Toward Intelligent and Resilient Public Safety Communications: A Review of FirstNet, 5G, AI, and Digital Twin Technologies.
- Al-Asady, H. A. J. A Cognitive Digital Twin Framework for Resilient Water Infrastructure under Climate Change. In *Smart Technologies for Sustainable Development Goals* (pp. 321-350). CRC Press.
- Olawade, D. B., Ijiwade, J. O., Ojo, A., Alabi, J. O., Makanjuola, B. D., & Wada, O. Z. (2026). Digital Twin Technology for Environmental Management: Applications, Benefits, and Implementation Challenges. *Environmental Pollution and Management*.
- olde Scheper, T. V., & Derkach, M. (2026). Securing Tomorrow's Cities: Smart Infrastructure for Emergency Response, Crisis Management, and Defence. *Sustainable, Innovative, and Intelligent Industries and Societies*, 69.
- Dhanaraj, R. K., & Mondal, G. (2026). Quantum-Inspired Predictive Digital Twins for Self-Healing Neuro-Fusion Control in Multi-UAV Swarms for Disaster Response. *International Journal of Computational Intelligence Systems*.
- Chen, H., & Chen, J. (2026, July). A Digital Twin-Based Study on Risk Early Warning and Emergency Response Plan Simulation for the Low-Altitude Economy. In *2026 IEEE 27th China Conference on System Simulation Technology and its Applications (CCSSTA)* (pp. 248-254). IEEE.
- Ristvej, J., Halúsková, B., Nováková, K., & Chovanec, D. (2026). Implementation Maturity Levels of Digital Twin Technology and Data Content Design for Flood Digital Twin. *Smart Cities*, 9(2), 28.
- Dao, J., Huang, Y., Ju, X., Yang, L., Yang, X., Liao, X., ... & Ding, D. (2025). A Semantic Digital Twin-Driven Framework for Multi-Source Data Integration in Forest Fire Prediction and Response. *Forests*, 16(11), 1661.