



ARTICLE

# A Conceptual Artificial Intelligence and Edge Computing-Based Framework for Rapid Post-Earthquake Management of Bridges in a Smart City

Abdullah Alariyan<sup>1</sup>, Mohammed Abdulaal<sup>2</sup>, Anas Alaryan<sup>3</sup>, Mohammed Alariyan<sup>4</sup>,  
Mahmoud Alhashash<sup>5</sup>, Abdulhadi Alzabout<sup>6</sup>, Abdulrahman Ahmed<sup>7</sup> and Ahed Habib<sup>8,\*</sup>

<sup>1</sup>Department of Civil Engineering, Eastern Mediterranean University, Famagusta, Northern Cyprus via Mersin 10, Mersin, Turkey

<sup>2</sup>Department of Architecture, Eastern Mediterranean University, Famagusta, Northern Cyprus via Mersin 10, Mersin, Turkey

<sup>3</sup>Department of Civil Engineering, Cairo University, Giza, Egypt

<sup>4</sup>Department of Civil Engineering, University of Science and Technology Yemen, Aden, Yemen

<sup>5</sup>Department of Civil Engineering, Cyprus International University, Famagusta, Cyprus

<sup>6</sup>Department of Civil Engineering, Isra University, Amman, Jordan

<sup>7</sup>Department of Civil Engineering, Fahd Bin Sultan University, Tabuk, Saudi Arabia

<sup>8</sup>Sustainable Systems, Technologies, and Infrastructure Research Center, Research Institute of Sciences & Engineering, University of Sharjah, Sharjah, United Arab Emirates

\*Corresponding Author: Ahed Habib. Email: [ahabib@sharjah.ac.ae](mailto:ahabib@sharjah.ac.ae)

Received: 21 April 2026; Accepted: 13 August 2026; Published: 23 October 2026

**ABSTRACT:** Bridges are critical links in urban transportation networks, and delayed post-earthquake assessment can compromise public safety, emergency access, and network continuity. Although structural health monitoring, artificial intelligence (AI), and edge computing have advanced individually, an integrated bridge-specific workflow that links sensing, decentralized screening, uncertainty-aware decision support, and city-level coordination remains insufficiently developed. This study proposes a conceptual framework based on AI and edge computing for rapid post-earthquake bridge management in a smart city. Using a traceable design-synthesis procedure, requirements identified from the literature were translated into system layers, data flows, edge-cloud task allocation, uncertainty controls, and parameterized decision rules. The framework integrates Internet of Things sensors, local edge analytics, central context and network fusion, AI-based time-series and visual screening, reliability-weighted evidence fusion, confidence assessment, communication-loss operation, and professional assessment triggers. Its principal contribution is a validation-ready design specification that connects technical damage screening with provisional operational states and coordinated response while preserving professional authority over uncertain, severe, and reopening decisions. Because this is a theoretical framework study, no empirical dataset, simulation result, or field deployment is reported; accuracy, latency, false-alarm performance, and operational effectiveness must be established through the proposed staged simulation, hardware-in-the-loop, and pilot validation protocol.

**KEYWORDS:** Earthquake resilience; artificial intelligence; edge computing; structural health monitoring; smart cities; conceptual framework; time-series analysis

## 1 Introduction

Urban transportation systems depend strongly on bridge structures, especially in seismic regions where their performance directly affects mobility, emergency response, and public safety during and after earthquakes [1–3]. Bridges often serve as critical links in road networks, and any damage or loss of functionality can lead to serious disruption in traffic flow and delay rescue operations, which increases the

overall risk in affected areas [4–6]. Earthquake events introduce complex structural responses due to ground motion variability, aftershocks, and cumulative damage, which makes post-event assessment a challenging engineering problem [7–9]. Traditional bridge inspection methods usually rely on manual evaluation and visual surveys, and these approaches often require significant time and human effort, which may not be suitable in emergency conditions where rapid decisions are required [10–12].

Recent developments in structural health monitoring systems have introduced new possibilities for continuous bridge assessment through sensor-based data collection and real-time analysis [13–15]. Wireless sensor networks and Internet of Things technologies have been widely investigated for their ability to provide distributed monitoring across bridge components, allowing engineers to detect changes in structural behavior more effectively [10,12,16]. Vision-based monitoring and computer vision methods have also gained attention as they offer non-contact measurement techniques for detecting cracks, displacements, and surface damage [17–19]. Data-driven approaches in structural health monitoring have further improved the ability to process large volumes of sensor data and extract meaningful patterns related to damage progression [20–22].

Artificial intelligence methods, particularly machine learning and deep learning, have shown strong performance in damage detection, classification, and prediction for bridge structures under seismic loading [23,24]. Convolutional neural networks and transformer-based models have been applied to identify damage states and predict seismic responses with improved accuracy compared to conventional analytical methods [25–27]. These models are capable of learning complex relationships between input data and structural behavior, which supports faster evaluation of bridge conditions after earthquakes [28–30]. Physics-informed machine learning approaches have also been introduced to combine data-driven models with engineering principles, which may improve the reliability and interpretability of structural response prediction [31,32].

At the same time, the increasing scale of data generated by monitoring systems has created challenges related to data transmission, processing speed, and system latency, especially in time-sensitive situations such as post-earthquake response [33–35]. Edge computing has been proposed as a solution to address these challenges by enabling data processing closer to the source, which reduces delay and allows faster decision-making [33,34,36]. Edge-based systems can support real-time monitoring and immediate analysis without relying fully on centralized cloud infrastructure, which is important during disaster scenarios where communication networks may be unstable [33,35,36]. Integration of edge computing with structural health monitoring has shown potential in improving system responsiveness and supporting distributed intelligence in smart city environments [33,34,36].

In digitally managed urban transport systems, bridge monitoring and post-earthquake decisions interact with wider traffic, emergency response, and network recovery functions, so bridges should be treated as components of a broader urban infrastructure system [4–6]. In such environments, rapid and reliable post-earthquake assessment becomes more critical due to the high dependency of urban activities on transportation networks [1–3]. Existing studies have addressed different aspects of bridge monitoring, seismic assessment, and decision-making, but many of them consider these components separately rather than as part of an integrated system [16,22,23]. Some research has focused on probabilistic assessment and resilience evaluation, while other studies have emphasized machine learning or sensor technologies, yet a unified approach that connects these elements in real-time applications is still limited [6–8].

Despite the progress in artificial intelligence, structural health monitoring, and edge computing, there is still a lack of a comprehensive automated framework that combines these technologies for rapid post-earthquake bridge management in smart city contexts. Most existing models do not fully address the interaction between real-time data acquisition, decentralized processing, and intelligent decision-making

under uncertain seismic conditions. There is also limited attention given to how these systems can operate together to reduce dependence on manual inspection and improve response time immediately after an earthquake.

The aim of this study is to propose a conceptual artificial intelligence and edge computing-based framework for rapid post-earthquake management of bridges in a smart city context. The study focuses on developing a structured system that integrates monitoring technologies, intelligent algorithms, and decentralized computing to support potentially faster and more consistent bridge safety evaluation. The proposed framework is intended to provide a foundation for future research and practical implementation in urban infrastructure systems where rapid decision-making is essential after seismic events. Because no case study, production-model training, simulation result, or field deployment is reported, the contribution is a conceptual design specification and validation protocol rather than evidence of achieved operational performance.

## 2 Literature Review

### 2.1 Post-Earthquake Bridge Assessment and Management

Post-earthquake bridge assessment has become a major topic in transportation engineering because bridges control accessibility, emergency response, and the continuity of urban movement after seismic events. Earlier post-earthquake management was mainly based on visual inspection, engineering judgment, and staged field reporting, which often caused delays in safety decisions and reopening actions [1,2,4]. This issue becomes more serious when bridge systems are part of a larger network, since the condition of one structure can influence congestion, route redundancy, and regional service loss across many connected roads [3,5,6]. Existing studies show that post-earthquake management is no longer limited to checking structural damage alone, because it now includes residual functionality, traffic consequences, aftershock exposure, and restoration priorities under uncertain conditions [4,7,8].

Historical earthquake observations also show why post-event management should evaluate operability rather than collapse alone. Gautam [37] revisited highway bridge performance after the 1988 Udaypur earthquake and reported that minor bridge damage could occur at relatively low shaking levels, emphasizing that serviceability can be affected before global failure. Field investigations after the 2010 Maule earthquake identified skew-induced rotation, insufficient seat support, bearing and foundation damage, and loss of superstructure continuity as mechanisms that could interrupt use even when complete collapse did not occur [38]. These observations indicate that a useful post-earthquake framework must distinguish among continued operation, precautionary restriction, urgent professional assessment, and closure rather than treating collapse as the only consequential outcome.

Recent literature has moved toward probabilistic and resilience-based assessment models. Akbari and Khanmohammadi [7] examined bridge functionality after earthquakes through damage, residual displacement, and aftershock effects, while Tubaldi et al. [8] proposed Bayesian updating of aftershock risk for bridges. Abo-El-Ezz et al. [1] considered scenario-based damage assessment at network scale, and Liu et al. [2] connected bridge damage with traffic congestion in highway systems. Zhang et al. [3] advanced resilience assessment by considering downtime resulting from interactions among parallel restoration actions, while Zhang et al. [6] developed a data-driven machine-learning approach for predicting the post-earthquake functionality and resilience of bridge networks. These works show clear progress, yet they mostly emphasize network modeling, probabilistic estimation, or restoration sequencing more than real-time automated support for field-level bridge management.

A critical point from this body of work is that post-earthquake bridge management needs rapid damage interpretation and immediate action logic, especially in smart cities where disruption spreads quickly across many services. Current models are strong in risk estimation and planning, but they are often less direct in linking live monitoring streams with automated operational decisions.

## ***2.2 Structural Health Monitoring, IoT Sensors, and Wireless Monitoring Systems***

Structural health monitoring has become one of the main technical bases for modern bridge management because it gives continuous information on the condition of structural components before, during, and after extreme events. Review papers explained that wireless sensor networks opened a new phase in bridge monitoring through distributed sensing, lower wiring needs, and easier installation across large structures [13–15]. Other reviews showed that bridge monitoring systems now include accelerometers, strain sensors, displacement sensors, environmental sensors, and communication modules working in connected platforms that support near real-time condition tracking [10–12]. This progress has improved data availability, yet data quality, sensor faults, communication stability, and long-term maintenance remain difficult issues in field deployment [16,39,40].

Bridge monitoring data are fundamentally multichannel time series rather than isolated measurements. Acceleration, strain, displacement, temperature, bearing movement, and visual sequences can be examined through time-domain peaks and residuals, modal and frequency trends, time-frequency energy, autoregressive residuals, and learned temporal representations. Long-term studies, however, show that temperature, traffic, wind, humidity, sensor drift, and changing excitation can produce response shifts comparable to or larger than those caused by damage, which creates false-alarm and missed-detection risks if the baseline is not conditioned on operational and environmental context [40,41]. Full-scale bridge studies have therefore emphasized bridge-specific baseline learning, local and global sensor groups, unsupervised or one-class detection, and validation under varying environmental conditions [42,43]. These findings support the use of time-series screening in the present framework, but they also require uncertainty reporting and professional confirmation rather than treating an automated anomaly as definitive damage.

The literature also shows a strong shift toward vision-based and hybrid monitoring methods. Bhowmick et al. [19] used deep learning with UAV video for crack detection on concrete surfaces, while Bhowmick et al. [44] measured full-field displacement histories from video data. Park et al. [17] reviewed computer vision-based structural health monitoring, and Ponsi et al. [18] discussed vision-based static and dynamic monitoring of bridges. Peng et al. [36] pushed this direction further through smart monitoring that combines computer vision with edge computing. These studies suggest that contact and non-contact sensing can work together, especially when a bridge needs fast screening after an earthquake.

Data interpretation is another strong topic in this area. Azimi et al. [20] reviewed deep learning for data-driven damage detection, while Sun et al. [16], Deng et al. [10], and Di Mucci et al. [22] showed that structural health monitoring is gradually becoming more intelligent through artificial intelligence and big-data methods. Still, many systems are developed for general condition assessment rather than earthquake-centered emergency management.

## ***2.3 Artificial Intelligence for Seismic Damage Detection and Decision Support***

Artificial intelligence has been widely studied in structural engineering because it can process large and complex datasets faster than many conventional analytical routines. Review studies have shown that machine learning and deep learning are now central tools in structural health monitoring for feature extraction, classification, anomaly detection, and damage prediction [21,23,24]. In bridge engineering, this development is strongly connected with seismic assessment, where structural responses are highly nonlinear

and often difficult to interpret rapidly after an earthquake [9,28,45]. Artificial intelligence helps convert response histories, images, sensor patterns, and performance indicators into estimated damage states and functional conditions.

Several studies specifically addressed earthquake-related bridge assessment. Mangalathu et al. [28] presented rapid seismic damage evaluation for bridge portfolios through machine learning methods, and Ogunjinmi et al. [27] applied convolutional neural networks with transfer learning for rapid post-earthquake structural damage assessment. Gautam et al. [29] developed soft voting ensemble classification for earthquake-induced bridge damage, while Liang [30] proposed pattern recognition with Bayesian optimization for seismic damage detection in highway bridge systems. Li et al. [25] predicted seismic damage states for in-service bridges through a feature-enhanced Swin Transformer, and Yazdanpanah et al. [26] used an attention-Mamba transformer for seismic time series response prediction in bearings and piers. Zhu et al. [46] also contributed with an AI-assisted analytical model for seismic displacement estimation in isolated bridge portfolios.

A second line of research links artificial intelligence with physically informed modeling and interpretability. Bhowmick and Nagarajaiah [32] and Pal et al. [31] worked on physics-guided and physics-informed system identification. These contributions show a move from simple prediction toward more reliable engineering use. Even so, many AI studies focus on estimation accuracy more than how predictions are translated into operational bridge decisions in real time.

## **2.4 Edge Computing and Smart City-Based Infrastructure Resilience**

Edge computing has received rising attention in civil infrastructure because modern monitoring systems generate a large volume of data that can overload centralized processing, especially when rapid post-earthquake action is needed. Review work by Qiu et al. [33] showed that edge computing is becoming an important direction in structural health monitoring, mainly because of lower latency, faster response, and better local processing capacity. Farjad et al. [35] proposed a secure edge computing reference architecture for data-driven structural health monitoring and discussed lessons from implementation and benchmarking. Wang et al. [34] developed a lightweight edge-based structural health monitoring prototype, while Peng et al. [36] linked edge computing with computer vision for smart monitoring. These studies suggest that data can be filtered, processed, and interpreted close to the structure, which is useful when network reliability becomes unstable after an earthquake.

The smart city context gives further importance to this issue. In smart cities, bridges are part of interconnected urban systems where transport, emergency movement, infrastructure control, and digital communication operate in close relation. Chen et al. [5] examined seismic risk management for bridge transportation networks through betweenness centrality, which shows how bridge importance changes across a network. Abo-El-Ezz et al. [1], Wu et al. [4], and Zhang et al. [6] also showed that bridge functionality and recovery have system-wide effects. In such settings, edge-supported monitoring can help local devices produce immediate safety signals before information is forwarded to central units for broader coordination.

Even with this progress, current studies often treat edge computing as a technical support layer rather than as part of a full seismic management logic. Many papers discuss architecture, security, response time, or smart monitoring, yet fewer works explain how edge units, sensor systems, AI models, and city-level decision platforms should interact during post-earthquake bridge emergencies.

## 2.5 Research Gap and Motivation for the Proposed Framework

The reviewed literature shows a strong body of work in four major streams, post-earthquake bridge assessment, structural health monitoring, artificial intelligence for seismic damage analysis, and edge computing for smart infrastructure. Each stream has produced useful methods and better technical performance. Probabilistic and resilience-based studies improved the estimation of bridge functionality, aftershock risk, traffic disruption, and recovery planning [6–8]. Monitoring studies improved sensing coverage, communication methods, and visual measurement of structural responses and damage [10,17,18]. Artificial intelligence studies improved classification, prediction, and fragility estimation under seismic loading [25,28,29]. Edge computing studies improved data handling speed and local processing efficiency in smart monitoring systems [34–36].

Resilience-based bridge management also extends beyond the first damage estimate. Pre-event inspection, maintenance, deterioration control, and seismic retrofit change the vulnerability that the monitoring system should use as prior context, while post-event restriction, repair sequencing, temporary stabilization, retrofit, and reopening determine the restoration trajectory. Life-cycle risk studies have shown that seismic hazard should be considered together with aging, traffic consequences, epistemic and aleatory uncertainty, and maintenance decisions [47,48]. In this sense, the proposed rapid framework does not replace a life-cycle bridge management model. It supplies a traceable post-event state and uncertainty record that can inform later maintenance, repair, retrofit, and network-recovery decisions under mainshock-aftershock uncertainty [3,4,8].

Even with this progress, the literature still shows a separation between these streams. Many studies stop at damage detection, response prediction, or resilience estimation without showing how these outputs become direct bridge management decisions during the urgent period after an earthquake. Sensor studies often focus on data acquisition, AI studies often focus on model accuracy, and edge studies often focus on architecture or latency. A fully connected framework that explains how IoT sensors, wireless monitoring, vision systems, edge devices, central computing, and AI-based decision logic should operate together for rapid post-earthquake bridge management in smart cities is still not well established.

The present study is motivated by this need for integration. The study proposes a conceptual framework that links real-time sensing, local edge processing, central support, and context-sensitive artificial intelligence for faster bridge safety decisions after earthquakes. The framework is intended to reduce dependence on slow manual inspection, support urban response systems, and provide a structured basis for future applied and validation studies.

## 3 Framework Development Method and Proposed Framework

### 3.1 Study Design, Scope, and Framework Construction Procedure

The present article is a conceptual framework-design study. No empirical bridge-monitoring dataset was generated or analyzed. It does not report a case study, a trained production model, a simulation result, or a field-performance test, and it does not claim that the proposed system has already achieved the intended operational benefits. Its contribution is a reproducible design specification and a validation-ready architecture for future implementation.

Framework construction used a structured design-synthesis procedure based on the literature reviewed in Section 2. First, the problem boundary was fixed as the period from pre-event readiness through initial post-event bridge-state recommendation, professional assessment, and recovery-status updating. Second, findings from the four literature streams were translated into functional requirements for bridge-specific baseline monitoring, multimodal time-series acquisition, local operation during network disruption, rapid

anomaly screening, uncertainty-aware evidence fusion, network-context adjustment, professional oversight, and auditable state updating. Third, each requirement was mapped to an architectural layer and assigned explicit inputs, processing tasks, outputs, failure behavior, and decision authority. Fourth, the edge-cloud allocation, screening model stack, latency budget, evidence-fusion equations, confidence calculation, and state-transition rules were specified. Fifth, the complete design was checked for requirement-to-layer traceability, safe behavior under missing or conflicting data, and consistency among the figures, tables, and narrative.

The final check is an internal logical verification of the framework, not empirical validation. It verifies that every stated requirement has an implementing component, that missing information produces a documented conservative response, that automated outputs remain provisional where professional judgment is required, and that the proposed quantities can be measured during future testing. Accuracy, latency, false-alarm performance, and application value remain hypotheses to be evaluated using the deployment and validation protocol in [Section 3.11](#).

### 3.2 Design Requirements and Traceability

Eight requirements guide the design. R1 requires bridge-specific operability states and a pre-event baseline. R2 requires synchronized multimodal time-series data with quality and device-health metadata. R3 requires a local edge path that remains functional when wide-area communication is unavailable. R4 requires an explicit and replaceable artificial intelligence model stack with calibrated probability outputs. R5 requires reliability-weighted evidence fusion and uncertainty reporting. R6 requires fail-safe escalation and professional engineer authority for uncertain, severe, or reopening decisions. R7 requires bridge vulnerability and transportation-network consequence to affect priority. R8 requires recovery to be represented through discrete, auditable inspection, repair, retrofit, and reopening states. [Table 1](#) maps these requirements to the literature basis and the implementing part of the proposed framework.

**Table 1:** Traceability of design requirements to the proposed framework.

| ID | Design Requirement                                                   | Literature or Design Basis                                     | Implemented in                                                   |
|----|----------------------------------------------------------------------|----------------------------------------------------------------|------------------------------------------------------------------|
| R1 | Bridge-specific baseline and operability-centered states             | Gautam [37]; Akbari & Khanmohammadi [7]; Tubaldi et al. [8]    | Bridge profile, context fusion, and state decision               |
| R2 | Synchronized multimodal time series with data-quality metadata       | Peeters & De Roeck [41]; Sen et al. [40]; Svendsen et al. [42] | Sensing, gateway, and edge quality screening                     |
| R3 | Local continuity during communication interruption                   | Peng et al. [36]; Farjad et al. [35]; Wang et al. [34]         | Edge inference, local buffer, and disconnected mode              |
| R4 | Explicit modular AI model stack with calibrated probabilities        | Mangalathu et al. [28]; Gautam et al. [29]; Li et al. [25]     | Autoencoder, feature classifier, visual classifier, and ensemble |
| R5 | Reliability-weighted fusion, confidence, and uncertainty propagation | Jana et al. [39]; Sen et al. [40]; Decò & Frangopol [47]       | Reliability scores, probabilistic fusion, and confidence filter  |

(Continued)

Table 1 (continued)

| ID | Design Requirement                                              | Literature or Design Basis                                | Implemented in                                                          |
|----|-----------------------------------------------------------------|-----------------------------------------------------------|-------------------------------------------------------------------------|
| R6 | Fail-safe escalation and professional engineer authority        | Engineering safety requirement and inspection integration | Conservative state, professional assessment, and no automated reopening |
| R7 | Network-aware priority and city coordination                    | Chen et al. [5]; Liu et al. [2]; Zhang et al. [6]         | Context and network fusion and city response interface                  |
| R8 | Discrete recovery, repair, retrofit, and reopening traceability | Han & Frangopol [48]; Wu et al. [4]; Zhang et al. [3]     | Inspection, repair or rehabilitation log, and recovery-state update     |

### 3.3 Layered System Architecture and Data Flow

The proposed framework is specified as a layered and event-driven system for rapid post-earthquake bridge management in a smart city context. Its main idea is that bridge safety information should move through a connected sequence that begins with field sensing and ends with an operational recommendation and professional follow-up, rather than waiting for a completely manual interpretation after the earthquake. This direction is supported by research showing the need for faster bridge condition evaluation after seismic events, especially where bridge disruption can affect emergency movement, traffic continuity, and regional functionality [1,2,4]. The full architectural logic of the framework is shown in Fig. 1, while Table 2 summarizes the role, inputs, outputs, and latency dependency of each layer.

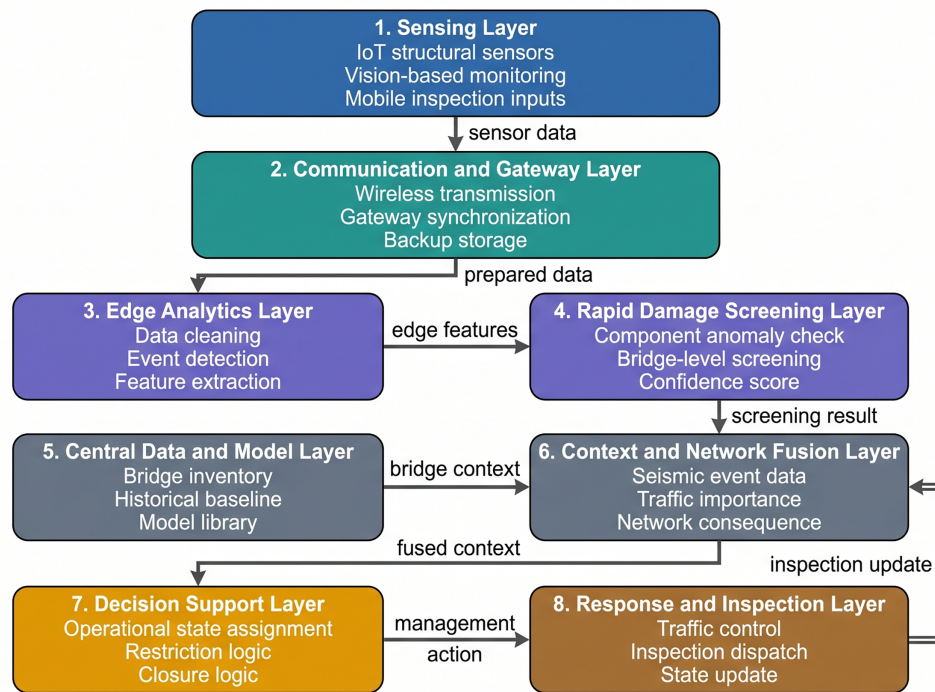


**Figure 1:** Multi-layer architecture of the proposed artificial intelligence and edge computing-based framework for rapid post-earthquake bridge management in a smart city context. The arrows show the connected-mode refinement path; the local provisional bypass is specified in Section 3.6 and Table 3.

**Table 2:** Full architecture of the proposed artificial intelligence and edge computing-based framework for rapid post-earthquake bridge management.

| Layer                        | Main Purpose                                                                                           | Main Hardware or Software Elements                                                                                                                                                              | Main Inputs                                                                         | Main Outputs                                                                                             | Latency Basis and Commissioning Metric                                                              |
|------------------------------|--------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------|
| Sensing layer                | Capture structural, visual, and field-condition data from bridge components and surrounding conditions | Accelerometers, strain gauges, displacement sensors, tilt sensors, bearing movement sensors, crack cameras, UAV imaging, mobile inspection inputs, environmental sensors, device-health sensors | Structural response, visual observations, environmental measurements                | Synchronized multichannel time-series records and time-aligned visual frames with sensor-health metadata | Continuous acquisition; event-window duration and sampling rate are bridge-specific                 |
|                              | Receive, synchronize, buffer, filter, and prioritize incoming data for emergency use                   | Local gateway, time synchronization service, wireless transmission modules, wired backup link, cellular link, packet scheduler, local backup storage                                            | Multichannel time-series packets, image streams, device status, and network status  | Synchronized and ordered time-series windows with quality and priority tags                              | $T_{\text{sync}} + T_{\text{buffer}}$ , measured at the 95th percentile during commissioning        |
| Edge analytics layer         | Perform first-stage local analytics before full screening                                              | Embedded processor, edge AI runtime, GPU or TPU board where needed, local cache, signal-processing module                                                                                       | Prepared time-series windows, visual frames, and bridge baseline features           | Quality-screened windows, event flags, and extracted edge features                                       | $T_{\text{quality}} + T_{\text{feature}}$ , dependent on hardware, window length, and preprocessing |
| Rapid damage screening layer | Carry out immediate bridge-level anomaly and damage screening with confidence estimation               | Rapid screening model, anomaly detection model, feature-based classifier, confidence module, and local provisional rule and notification modules                                                | Edge features, anomaly indicators, bridge-level response summaries, and visual cues | Damage-state probability vector, confidence, uncertainty record, and provisional recommendation          | Local latency terms are defined in Eq. (1) and measured by event replay on the selected edge device |

(Continued)

Table 2 (continued)

| Layer                            | Main Purpose                                                                                   | Main Hardware or Software Elements                                                                                                          | Main Inputs                                                                                              | Main Outputs                                                                                             | Latency Basis and Commissioning Metric                                                                              |
|----------------------------------|------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|
| Central data and model layer     | Provide background bridge knowledge and model support for refined assessment                   | Agency server or cloud platform, bridge inventory database, historical baseline repository, model library, digital twin or reference models | Bridge metadata, historical records, baseline response patterns, model resources                         | Bridge context, historical baseline reference, model support inputs                                      | $T_{\text{uplink}} + T_{\text{query}}$ ; unavailable links do not block the local provisional support inputs result |
| Context and network fusion layer | Combine screening results with seismic, bridge, and network context for refined interpretation | Data fusion engine, seismic event feed, GIS platform, traffic data interface, network consequence module, vulnerability library             | Screening result, bridge context, seismic event data, traffic importance, network consequence indicators | Fused context, refined bridge state input, inspection priority recommendation                            | $T_{\text{fusion}}$ , dependent on seismic, GIS, and traffic-feed availability                                      |
| Decision support layer           | Convert centrally fused evidence into a refined operational state and management logic         | Rule engine, threshold manager, uncertainty engine, policy library, state-assignment module                                                 | Fused context, confidence score, vulnerability score, importance score                                   | Refined operational state assignment, restriction or closure logic, and management action recommendation | Refined rule and notification terms are defined in Eq. (2); local terms are included in rapid damage screening      |
| Response and inspection layer    | Execute field and traffic actions and update bridge status after inspection or aftershocks     | Traffic control platform, inspection dispatch system, bridge management dashboard, notification system, audit log                           | Management action, assigned bridge state, inspection requests                                            | Traffic control action, inspection dispatch, state update, recovery tracking                             | Agency-procedure dependent; major recovery is discrete and may take weeks to months                                 |

**Table 3:** Proposed edge-cloud task allocation and disconnected-mode behavior.

| Function                        | Edge Responsibility                                                                                 | Central Responsibility                                                                   | Disconnected-Mode Behavior                                                                                                                                                                      |
|---------------------------------|-----------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Data acquisition and quality    | Synchronization, completeness, saturation, drift, sensor-health checks, and local buffering         | Fleet-level quality review and long-term diagnostics                                     | Continue local quality screening and buffer event windows                                                                                                                                       |
| Time-series and visual analysis | Conditioning, feature extraction, autoencoder, compact classifier, and lightweight visual inference | Full-resolution reanalysis, heavier models, and model recalibration                      | Use the last approved edge model and mark missing central evidence                                                                                                                              |
| Context and decision            | Provisional probability, confidence, hard-trigger check, and local recommendation                   | Inventory, aftershock, GIS, traffic, network-priority fusion, and refined recommendation | Issue and locally communicate a provisional recommendation; bypass central fusion and mark context unavailable                                                                                  |
| Storage and model management    | Ring buffer, signed event record, and model or version hash                                         | Long-term archive, model registry, and audit database                                    | Store-and-forward after reconnection                                                                                                                                                            |
| Notification and authority      | Local alarm and agency message                                                                      | City coordination and cross-bridge prioritization                                        | Low-confidence non-severe evidence: Restricted or Urgent Inspection with assessment; severe result or hard trigger: Closed with immediate assessment; no automated less-conservative transition |

The framework is represented in Fig. 1 as eight operational layers, but for explanation and implementation these are grouped into six functional modules: sensing; communication and gateway; edge analytics and rapid damage screening; central data and context fusion; decision support; and response and inspection. The field sensing layer captures structural response, environmental information, and visual evidence through sensors placed on bridge components that are likely to experience severe seismic demand, such as bearings, piers, deck zones, joints, and supports. The communication and gateway layer receives these data, arranges them in a time-consistent form, and assigns transmission priority according to urgency. The edge analytics layer then performs first-stage screening, event confirmation, feature extraction, and early damage inference. This part is especially important because recent studies have shown that local processing can reduce delay in structural health monitoring systems and support faster near-source analysis, with growing potential for post-earthquake bridge applications [33,34,36].

When wide-area communication is available, the central intelligence layer extends the local edge result through integration with bridge records, historical baselines, seismic intensity information, and network importance indicators. This allows the bridge to be assessed in relation to its own design and service role

rather than through one fixed generic rule. The central decision layer converts the refined evidence into an updated operational recommendation, and the city coordination layer distributes it to bridge agencies, traffic control units, emergency routing systems, and inspection teams. During communication interruption, however, the edge-side rule engine issues and locally communicates the provisional recommendation without waiting for the central layers; central refinement resumes after reconnection. This dual-path arrangement responds to the gap found in the literature, where sensing, artificial intelligence, and resilience planning are often studied separately even though real post-earthquake management requires them to act together [6,7,16].

A key feature of the architecture is the division between immediate and refined intelligence. The edge-side rapid screening and local rule modules produce and communicate a provisional recommendation after an event window becomes available. When communication and supporting data are available, the central path shown in Fig. 1 receives the screening record and may retain or increase the conservatism of that recommendation using bridge, event, and network context. The direct local-notification bypass is specified in Section 3.6 and Table 3. This arrangement is designed to preserve local functionality during the urgent post-event period and improve subsequent assessment, but its latency and accuracy must be measured during commissioning.

### 3.4 Sensing, Edge Analytics, Central Intelligence, and Management Components

The framework contains several major components, and each one is designed to support a specific part of post-earthquake bridge management. The first component is the sensing subsystem, which includes structural, visual, environmental, and device-health sensing. The deployment concept in Fig. 2 shows that sensors are not distributed randomly across the bridge. Instead, they are assigned to zones where earthquake damage is more likely to affect safety and functionality, such as bearings, joints, deck regions, piers, and abutments. This arrangement follows the understanding that seismic bridge damage often develops in concentrated components rather than uniformly across the whole structure [10,30,38]. Accelerometers, strain gauges, tilt sensors, displacement sensors, and crack cameras form the core package, while UAV imaging and temporary mobile devices can support rapid visual confirmation in inaccessible areas [17,19,36]. For the continuous-deck bridge shown in Fig. 2, expansion-joint monitoring is located only at the deck ends adjacent to the abutments. Interior spans are represented as continuous-deck and pier monitoring zones and are not shown as containing an expansion joint.

The second component is the communication and gateway subsystem. This part receives data from the sensing layer, synchronizes them, filters low-priority traffic, and prepares emergency transmission when seismic triggers are detected. The gateway also stores data locally if network interruption occurs, which is important because earthquakes may disturb communication channels at the same moment when condition information becomes most urgent [33–35]. The third component is the edge analytics subsystem, where the first damage-related interpretation is carried out. This subsystem checks data quality, confirms whether the signal corresponds to an actual seismic event, extracts damage-sensitive features, and produces an early condition score. Such local processing is consistent with recent studies that support edge-side monitoring for lower latency and faster response in time-critical infrastructure systems [33,34,36].

The fourth component is the central intelligence subsystem. This component fuses edge results with bridge inventory data, historical response baselines, seismic event characteristics, and transport network information. The fifth component is the artificial intelligence model stack, which includes anomaly detection, damage classification, functionality estimation, and confidence assessment. Current literature shows that machine learning and deep learning methods can support rapid damage screening and bridge performance prediction after earthquakes when they are paired with strong data preparation and consistent interpretation

logic [25,28,29]. The final component is the management interface, which turns technical outputs into operational decisions that can be used by bridge agencies and city response systems.

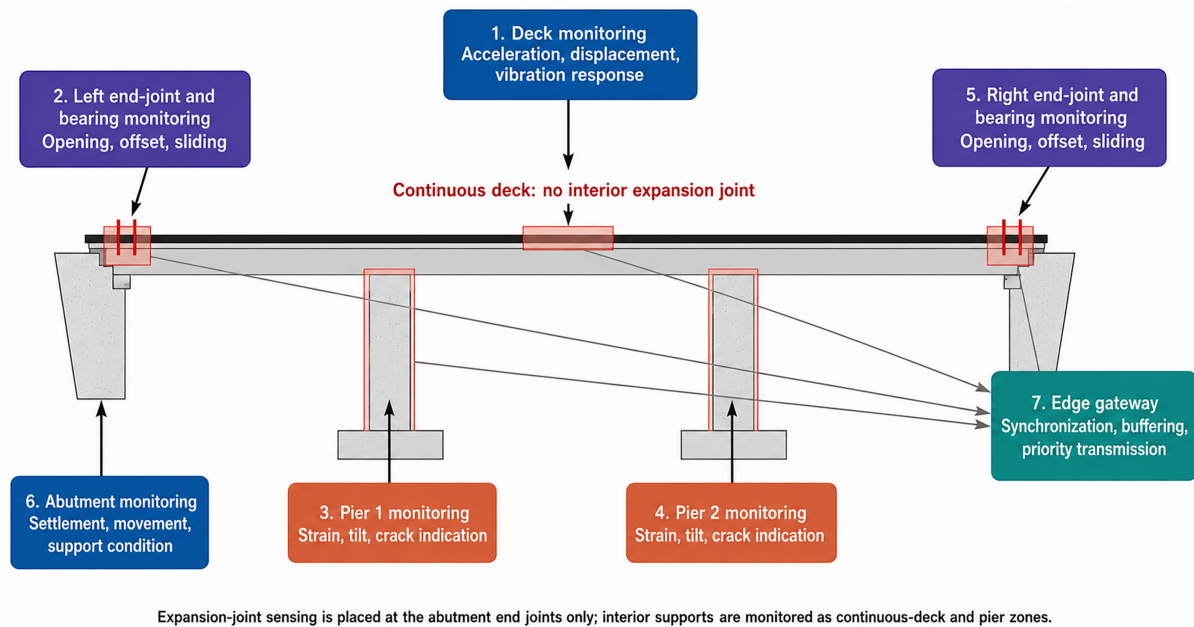


**Figure 2:** Bridge-level deployment concept for a continuous-deck bridge, with expansion-joint sensing at the abutment end joints and monitored deck, bearing, pier, and abutment zones connected to the edge gateway.

### 3.5 Pre-Event Preparation, Post-Event Screening, and State Updating

The proposed framework operates through a staged process that begins before the earthquake and continues through response, verification, and recovery updating. The connected-mode operational sequence is presented in Fig. 3 and the disconnected local bypass and the severe or hard-trigger override are specified in Section 3.6 and Tables 3–5. The first stage is pre-event readiness. In this stage, each bridge receives a digital profile containing its structural type, vulnerability class, route importance, monitoring layout, and historical baseline data. This preparation is necessary because bridge response cannot be judged well without reference to its normal condition and known seismic weakness. Research on structural health monitoring and seismic bridge assessment has shown that bridge-specific information strongly affects the quality of anomaly interpretation and damage prediction [10,20,25].

The second stage begins when an earthquake or strong seismic trigger is detected. At this point, the monitoring system changes from routine mode to emergency mode. Sampling intensity increases, gateway priority rules are activated, and local storage becomes more important in case communication becomes unstable. The framework then moves to data integrity checking and seismic confirmation. This step is necessary because false readings, missing channels, or non-seismic vibration may lead to misleading conclusions if they are treated as earthquake damage evidence. Existing studies on sensor fault detection and signal interpretation support the inclusion of this stage before the main damage inference process [16,39,40].

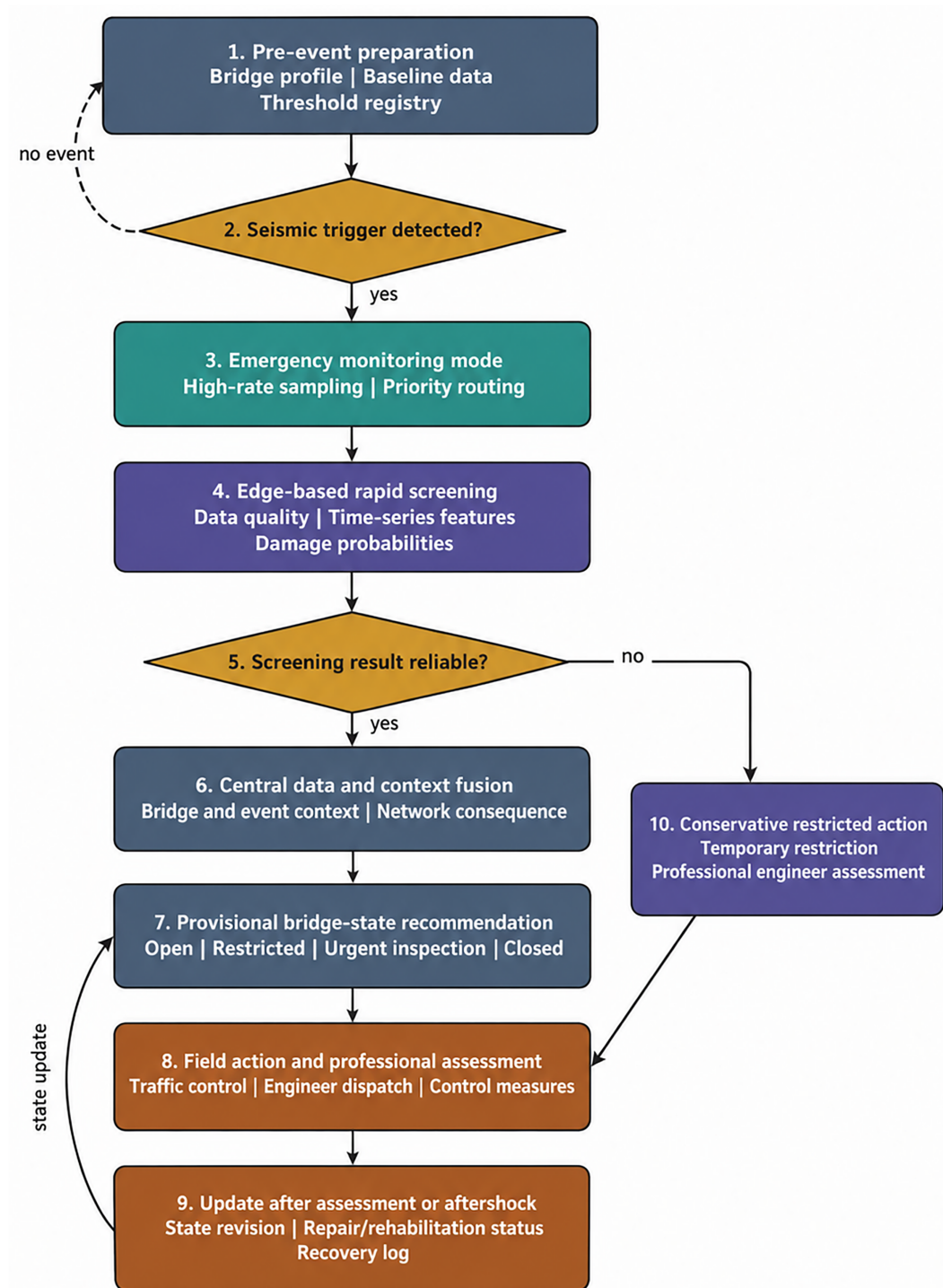


**Figure 3:** Connected-mode operational flow of the proposed framework.

**Table 4:** Decision quantities, provisional initialization values, and calibration guardrails.

| Quantity or Rule                     | Definition                                                       | Provisional Initialization                                                                           | Calibration or Guardrail                                                                                                 |
|--------------------------------------|------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------|
| Modality reliability $r_m$           | Quality, completeness, and freshness weight in $[0, 1]$          | Calculated from sensor and data-quality checks                                                       | A missing modality has $r_m = 0$ ; each component is audited                                                             |
| Damage probabilities $P_D$ and $P_U$ | Defined in Eq. (10)                                              | Computed after reliability-weighted fusion                                                           | Total damage probability controls escalation; high-severity probability controls closure                                 |
| Open                                 | Low total damage probability and high confidence                 | $P_D < 0.10$ and $C \geq 0.80$                                                                       | No hard trigger or prior-state restriction; no automated less-conservative transition                                    |
| Restricted                           | Mild damage probability, reduced confidence, or high consequence | $0.10 \leq P_D < 0.35$ , or $C < 0.80$ when no more conservative rule applies, or context escalation | Temporary action pending recheck or professional review                                                                  |
| Urgent inspection                    | Material risk, conflict, or low confidence                       | $P_D \geq 0.35$ and $P_U < 0.70$ , or $C < 0.60$ with anomaly or conflict                            | Dispatch professional assessment and seek redundant evidence                                                             |
| Closed                               | High risk or direct instability evidence                         | $P_U \geq 0.70$ , severe direct evidence, or a hard trigger                                          | Immediate closure recommendation; engineer and agency authority govern continuation and any less-conservative transition |

The third stage is rapid edge-based assessment. Here, the system extracts response features such as residual movement, modal changes, support irregularity, and visual damage indications, then applies the proposed local artificial intelligence model stack to estimate bridge-condition probabilities. A hard physical trigger or severe local result immediately produces a provisional Closed recommendation and bypasses the reliability branch. Otherwise, if data quality and model confidence satisfy the configured criteria, the edge system produces and locally communicates a provisional bridge-state recommendation. Incomplete, conflicting, or out-of-domain non-severe evidence follows the conservative Restricted or Urgent Inspection path and requests professional engineer assessment. When connectivity is available, the fourth stage is central fusion and network adjustment; the central platform may retain or increase, but not reduce, the conservatism of the local recommendation on the basis of route importance, aftershock risk, historical vulnerability, and surrounding network condition [6–8]. In Fig. 3, the “no” branch from the reliability check therefore applies only to non-severe unreliable evidence.

Table 5: Parameterized automated decision matrix for the proposed framework.

| Condition Pattern                                                                                                                      | Structural Evidence | Visual Evidence                   | Data Reliability | Bridge Vulnerability | Network Importance | Assigned State    | Required Action                                                                      | Professional Assessment                                                                                                                                                       |
|----------------------------------------------------------------------------------------------------------------------------------------|---------------------|-----------------------------------|------------------|----------------------|--------------------|-------------------|--------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Stable response within baseline; $P_D < 0.10$ and $C \geq 0.80$                                                                        | Low                 | None                              | High             | Any                  | Any                | Open              | Keep bridge provisionally open and continue monitoring                               | No immediate assessment for a new Open recommendation; any transition from Restricted, Urgent Inspection, or Closed requires professional assessment and agency authorization |
| Low-risk or mild-anomaly case not assigned below; $0.10 \leq P_D < 0.35$ , or $C < 0.80$ without a nontrivial anomaly; no hard trigger | Low to moderate     | None or minor                     | High             | Low to moderate      | Low                | Restricted        | Apply precautionary traffic restriction, speed control, and a short recheck interval | Agency-defined recheck; engineer assessment if an anomaly persists or confidence remains below 0.80                                                                           |
| Mild anomaly on a vulnerable or important bridge                                                                                       | Low to moderate     | None or minor                     | High             | High                 | Medium to high     | Restricted        | Restrict traffic, intensify monitoring, and request an engineering check             | Professional check prioritized                                                                                                                                                |
| Moderate anomaly with visual support; $P_D \geq 0.35$ and $P_U < 0.70$                                                                 | Moderate            | Present                           | High             | Any                  | Any                | Urgent Inspection | Restrict traffic and dispatch urgent field inspection                                | Yes—professional bridge engineer                                                                                                                                              |
| Moderate anomaly with conflicting or incomplete evidence, or $C < 0.60$                                                                | Moderate            | Unclear or minor                  | Medium to low    | Any                  | Any                | Urgent Inspection | Restrict traffic, seek redundant evidence, and dispatch urgent inspection            | Yes—professional bridge engineer                                                                                                                                              |
| Moderate to high anomaly on a high-consequence bridge                                                                                  | Moderate to high    | Absent, minor, or unclear         | Medium to low    | High                 | High               | Urgent Inspection | Immediate restriction, central review, and priority field inspection                 | Yes—priority professional assessment                                                                                                                                          |
| Severe anomaly, $P_U \geq 0.70$ , or a hard physical trigger                                                                           | Very high           | Present or direct instability cue | Any              | Any                  | Any                | Closed            | Close the bridge immediately, barricade access, and activate a detour                | Yes—immediate professional assessment                                                                                                                                         |
| Unsafe condition confirmed by route reconnaissance or professional inspection                                                          | High or unknown     | Field-confirmed damage            | Any              | Any                  | Any                | Closed            | Maintain closure and proceed with detailed engineering assessment                    | Yes—detailed engineering assessment and agency decision                                                                                                                       |

The final stage is coordinated action and state updating. Traffic control, emergency access management, professional assessment dispatch, and later recovery review are informed by the assigned bridge state. Inspection findings and aftershock information return to the system and revise the status when needed. Recovery is represented as a discrete set of agency-controlled states rather than a continuously predicted process. The automated part can log emergency stabilization, restricted operation, inspection completion, and repair or retrofit status, but any transition from Restricted, Urgent Inspection, or Closed to a less conservative state requires documented professional engineering assessment and responsible-agency authorization. Minor repair and controlled reopening may occur relatively quickly, whereas major damage, reconstruction, or replacement can require weeks to months or longer depending on damage, access, aftershocks, procurement, and construction capacity [3,4]. The framework therefore supports prioritization and traceability; it does not automatically predict or authorize major recovery.

### ***3.6 Edge-Cloud Task Allocation and Communication-Interruption Operation***

The proposed reference implementation uses a split-computing design rather than sending all raw data to a central platform. The edge node is assigned the safety-critical tasks that should continue without wide-area connectivity: sensor-health screening; time synchronization; seismic trigger confirmation; detrending, filtering, and windowing of synchronized time series; feature extraction; bridge-specific anomaly inference; lightweight visual screening when the local hardware permits; confidence calculation; provisional state assignment; and local logging and notification. The central platform is assigned tasks that benefit from broader data and greater computing resources: bridge-inventory and historical-baseline queries; full-resolution image reanalysis; model version management and recalibration; seismic, aftershock, GIS, and traffic fusion; cross-bridge prioritization; long-term storage; and audit reporting. This division follows the edge-monitoring direction reported by Peng et al. [36], Farjad et al. [35], and Wang et al. [34], but it is presented here as a proposed allocation that must be profiled on the selected hardware.

The proposed reference model stack is modular and explicit. For vibration and strain time series, a bridge-specific convolutional autoencoder is used as the first-line one-class anomaly detector because undamaged baseline data are more obtainable than labeled earthquake-damage data. The autoencoder does not directly assign a damage class; its normalized reconstruction error is combined with engineered seismic-response features in a compact gradient-boosted tree classifier that produces a four-class probability vector. For visual frames, a quantized MobileNetV2 model screens crack, spalling, end-joint, bearing, and alignment cues, and a bridge-specific mapping converts the cue scores to the same four damage-state classes; higher-resolution images can be reprocessed centrally. Each classifier is calibrated on held-out commissioning data using a predeclared calibration method, and only calibrated four-class vectors enter the ensemble. The resulting ensemble vector is used by the decision layer. These model choices are a reproducible reference configuration and may be replaced only if the same input, calibrated-probability, uncertainty, and audit interfaces are preserved.

During communication interruption, the gateway enters disconnected mode. It retains the last agency-approved model package and threshold registry, writes raw and processed event windows to a checksum-protected local ring buffer, issues and locally communicates the provisional recommendation, and queues results for store-and-forward upload after reconnection. Missing central context is explicitly marked, and stale central data cannot authorize a transition to a less conservative state. If power becomes limited, the gateway prioritizes accelerometers, bearing and displacement channels, trigger logic, and event-window storage over noncritical full-resolution video. Low-confidence non-severe evidence produces at least a provisional Restricted recommendation and a professional assessment request; a nontrivial anomaly or conflict may escalate the state to Urgent Inspection. A severe local result or hard physical trigger produces

a provisional Closed recommendation and immediate professional assessment. Table 3 summarizes the allocation and degraded-mode behavior.

Latency is defined as a measurable budget rather than a universal time claim. Let  $T_{\text{common}}$  denote the sum of  $T_{\text{window}}$ ,  $T_{\text{sync}}$ ,  $T_{\text{buffer}}$ ,  $T_{\text{quality}}$ ,  $T_{\text{feature}}$ ,  $T_{\text{infer}}$ , and  $T_{\text{confidence}}$ :

$$T_{\text{prov}} = T_{\text{common}} + T_{\text{rule,loc}} + T_{\text{notify,loc}} \quad (1)$$

$$T_{\text{ref,conn}} = T_{\text{common}} + T_{\text{uplink}} + T_{\text{query}} + T_{\text{fusion}} + T_{\text{rule,ref}} + T_{\text{notify,ref}} \quad (2)$$

During commissioning, each term is measured on the selected sensors, gateway, edge processor, models, and network. Serial terms are summed, whereas operations that execute in parallel are represented by the measured critical path rather than counted twice. The 95th-percentile local provisional latency is reported under nominal, bandwidth-limited, packet-loss, and fully disconnected conditions. Connected refined latency is reported only while a central link is available, and post-reconnection recovery latency is measured separately from link restoration through store-and-forward upload, central fusion, refined rule execution, and refined notification. Consequently, the latency entries in Table 2 identify dependencies and measurement terms rather than presenting unverified second- or minute-level performance.

### 3.7 Rapid Damage Screening and Time-Series Processing

Rapid damage screening begins only after an event window is synchronized and each channel receives a quality score  $q_i$  between 0 and 1 based on completeness, saturation, timing error, signal-to-noise ratio, calibration status, and device-health information. Features are normalized against a bridge-specific baseline conditioned on the available operational and environmental context  $c_i$ . For feature  $j$  on channel  $i$ , the standardized deviation is defined as:

$$z_{ij} = \frac{f_{ij} - \mu_j(c_i)}{\sigma_j(c_i) + \varepsilon} \quad (3)$$

where  $\mu_j(c_i)$  and  $\sigma_j(c_i)$  are the baseline conditional mean and standard deviation and  $\varepsilon$  prevents unstable division. The time-series evidence score is:

$$A_{\text{ts}} = \frac{\sum_i \sum_j q_i w_{ij} \min\left(\frac{|z_{ij}|}{z_{\text{lim},j}}, 1\right)}{\sum_i \sum_j q_i w_{ij}} \quad (4)$$

where  $w_{ij}$  is an agency-approved feature weight and  $z_{\text{lim},j}$  is the bridge-specific normalized warning limit. Missing channels receive  $q_i = 0$  rather than being imputed as normal. If the valid-weight denominator is zero or below an agency-approved minimum,  $A_{\text{ts}}$  is not calculated; the result is recorded as insufficient evidence and enters the conservative Restricted or Urgent Inspection pathway, unless a hard trigger or severe evidence requires Closed.

Candidate features include peak and residual displacement, peak strain, acceleration- and velocity-related intensity measures, cumulative absolute velocity, Arias-type energy, natural-frequency and damping change, wavelet-band energy, support-to-deck phase and coherence change, and bearing or joint residual movement. The autoencoder reconstruction score is normalized against its healthy-baseline distribution and combined with these engineered features. Visual evidence is processed separately so that an image cue does not silently duplicate the same physical evidence already represented by a displacement or strain channel.

Extraction of damage signatures from operational bridges is intrinsically difficult. Temperature, traffic, wind, humidity, changing boundary conditions, sensor drift, and excitation variability can mask or mimic

damage; earthquake labels are sparse; local component damage may have little influence on global modal features; and strong-motion saturation or missing channels may occur precisely when the information is needed [40–43]. The rapid screening layer is therefore an anomaly-triage mechanism, not a definitive structural diagnosis. An out-of-distribution input, inadequate baseline coverage, disagreement among modalities, or low data quality returns an unknown or low-confidence result and leads to a Restricted or Urgent Inspection recommendation and professional engineer assessment rather than an automated declaration of safety, unless severe evidence or a hard trigger requires Closed.

### 3.8 Evidence Fusion, Confidence, and Context-Sensitive Thresholds

Each modality  $m$  produces a calibrated probability vector  $p_m(k)$  over the damage states  $k = \{\text{none or slight, moderate, extensive, near-collapse}\}$  and a reliability value  $r_m$  between 0 and 1. Missing evidence has  $r_m = 0$ . Correlated channels are grouped before fusion to reduce double counting. The fused probability is obtained by reliability-weighted logarithmic pooling:

$$p_f(k) = \frac{p_0(k) \prod_m [\max(p_m(k), \epsilon)]^{r_m}}{\sum_{\ell} p_0(\ell) \prod_m [\max(p_m(\ell), \epsilon)]^{r_m}} \quad (5)$$

where  $p_0(k)$  is a bridge-specific prior derived from vulnerability and event intensity. Fusion is performed only when  $\text{sum}(r_m) > 0$  and the agency-approved minimum current-event evidence requirement is met. Otherwise, no fused posterior is used for an Open recommendation: the prior alone cannot establish safety, and the record is classified as insufficient evidence for conservative action and professional review.

Three confidence components are retained.  $C_{\text{data}}$  is the mean reliability of the configured independent modality groups,  $C_{\text{data}} = (r_1 + \dots + r_M)/M$ , with missing groups retained as  $r_m = 0$ .  $C_{\text{sharp}}$  measures the concentration of the fused probability, and  $C_{\text{agree}}$  measures agreement among the modality distributions. The latter two components and the reported confidence are defined as follows:

$$C_{\text{sharp}} = 1 - \frac{H(p_f)}{\log K} \quad (6)$$

$$C_{\text{agree}} = 1 - \text{JSD}_{\text{norm}} \quad (7)$$

$$C = (C_{\text{data}} C_{\text{sharp}} C_{\text{agree}})^{1/3} \quad (8)$$

For at least two available independent modality groups,  $\text{JSD}_{\text{norm}}$  is the reliability-weighted generalized Jensen-Shannon divergence computed with normalized weights  $\omega_m = r_m/\text{sum}(r_m)$  and the corresponding weighted mixture distribution; it is divided by the entropy of the normalized weights so that it lies in  $[0, 1]$ . If fewer than two independent modalities are available,  $C_{\text{agree}} = 0$ ; if none is available,  $C_{\text{data}} = 0$  and no fused decision is permitted. The output record also stores ensemble variance, out-of-distribution status, context-data age, and the model and threshold versions.

The preferred deployed decision is the action  $a^*$  that minimizes expected agency-approved loss:

$$a^* = \arg \min_a \sum_k L(a, k) p_f(k) \quad (9)$$

where  $L(a, k)$  includes life-safety, traffic, emergency-access, and false-alarm consequences. Table 4 thresholds are conservative commissioning guardrails rather than a competing decision method. Operational precedence is: severe or hard-trigger override; insufficient-evidence or low-confidence escalation; prior-state and reopening restrictions; the more conservative of the expected-loss action and the threshold guardrail;

and context escalation, which may only increase conservatism. The total nontrivial-damage probability  $P_D$  and high-severity unsafe probability  $P_U$  are defined using NS, E, and NC for none/slight, extensive, and near-collapse, respectively:

$$P_D = 1 - p_f(NS), P_U = p_f(E) + p_f(NC) \quad (10)$$

For a reproducible conservative initialization before local calibration, the rules are applied in the following order so that every input receives one state: Closed for a hard trigger, severe direct evidence, or  $P_U \geq 0.70$ ; Urgent Inspection for  $P_D \geq 0.35$  with  $P_U < 0.70$ , or for reported confidence  $C < 0.60$  with a nontrivial anomaly or conflicting evidence; Restricted for  $0.10 \leq P_D < 0.35$ , for  $C < 0.80$  when no more conservative rule applies, or for context escalation; and Open only for  $P_D < 0.10$ ,  $C \geq 0.80$ , no hard trigger, and no prior-state restriction. Hard triggers include visible loss of support, exhausted unseating margin, residual movement beyond an agency-approved component limit, or other direct evidence of instability. These numerical values are proposed commissioning starting points, not validated or universal bridge-safety limits, and they must be calibrated and approved before operational use. Context may make the action more conservative but cannot by itself downgrade a structural warning.

### 3.9 Layerwise Uncertainty Sources and Fail-Safe Management

Uncertainty enters every layer and is retained rather than collapsed into one undocumented score. The sensing layer includes noise, bias, drift, saturation, placement, and environmental and operational confounding. The gateway layer includes clock error, packet loss, bandwidth limitation, and incomplete event windows. The edge layer includes preprocessing sensitivity, model-fit error, scarce damage labels, out-of-distribution behavior, and hardware resource limits. The central layer includes incomplete inventory, stale seismic or traffic feeds, and uncertain vulnerability or aftershock context. The fusion layer includes prior sensitivity, dependence among modalities, and potential double counting. The decision and response layers include threshold uncertainty, asymmetric consequences, access limitations, and professional or organizational delay.

Model uncertainty is represented with an ensemble of independently initialized models or resampled training sets. The mean class probability is used for fusion, while between-model variance is recorded as epistemic uncertainty and class entropy represents predictive ambiguity. Sensor and communication uncertainties reduce  $r_m$ ; missing evidence is not interpreted as a healthy condition. Context freshness is time-stamped, and an out-of-distribution detector prevents a confident decision when the current event lies outside the baseline or training domain.

The combined uncertainty record accompanies every recommendation and includes data completeness, sensor-quality score, model entropy, ensemble variance, modality disagreement, context freshness, threshold version, and hard-trigger status. The states are ordered Open < Restricted < Urgent Inspection < Closed, and the reported state is the most conservative of the structural-probability, uncertainty, hard-trigger, prior-state, and context states:  $S_{\text{final}} = \max(S_{\text{prob}}, S_{\text{unc}}, S_{\text{hard}}, S_{\text{history}}, S_{\text{context}})$ . Therefore, reducing data reliability or removing evidence cannot produce a less conservative action or downgrade a severe physical warning. Uncertain or severe recommendations require documented professional engineer assessment, and any transition from Restricted, Urgent Inspection, or Closed to a less conservative state additionally requires responsible-agency authorization.

### 3.10 Parameterized Decision Logic and Professional Oversight

The decision-making logic converts technical evidence into explicit, auditable operational recommendations. Table 4 defines the probability, confidence, and threshold quantities; Table 5 and Fig. 4 present the parameterized decision matrix and state logic; and Table 6 integrates automated assessment with professional reconnaissance, inspection, repair verification, and reopening authority. Rather than using one universal sensor threshold, the framework combines bridge-specific physical limits, calibrated probabilities, structural and visual evidence, data reliability, vulnerability, and network importance before assigning a provisional state.

The first step in the decision logic is evidence formation. Structural evidence may include residual displacement, abnormal support motion, strong modal shift, unusual deck and pier response, or a hard component limit. Visual evidence may include crack growth, spalling, end-joint opening, bearing movement, loss of support, or visible misalignment. These evidence streams are checked against data reliability and modality agreement before fusion. This is essential because low-quality or contradictory signals should not lead directly to a confident management decision. Because sensor and data-quality uncertainty can strongly affect automated interpretation [34,39,40], Fig. 4 represents an evidence-to-recommendation filter rather than an autonomous replacement for professional engineering judgment. On the other hand, all transitions to a less conservative state are provided in Table 6.

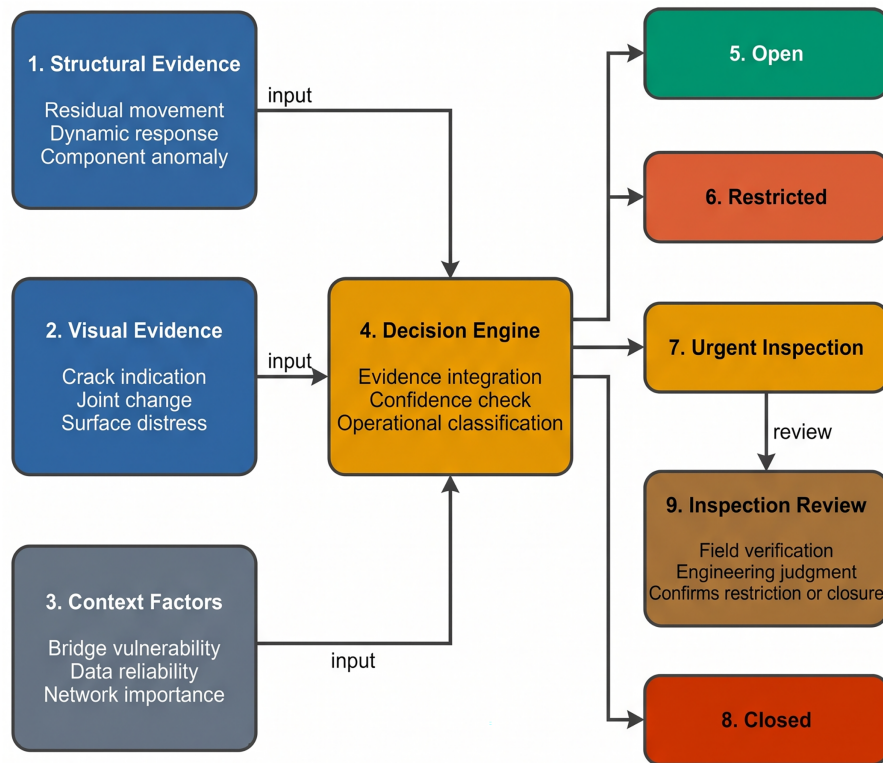


**Figure 4:** Detailed decision logic showing evidence inputs, confidence filtering, provisional operational state assignment, and the professional inspection-review pathway for urgent-inspection cases.

**Table 6:** Integration of automated assessment with professional inspection, repair verification, and reopening authority.

| Stage                                   | Trigger                                                                                    | Responsible Party                                                    | Main Purpose                                                                                | Main Evidence Collected                                                             |
|-----------------------------------------|--------------------------------------------------------------------------------------------|----------------------------------------------------------------------|---------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Automated trigger screening             | Seismic event and local anomaly                                                            | Edge node under an agency-approved configuration                     | Provisional screening and advisory action                                                   | Sensor anomalies, image cues, probabilities, confidence, and uncertainty            |
| Route reconnaissance                    | Moderate to strong event or system alarm                                                   | Agency staff or trained reconnaissance team                          | Rapid unsafe-bridge identification and access-status confirmation                           | Quick visual evidence, closure need, and route status                               |
| Professional post-earthquake assessment | Restricted, Urgent Inspection, Closed, or uncertain state                                  | Licensed or professional bridge engineer and inspection team         | Structural integrity assessment and action update                                           | Component damage, severity, probable cause, photographs, and overall damage state   |
| Repair or retrofit verification         | Temporary stabilization, repair, or retrofit completed                                     | Agency engineering team and responsible professional                 | Verify adequacy before a state transition                                                   | Work records, measurements, residual defects, and aftershock condition              |
| Reopening authorization                 | Request to move from Restricted, Urgent Inspection, or Closed to a less conservative state | Responsible agency based on a documented professional recommendation | Formal authorization of a less conservative state or continuation of restriction or closure | Signed engineering assessment, threshold review, and traffic and network conditions |

The assigned operational states range from provisional normal service to full closure. In [Table 5](#), an Open recommendation is permitted only under low total damage probability, high confidence, and absence of a hard trigger or prior-state restriction. Mild anomalies or reduced confidence lead to Restricted, while moderate anomalies, conflicting evidence, or low confidence with a nontrivial anomaly lead to Urgent Inspection. Severe anomalies, high-severity unsafe probability, or direct evidence of instability lead to Closed. High-consequence bridges may receive a more conservative action because network importance affects consequence, but network context cannot override a severe structural warning [4–6]. [Table 6](#) connects automated screening with route reconnaissance, professional engineering assessment, repair or retrofit verification, and reopening authorization. Automation provides the first filter and audit record; professional engineers and the responsible agency retain authority for structural confirmation and any transition from Restricted, Urgent Inspection, or Closed to a less conservative state.

### 3.11 Proposed Deployment and Validation Protocol

This subsection provides a prospective deployment and verification scenario; it is not a case study and does not constitute evidence that the framework currently works on an operational bridge. The proposed first phase is agency preparation: select a pilot bridge, verify drawings and component limits, create the digital profile, install time-synchronized sensors at critical zones, define the professional authority chain, and collect baseline data across representative environmental and traffic conditions. The models and the provisional thresholds in [Table 4](#) would then be calibrated offline using baseline records, archived events where available,

physics-based simulations, and controlled-damage or laboratory data. Any simulated or transferred data must be separated from field observations in the training and test sets.

The second phase is hardware-in-the-loop verification. Recorded or synthetic event windows would be replayed through the actual gateway and edge hardware while bandwidth limitation, packet loss, clock drift, sensor dropout, and power interruption are introduced. The study would report the 95th-percentile latency terms from [Section 3.6](#), event-detection sensitivity and specificity, false-alarm and missed-detection rates, damage-state macro-F1, Brier score, expected calibration error, uncertainty-escalation rate, data availability, and store-and-forward recovery. Leave-one-event-out and, where multiple bridges are available, leave-one-bridge-out testing would be used to examine generalization.

The third phase is a field pilot in shadow mode. The system would issue recommendations to the agency without autonomous traffic control, and its outputs would be compared with scheduled inspections, controlled load tests, and professional post-event assessments. Only after documented acceptance criteria, cybersecurity review, maintenance planning, and professional approval could selected advisory functions be integrated with traffic and emergency platforms. Automated transitions from Restricted, Urgent Inspection, or Closed to a less conservative state would remain prohibited; state-change authority would follow local law and agency procedure.

Pragmatic application is therefore conditional on sensor durability, backup power, time synchronization, communications, baseline representativeness, model-drift monitoring, cybersecurity, data governance, interagency responsibility, staff training, and long-term maintenance funding. These operational constraints are treated as validation requirements rather than assumed away.

### ***3.12 Intended Practical and Research Significance***

The intended value of the framework is that it joins several technical streams into one connected design for bridge response after earthquakes. Existing studies have shown progress in wireless monitoring, vision-based sensing, machine learning, edge computing, and resilience assessment, yet these areas are often treated as separate research directions instead of being assembled into a full emergency decision process [[16,22,33](#)]. The present framework responds to that separation by arranging sensing, local interpretation, central fusion, uncertainty handling, professional oversight, and coordinated response into one sequence. It is therefore a structured basis for future simulation, hardware-in-the-loop testing, pilot deployment, and applied system design, not evidence of completed implementation.

A major intended advantage of the framework is that it could reduce dependence on slow manual inspection during the first and most sensitive stage after shaking, subject to future validation. Manual inspection remains necessary, especially for detailed structural verification, yet it may take time to mobilize teams, reach damaged routes, and inspect many bridges in a short period. The proposed system is designed to produce provisional bridge-state recommendations that may help agencies rank inspection needs and select precautionary traffic actions before full field reports are available. It does not replace detailed inspection or professional authority. This intended role is consistent with research on rapid bridge damage screening, functionality prediction, and network-aware prioritization in seismic events [[2,6,28](#)].

Another important value of the framework lies in its fit with smart city conditions. In large urban systems, a bridge is more than a single structure. Its operational state affects emergency corridors, traffic redistribution, travel delay, and the continuity of essential services. The proposed framework recognizes this by including city coordination as an explicit layer rather than treating the bridge as an isolated engineering asset. This aligns with studies that connect bridge safety with transportation network performance and post-earthquake functional recovery [[3–5](#)].

The framework also has academic value because it offers a validation-ready specification rather than only a high-level diagram. Researchers can test its sensing strategy, edge-cloud allocation, model stack, latency budget, evidence fusion, uncertainty record, decision matrix, and inspection integration in simulations or pilot deployments. The contribution is therefore a conceptual path for future work; claims of speed, reliability, and context-aware performance remain subject to the validation protocol.

#### 4 Discussion

The proposed framework presents a structured design proposal that connects sensing, data processing, artificial intelligence, uncertainty management, professional oversight, and operational decision-making into one continuous system for post-earthquake bridge management. This integration responds to a limitation in the literature where monitoring systems, analytical models, and decision processes are often developed in isolation. Earlier studies have shown strong progress in each of these areas, yet their application during emergency conditions remains fragmented [16,22,33]. The framework described in this study brings these elements into a unified conceptual process, and this section examines its design strengths, limitations, and future validation needs.

A principal design feature of the framework lies in its layered structure, where each level performs a defined function and feeds the next stage. The use of edge analytics before central processing is intended to support a provisional response during the first period after an earthquake. This approach aligns with research that highlights the importance of low-latency processing in structural health monitoring systems, especially when communication networks may be unstable [34–36]. The proposed edge layer can produce a local recommendation based on the last approved model and available evidence, while the central layer can later refine the recommendation using network importance and seismic context. Whether this division achieves the intended balance between speed and reliability remains to be tested with the latency and performance metrics in [Section 3.11](#).

Another intended feature is the integration of multiple data types. Structural sensors, visual data, and environmental measurements are treated as complementary sources of evidence. Many existing systems rely mainly on one type of data, which can limit their performance when signals are incomplete or noisy. The inclusion of contact and non-contact sensing, as shown in [Fig. 2](#), supports a broader view of bridge condition and is consistent with trends in hybrid structural health monitoring systems [17–19]. The reliability-weighted fusion mechanism is intended to reduce dependence on a single data stream, but the size of this benefit requires empirical validation.

The parameterized decision logic described in [Tables 4 and 5](#), and [Fig. 4](#) also adds technical specificity to the proposal. Instead of relying on an undefined qualitative threshold, the system uses calibrated damage-state probabilities, data quality, modality agreement, bridge vulnerability, and network importance. This multi-factor approach reflects the complexity of post-earthquake conditions, where different actions may be justified depending on consequence and evidence reliability. Previous studies have emphasized context-aware evaluation in resilience and functionality assessment [5–7]. The present framework converts that principle into a reproducible proposed rule set, but the provisional thresholds must be calibrated before operational use.

Despite these design features, several limitations must be considered. Because no empirical bridge-monitoring dataset was generated or analyzed, the present study cannot quantify accuracy, latency, false-alarm rates, or generalizability. Operational damage signatures can be weaker than environmental and traffic variability, and structural health monitoring systems can experience noise, signal loss, saturation, and calibration drift, especially under strong seismic motion [10,39,40]. Local damage may not produce a clear global modal change, while temperature or boundary-condition changes may produce a

large apparent anomaly. The framework includes data-quality, baseline-conditioning, out-of-distribution, and disagreement checks, but these controls have not yet been validated on the proposed integrated system. Another limitation concerns artificial intelligence generalization. Models trained on specific bridge types or seismic conditions may not perform equally well in different regions or structural configurations [23,24]. Model calibration, local adaptation, and professional confirmation are therefore necessary for any future application.

Resilience in this study should not be interpreted as rapid screening alone. Pre-event maintenance, deterioration, and retrofit alter vulnerability; post-event repair sequencing, available crews, aftershocks, and network detours control recovery. Life-cycle risk and maintenance studies show that these decisions should combine aging, hazard, direct and indirect consequences, and resource limits [47,48]. The proposed framework can export a probabilistic state and audit record to those models, but it does not optimize maintenance budgets, retrofit strategies, or reconstruction schedules.

Recovery must also be treated discretely. The rapid system concerns initial state assignment and prioritization. Major damage or destruction requires detailed engineering analysis, design, procurement, repair or retrofit, or replacement and can consume weeks to months or longer. The framework tracks these state transitions but does not continuously infer structural recovery or reopen a bridge automatically.

Implementation complexity also represents a practical concern. The framework requires coordination among sensing infrastructure, communication systems, edge devices, central platforms, and multiple agencies. Such integration may demand significant investment, technical expertise, maintenance capacity, defined professional liability, and institutional coordination. Smart city environments may support this level of integration, yet smaller regions may face resource and system-maintenance limitations. Cybersecurity, data protection, signed model and threshold updates, and control of reopening authority are also important when infrastructure data are processed across distributed systems [33–35].

Future research should begin with the staged validation protocol in [Section 3.11](#) rather than an immediate autonomous deployment. Simulation and hardware-in-the-loop studies are needed to quantify latency, false alarms, missed detections, probability calibration, uncertainty escalation, and communication-loss behavior. Shadow-mode field pilots are then needed to compare recommendations with professional assessments. Hybrid modeling approaches that combine physics-based and data-driven methods may improve reliability and interpretability [31,32]. Further work should also examine adaptive but agency-governed thresholds, aftershock updating, model drift, digital-twin integration, and maintenance of sensor and edge hardware. These staged studies should generate the empirical datasets required to support the quantitative analysis that is outside the scope of the present theoretical paper.

Overall, the paper provides a conceptual and validation-ready design specification for rapid post-earthquake bridge management. The proposed integration could support faster information processing, improved coordination, and more consistent safety evaluation if its models, thresholds, latency, and organizational procedures are successfully validated. No claim of operational effectiveness is made before that validation.

## 5 Conclusion

The principal contribution of this study is a traceable, validation-ready conceptual framework that integrates bridge-specific sensing, edge analytics, central context and network fusion, artificial intelligence-based screening, uncertainty management, professional oversight, and city-level post-earthquake coordination within one operational architecture. Beyond a high-level concept, the framework specifies design requirements, edge-cloud task allocation, a reference model stack, time-series processing, reliability-weighted

evidence fusion, confidence and uncertainty records, parameterized decision rules, communication-loss behavior, and professional-assessment and reopening controls.

This specification provides a reproducible basis for testing how provisional bridge-state recommendations can be generated and escalated without treating automated outputs as final engineering judgments. Its contribution is therefore methodological rather than empirical: it defines the system logic, interfaces, safety constraints, and validation pathway needed to move future work from conceptual design toward simulation, hardware-in-the-loop evaluation, and pilot implementation.

**Acknowledgement:** Not applicable.

**Funding Statement:** The authors received no specific funding for this study.

**Author Contributions:** The authors confirm their contribution to the paper as follows: study conception and design: Abdullah Alariyan, Mohammed Abdulaal, Anas Alaryan, Mohammed Alariyan, Mahmoud Alhashash, Abdulhadi Alzabout, Abdulrahman Ahmed, Ahed Habib; analysis and interpretation of results: Abdullah Alariyan, Mohammed Abdulaal, Anas Alaryan, Mohammed Alariyan, Mahmoud Alhashash, Abdulhadi Alzabout, Abdulrahman Ahmed, Ahed Habib; draft manuscript preparation: Abdullah Alariyan, Mohammed Abdulaal, Anas Alaryan, Mohammed Alariyan, Mahmoud Alhashash. Manuscript review & editing: Abdulhadi Alzabout, Abdulrahman Ahmed, Ahed Habib. All authors reviewed and approved the final version of the manuscript.

**Availability of Data and Materials:** No new empirical data were generated or analyzed in this conceptual framework study.

**Ethics Approval:** Not applicable.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## References

1. Abo-El-Ezz A, Farzam A, Fezai H, Nollet MJ. Scenario-based earthquake damage assessment of highway bridge networks. *Adv Bridge Eng.* 2023;4(1):3. doi:10.1186/s43251-023-00083-4.
2. Liu Z, Li S, Zhao W, Guo A. Post-earthquake assessment model for highway bridge networks considering traffic congestion due to earthquake-induced bridge damage. *Eng Struct.* 2022;262(10):114395. doi:10.1016/j.engstruct.2022.114395.
3. Zhang Z, Ji T, Wei HH. Assessment of post-earthquake resilience of highway-bridge networks by considering downtime due to interaction of parallel restoration actions. *Struct Infrastruct Eng.* 2023;19(5):589–605. doi:10.1080/15732479.2021.1961826.
4. Wu C, Burton HV, Zsarnóczy Á., Chen S, Xie Y, Terzić V, et al. Modeling post-earthquake functional recovery of bridges. *Earthq Spectra.* 2025;41(3):2089–122. doi:10.1177/87552930251321301.
5. Chen M, Mangalathu S, Jeon JS. Betweenness centrality-based seismic risk management for bridge transportation networks. *Eng Struct.* 2023;289(5):116301. doi:10.1016/j.engstruct.2023.116301.
6. Zhang W, Wen J, Dong H, Han Q, Du X. Post-earthquake functionality and resilience prediction of bridge networks based on data-driven machine learning method. *Soil Dyn Earthq Eng.* 2025;190(2):109127. doi:10.1016/j.soildyn.2024.109127.
7. Akbari S, Khanmohammadi M. A probabilistic framework to make a decision on the post-earthquake functionality of bridges considering the damage, residual displacement, and aftershock. *Bull Earthq Eng.* 2022;20(2):1193–218. doi:10.1007/s10518-021-01269-9.
8. Tubaldi E, Turchetti F, Ozer E, Fayaz J, Gehl P, Galasso C. A Bayesian network-based probabilistic framework for updating aftershock risk of bridges. *Earthq Eng Struct Dyn.* 2022;51(10):2496–519. doi:10.1002/eqe.3698.
9. Todorov B, Muntasir Billah AHM. Post-earthquake seismic capacity estimation of reinforced concrete bridge piers using machine learning techniques. *Structures.* 2022;41(8):1190–206. doi:10.1016/j.istruc.2022.05.067.

10. Deng Z, Huang M, Wan N, Zhang J. The current development of structural health monitoring for bridges: a review. *Buildings*. 2023;13(6):1360. doi:10.3390/buildings13061360.
11. Elsis A, Zamrawi A, Emad S. A comprehensive review of structural health monitoring for steel bridges: technologies, data analytics, and future directions. *Appl Sci*. 2025;15(22):12090. doi:10.3390/app152212090.
12. Sonbul OS, Rashid M. Towards the structural health monitoring of bridges using wireless sensor networks: a systematic study. *Sensors*. 2023;23(20):8468. doi:10.3390/s23208468.
13. Aygün B, Cagri Gungor V. Wireless sensor networks for structure health monitoring: recent advances and future research directions. *Sens Rev*. 2011;31(3):261–76. doi:10.1108/02602281111140038.
14. Yu X, Fu Y, Li J, Mao J, Hoang T, Wang H. Recent advances in wireless sensor networks for structural health monitoring of civil infrastructure. *J Infrastruct Intell Resil*. 2024;3(1):100066. doi:10.1016/j.iintel.2023.100066.
15. Singh S, Shanker R. Wireless sensor networks for bridge structural health monitoring: a novel approach. *Asian J Civ Eng*. 2023;24(6):1425–39. doi:10.1007/s42107-023-00578-5.
16. Sun L, Shang Z, Xia Y, Bhowmick S, Nagarajaiah S. Review of bridge structural health monitoring aided by big data and artificial intelligence: from condition assessment to damage detection. *J Struct Eng*. 2020;146(5):04020073. doi:10.1061/(asce)st.1943-541x.0002535.
17. Park JS, An J, Park HS. Computer vision-based structural health monitoring: a review. *Int J High Rise Build*. 2023;12(4):321–33.
18. Ponsi F, Buoli E, Varzaneh GE, Bassoli E, Briseghella B, Vincenzi L. Vision-based approach for the static and dynamic monitoring of bridges. *Procedia Struct Integr*. 2024;62(11):946–54. doi:10.1016/j.prostr.2024.09.127.
19. Bhowmick S, Nagarajaiah S, Veeraraghavan A. Vision and deep learning-based algorithms to detect and quantify cracks on concrete surfaces from UAV videos. *Sensors*. 2020;20(21):6299. doi:10.3390/s20216299.
20. Azimi M, Eslamlou AD, Pekcan G. Data-driven structural health monitoring and damage detection through deep learning: state-of-the-art review. *Sensors*. 2020;20(10):2778. doi:10.3390/s20102778.
21. Bao Y, Sun H, Xu Y, Guan X, Pan Q, Liu D. Recent advances in structural health diagnosis: a machine learning perspective. *Adv Bridge Eng*. 2025;6(1):7. doi:10.1186/s43251-024-00155-z.
22. Di Mucci VM, Cardellicchio A, Ruggieri S, Netti A, Renò V, Uva G. Artificial intelligence in structural health management of existing bridges. *Autom Constr*. 2024;167(4):105719. doi:10.1016/j.autcon.2024.105719.
23. Gomez-Cabrera A, Escamilla-Ambrosio PJ. Review of machine-learning techniques applied to structural health monitoring systems for building and bridge structures. *Appl Sci*. 2022;12(21):10754. doi:10.3390/app122110754.
24. Jia J, Li Y. Deep learning for structural health monitoring: data, algorithms, applications, challenges, and trends. *Sensors*. 2023;23(21):8824. doi:10.3390/s23218824.
25. Li Y, Sun Z, Mangalathu S, Li Y, Yang H, He W. Seismic damage states prediction of in-service bridges using feature-enhanced swin transformer without reliance on damage indicators. *Eng Appl Artif Intell*. 2025;159(2):111651. doi:10.1016/j.engappai.2025.111651.
26. Yazdanpanah O, Park M, Chang M, Chae Y. Mastering seismic time series response predictions using an attention-Mamba transformer model for bridge bearings and piers across varied testing conditions. *Sci Rep*. 2024;14(1):29751. doi:10.1038/s41598-024-79195-4.
27. Ogunjinmi PD, Park SS, Kim B, Lee DE. Rapid post-earthquake structural damage assessment using convolutional neural networks and transfer learning. *Sensors*. 2022;22(9):3471. doi:10.3390/s22093471.
28. Mangalathu S, Hwang SH, Choi E, Jeon JS. Rapid seismic damage evaluation of bridge portfolios using machine learning techniques. *Eng Struct*. 2019;201(S1):109785. doi:10.1016/j.engstruct.2019.109785.
29. Gautam D, Bhattarai A, Rupakhety R. Machine learning and soft voting ensemble classification for earthquake induced damage to bridges. *Eng Struct*. 2024;303(4):117534. doi:10.1016/j.engstruct.2024.117534.
30. Liang X. Enhancing seismic damage detection and assessment in highway bridge systems: a pattern recognition approach with Bayesian optimization. *Sensors*. 2024;24(2):611. doi:10.3390/s24020611.
31. Pal A, Bhowmick S, Nagarajaiah S. Physics-informed AI and ML-based sparse system identification algorithm for discovery of PDE's representing nonlinear dynamic systems. *Mech Syst Signal Process*. 2025;238(3):113238. doi:10.1016/j.ymsp.2025.113238.

32. Bhowmick S, Nagarajaiah S. Physics-guided identification of Euler–Bernoulli beam PDE model from full-field displacement response with SimultaNeous basis function Approximation and Parameter Estimation (SNAPE). *Eng Struct.* 2023;289:116231. doi:10.1016/j.engstruct.2023.116231.
33. Qiu S, Malik M, Ehsan H, Wang W, Wang J, Cheng R, et al. Trends and perspectives in structural health monitoring through edge computing: a review with zero-shot natural language processing categorization. *J Railw Sci Technol.* 2025;1(2):59–74. doi:10.1016/j.jrst.2025.08.003.
34. Wang Y, Tang Z, Qian G, Xu W, Huang X, Fang H. A prototype of a lightweight structural health monitoring system based on edge computing. *Sensors.* 2025;25(18):5612. doi:10.3390/s25185612.
35. Farjad SM, Patllola SR, Kassa Y, Grispos G, Gandhi R. Secure edge computing reference architecture for data-driven structural health monitoring: lessons learned from implementation and benchmarking. In: *Proceedings of the 2025 ACM Southeast Conference*; 2025 Apr 24–26; Cape Girardeau, MO, USA. p. 145–54. doi:10.1145/3696673.3723074.
36. Peng Z, Li J, Hao H, Zhong Y. Smart structural health monitoring using computer vision and edge computing. *Eng Struct.* 2024;319:118809. doi:10.1016/j.engstruct.2024.118809.
37. Gautam D. On seismic vulnerability of highway bridges in Nepal: 1988 Udaypur earthquake ( $M_w$  6.8) revisited. *Soil Dyn Earthq Eng.* 2017;99(2):168–71. doi:10.1016/j.soildyn.2017.05.014.
38. Kawashima K, Unjoh S, Hoshikuma JI, Kosa K. Damage of bridges due to the 2010 Maule, Chile, Earthquake. *J Earthq Eng.* 2011;15(7):1036–68. doi:10.1080/13632469.2011.575531.
39. Jana D, Patil J, Herkal S, Nagarajaiah S, Duenas-Ororio L. CNN and Convolutional Autoencoder (CAE) based real-time sensor fault detection, localization, and correction. *Mech Syst Signal Process.* 2022;169(5):108723. doi:10.1016/j.ymssp.2021.108723.
40. Sen D, Erazo K, Zhang W, Nagarajaiah S, Sun L. On the effectiveness of principal component analysis for decoupling structural damage and environmental effects in bridge structures. *J Sound Vibr.* 2019;457(1):280–98. doi:10.1016/j.jsv.2019.06.003.
41. Peeters B, De Roeck G. One-year monitoring of the Z24-bridge: environmental effects versus damage events. *Earthq Eng Struct Dyn.* 2001;30(2):149–71. doi:10.1002/1096-9845(200102)30:.
42. Svendsen BT, Frøseth GT, Øiseth O, Rønnquist A. A data-based structural health monitoring approach for damage detection in steel bridges using experimental data. *J Civ Struct Health Monit.* 2022;12(1):101–15. doi:10.1007/s13349-021-00530-8.
43. Svendsen BT, Øiseth O, Frøseth GT, Rønnquist A. A hybrid structural health monitoring approach for damage detection in steel bridges under simulated environmental conditions using numerical and experimental data. *Struct Health Monit.* 2023;22(1):540–61. doi:10.1177/14759217221098998.
44. Bhowmick S, Nagarajaiah S, Lai Z. Measurement of full-field displacement time history of a vibrating continuous edge from video. *Mech Syst Signal Process.* 2020;144(5):106847. doi:10.1016/j.ymssp.2020.106847.
45. Wang M, Zhang H, Dai H, Shen L. A deep learning-aided seismic fragility analysis method for bridges. *Structures.* 2022;40(4):1056–64. doi:10.1016/j.istruc.2022.04.058.
46. Zhu Y, Zhou S, Zhong J, Wang H. AI-assisted analytical model of seismic displacement estimation for frictional isolated bridge portfolios under pulse-like ground motions. *Soil Dyn Earthq Eng.* 2024;187(2):108991. doi:10.1016/j.soildyn.2024.108991.
47. Decò A, Frangopol DM. Life-cycle risk assessment of spatially distributed aging bridges under seismic and traffic hazards. *Earthq Spectra.* 2013;29(1):127–53. doi:10.1193/1.4000094.
48. Han X, Frangopol DM. Life-cycle risk-based optimal maintenance strategy for bridge networks subjected to corrosion and seismic hazards. *J Bridge Eng.* 2023;28(1):04022128. doi:10.1061/jbenf2.beeng-5799.