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Advances in Intelligent Bridge Structural Health Monitoring in Indonesia: Integrating AI-Driven Damage Detection, IoT-Based Sensing, Digital Twins, Predictive Maintenance, Environmental Monitoring, and Seismic Resilience

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ABSTRACT

The increasing scale, structural complexity, and service requirements of bridge infrastructure have created a growing need for reliable and intelligent structural health monitoring (SHM) systems capable of continuously assessing structural condition and supporting timely maintenance decisions. This need is particularly important in Indonesia, where bridges operate under combinations of heavy traffic loading, tropical rainfall, high humidity, temperature variation, coastal exposure, corrosion, geological variability, and recurrent seismic activity. Conventional inspection-based approaches, although still important, are increasingly constrained by intermittent observations, limited spatial coverage, data fragmentation, and difficulties in identifying early-stage deterioration. Recent developments in artificial intelligence (AI), Internet of Things (IoT) technologies, wireless sensor networks (WSNs), cloud-edge computing, computer vision, digital twins (DTs), and predictive analytics provide opportunities to transform bridge SHM from periodic inspection toward continuous, data-driven, and lifecycle-oriented management.

This review examines the development of intelligent bridge SHM through an integrated framework encompassing intelligent sensing, IoT-enabled data transmission, edge-cloud data processing, multimodal information fusion, AI-driven damage detection, environmental monitoring, digital twins, predictive maintenance, and seismic resilience assessment. Fiber-optic sensors, piezoelectric devices, GNSS, machine vision, photogrammetry, and UAV-based inspection are examined as complementary sensing technologies. Machine learning and deep learning approaches are discussed for anomaly detection, crack recognition, damage classification, sensor-fault diagnosis, and structural-condition assessment. The review further considers BIM and digital twin technologies as mechanisms for integrating heterogeneous monitoring data with three-dimensional structural representations and lifecycle management systems. Particular attention is given to Indonesian operating conditions, including rainfall-induced deterioration, humidity, chloride-related corrosion in coastal environments, traffic-induced vibration, and earthquake-related structural demand.

The review identifies several persistent challenges, including sensor durability, data reliability, communication constraints, limited labeled datasets, cross-bridge algorithm generalization, model interpretability, interoperability, cybersecurity, and the absence of fully integrated lifecycle management architectures. A future-oriented framework combining multimodal sensing, transfer learning, synthetic data generation, active learning, cloud-edge collaboration, digital twins, and predictive maintenance is proposed. The resulting perspective provides a conceptual basis for developing intelligent and resilient bridge monitoring systems capable of supporting safer, more sustainable, and more responsive infrastructure management in Indonesia.

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1. Introduction

Bridges constitute critical components of transportation networks[1]; because their operational condition directly influences mobility, economic activity, emergency response, and regional connectivity[2,3]. As bridge networks expand and individual structures remain in service for increasingly long periods, ensuring structural safety and durability has become a central concern in infrastructure management[4]. Bridge performance is influenced by multiple interacting mechanisms, including traffic loading, material deterioration, environmental exposure, construction quality, fatigue, foundation movement, temperature variation, and extreme natural events[5]. When deterioration progresses without timely identification and intervention, local defects can develop into more extensive structural deficiencies and, in severe cases, compromise serviceability or safety[6].

These challenges are particularly relevant to Indonesia because bridge infrastructure is exposed to a combination of environmental and geotechnical conditions that can accelerate deterioration[7]. Tropical rainfall and high relative humidity can influence moisture-related deterioration, while bridges located in coastal regions may experience chloride exposure and corrosion-related damage [8]. Heavy and heterogeneous traffic loads introduce repeated dynamic effects, and the country's tectonic setting creates a significant requirement for monitoring structural response to seismic excitation[9]. Consequently, a bridge monitoring strategy designed for Indonesia needs to consider not only conventional parameters such as strain, acceleration, displacement, and crack development, but also environmental variables, corrosion-related indicators, rainfall, temperature, humidity, and earthquake-induced response[10,11].

Structural health monitoring has emerged as an important technological approach for addressing these requirements. In its conventional form[12], SHM involves the acquisition of structural-response data, transmission and processing of monitoring signals, identification of abnormal conditions, and evaluation of structural performance [13,14,15]. Sensors installed at strategically selected locations provide information concerning parameters such as strain, acceleration, displacement, temperature, vibration, and environmental conditions. These measurements can subsequently be analyzed to identify changes in structural behavior and support inspection and maintenance decisions[16,17,18].

Traditional bridge inspection systems, however, generally depend on scheduled visual inspections and isolated measurements[19]. Such approaches may provide valuable information about visible deterioration but can have limited capability for continuous monitoring, early-stage damage identification, and simultaneous assessment of multiple structural components[20,21]. Furthermore, heterogeneous monitoring systems can create information silos in which data obtained from different sensors, inspection teams, or software platforms cannot easily be integrated[22]. Communication delays, sensor noise, missing observations, and differences in data formats can further complicate the interpretation of long-term monitoring records[23].

The rapid development of artificial intelligence, big-data analytics, IoT technologies, cloud computing, and digital twins is creating a new generation of intelligent SHM systems[24]. Rather than treating sensing, data transmission, diagnosis, and maintenance as independent activities, intelligent SHM seeks to connect these components into an integrated information chain[25]. In this architecture, sensors continuously perceive the physical state of a bridge; communication

systems transfer observations through distributed networks[26]; edge and cloud platforms process large volumes of heterogeneous data; AI algorithms identify patterns associated with damage or abnormal behavior[27]; and digital representations of the bridge provide an environment for visualization, prediction, and maintenance planning[28].

Recent research demonstrates the potential of this technological transition. Fiber-optic sensing can provide high-resolution strain and temperature measurements, including distributed observations along structural elements[29,30,31,32,33] Piezoelectric sensors can detect changes associated with local damage and connection deterioration[34]. Machine vision and photogrammetry allow non-contact identification of cracks and surface defects, while GNSS technologies can provide three-dimensional displacement information for large-scale structural movements[35]. The integration of these technologies can overcome some of the limitations associated with relying on a single sensing principle[36].

At the data-processing level, wireless sensor networks can reduce cabling requirements and facilitate distributed monitoring, while edge computing can move selected processing tasks closer to the sensing location[37]. Cloud platforms provide computational resources for large-scale storage and advanced analysis[38]. Intelligent compression and denoising methods can reduce redundant information and improve the usability of monitoring signals. These developments become increasingly important as the number of sensors and monitoring frequency increase[39].

AI-based analysis represents another major transformation. Machine-learning methods can learn relationships between monitoring features and structural states, whereas deep-learning architectures can automatically extract complex representations from vibration signals, images, and other high-dimensional data[40,41]. Computer-vision models have been applied to crack detection and surface-defect segmentation, while transfer learning provides a potential mechanism for adapting knowledge developed for one bridge or dataset to another[42,43]. Autoencoder-based approaches can additionally assist in detecting sensor faults and reconstructing expected signals[44].

At the management level, Building Information Modeling (BIM) and digital twin technologies provide mechanisms for connecting monitoring information with three-dimensional representations of bridge assets[45,46]. BIM can organize structural and maintenance information within a unified digital environment, whereas digital twins extend this concept by continuously associating the virtual representation with time-dependent physical observations[47,48]. Such systems can facilitate condition visualization, deterioration prediction, maintenance prioritization, and lifecycle decision-making[49].

Despite these advances, the direct transfer of intelligent SHM technologies into complex infrastructure environments remains challenging[50]. AI models frequently depend on large and representative datasets, while actual bridge damage is relatively rare and often poorly labeled[51]. Models trained on one structural configuration may also experience reduced performance when applied to different bridge types, climates, sensor layouts, or operational conditions[52]. Environmental effects can produce changes in measured responses that resemble structural anomalies[53]. In addition, data interoperability, cybersecurity, computational limitations, and sensor durability remain important engineering concerns[54].

Accordingly, this review reorganizes the development of intelligent bridge SHM around the specific operational context of Indonesia. This study develops a new integrated conceptual framework for intelligent structural health monitoring (SHM) of bridges in Indonesia. It establishes

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a unified approach that connects advanced sensing, intelligent damage detection, data analytics, digital twins, predictive maintenance, environmental assessment, and seismic resilience with the specific operational and management requirements of Indonesian bridge infrastructure. The study focuses on six interconnected dimensions: intelligent data acquisition, IoT-based transmission and edge-cloud processing, AI-driven diagnosis, environmental monitoring, digital twins and BIM, and predictive maintenance with seismic resilience.

Figure 1. Overview of the integrated intelligent bridge structural health monitoring framework for Indonesian bridge infrastructure.

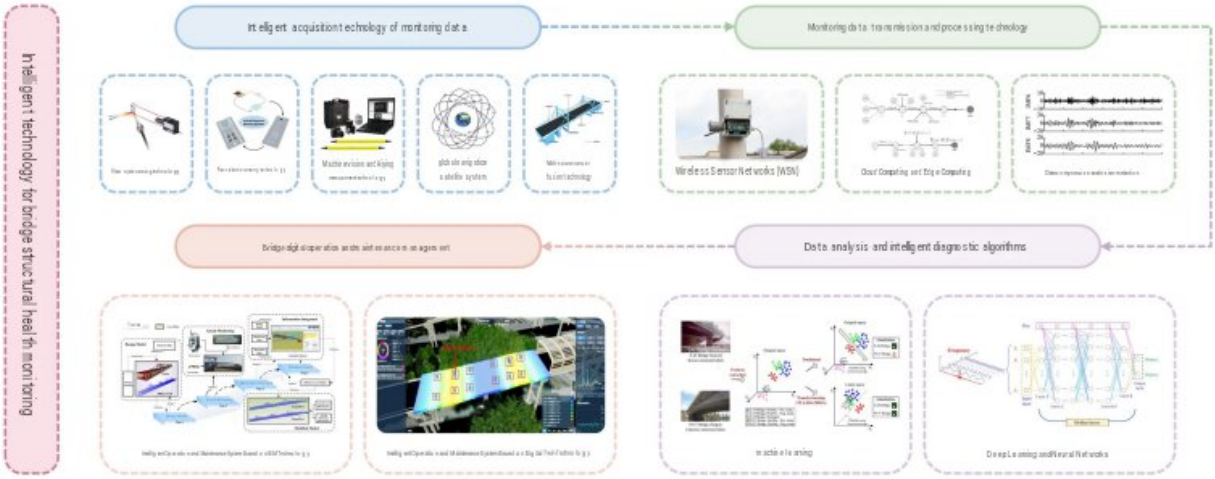

Figure 1. Overview diagram of intelligent technology for bridge structural health monitoring

Figure 1. Overview of Intelligent Technology for Bridge Structural Health Monitoring

2. Intelligent Acquisition of Bridge Structural Health Monitoring Data

The reliability of an intelligent SHM system begins with the quality of the information acquired from the physical structure[55]. No matter how sophisticated the subsequent AI algorithm may be, unreliable, incomplete, or poorly calibrated observations can compromise the resulting diagnosis[56]. Consequently, sensor technology has become one of the most important research directions in bridge SHM[57].

Modern monitoring systems increasingly combine multiple sensing principles rather than relying on a single sensor type[58]. Fiber-optic sensors provide high-resolution strain and temperature measurements[59]; piezoelectric devices can detect vibration and local damage[60]; machine vision enables non-contact inspection of surface defects[61]; GNSS can monitor global displacement[62]; and environmental sensors can characterize temperature, humidity, rainfall, and other external influences[63]. The resulting multimodal sensing architecture is particularly relevant to Indonesia because bridge deterioration may result from simultaneous mechanical and environmental mechanisms[64].

Table 1. Principal sensing technologies for intelligent bridge SHM

Sensing technology	Primary	Typical	Main	Principal

	parameters	application	advantage	limitation
Fiber-optic sensing	Strain, temperature	Girders, cables, structural members	High sensitivity and distributed measurement	Installation and interrogation cost
Piezoelectric sensing	Vibration, strain, local damage	Connections, joints, structural nodes	High local sensitivity	Environmental and temperature sensitivity
Machine vision/photogrammetry	Cracks, surface defects, deformation	Concrete and steel surfaces	Non-contact inspection	Illumination and occlusion
GNSS	Displacement and deformation	Girders, towers, large structural systems	Three-dimensional positioning	Multipath and signal obstruction
Environmental sensing	Temperature, humidity, rainfall, corrosion-related conditions	Bridge environment and vulnerable components	Supports deterioration interpretation	Spatial variability
UAV-based sensing	Images, geometry, surface condition	Large or difficult-to-access areas	Rapid remote inspection	Weather, flight conditions, and image quality

2.1 Fiber-Optic Sensing

Fiber-optic sensing technologies have attracted considerable attention because optical fibers are resistant to electromagnetic interference and can operate in environments where conventional electrical sensors may be difficult to deploy[65]. Their small dimensions and potential for distributed measurement make them particularly suitable for long bridge components[66].

Fiber Bragg Grating (FBG) sensors constitute one important category. An FBG sensor responds to changes in strain and temperature through shifts in its characteristic reflected wavelength[67]. Multiple gratings can be incorporated along an optical fiber, enabling quasi-distributed measurements at several structural locations[68]. Their high measurement stability and sensitivity make them useful for monitoring bridge girders, cables, joints, and other critical components[69].

Distributed fiber-optic sensing provides another important capability. Instead of measuring only discrete locations, distributed optical systems can obtain information along substantial portions of the sensing fiber [70]. Techniques based on optical time-domain or frequency-domain interrogation can therefore provide continuous or quasi-continuous information concerning strain and temperature[71]. This characteristic is especially valuable for large-span bridges where localized instrumentation may fail to capture deformation patterns extending over long distances[72].

Previous research has demonstrated the application of fiber-optic technology to transportation infrastructure and deformation monitoring[73,74]. For example, research using zigzag fiber arrangements combined with MATLAB-based three-dimensional spline interpolation demonstrated the possibility of reconstructing settlement and deformation patterns at millimeter-level

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resolution[75]. Such studies illustrate how sensor configuration and computational interpolation can be integrated to transform discrete or distributed measurements into spatially interpretable structural information.

For Indonesian bridges, fiber-optic systems may provide particular value in long-span structures and components exposed to harsh environmental conditions. Nevertheless, long-term performance depends on installation quality, protective packaging, temperature compensation, connector reliability, and maintenance of interrogation equipment[76].

2.2 Piezoelectric Sensing

Piezoelectric materials exhibit direct and inverse piezoelectric effects, allowing them to operate as sensors and actuators [77]. Mechanical excitation can generate electrical signals, while electrical excitation can produce mechanical responses[78]. These characteristics enable piezoelectric devices to measure or interrogate pressure, acceleration, strain, force, and vibration-related phenomena.

One important application is electromechanical impedance monitoring. In this approach, changes in the electromechanical impedance response of a piezoelectric element can indicate modifications in the local structural system [79]. Such methods are particularly suitable for monitoring bolted and welded connections, where small changes in stiffness or contact conditions can produce measurable changes in impedance [80].

Previous investigations have reported the use of advanced piezoelectric materials, including PMN-PT-based devices, for detecting high-strength bolt loosening[81]. Some reported configurations demonstrated substantially higher sensitivity than conventional piezoelectric sensors[82]. Other studies have applied piezoelectric guided-wave methods to detect defects in grouted sleeves used in prefabricated bridge systems, including incomplete compaction, cavities, and changes associated with water-to-material ratios[83].

These findings indicate that piezoelectric sensing can provide information that is difficult to obtain through conventional visual inspection. However, many experimental studies have been conducted under controlled or relatively idealized conditions. Long-term stability, temperature effects, environmental interference, sensor bonding quality, and scalability to operational bridges remain important considerations[84].

2.3 Machine Vision and Photogrammetry

Machine vision has fundamentally changed the possibilities for non-contact bridge inspection[85]. Cameras can acquire high-resolution images of structural surfaces, while image-processing and AI algorithms can subsequently identify cracks, corrosion, spalling, delamination indicators, and other visible defects[86].

The general workflow consists of image acquisition, geometric calibration, preprocessing, defect recognition, segmentation, and quantitative measurement. Recent research has increasingly integrated object-detection and semantic-segmentation networks into this workflow [87].

Studies applying YOLO-based detection architectures together with U-Net-family segmentation networks have demonstrated the potential for simultaneous crack recognition and measurement

[88]. Some investigations reported improvements over baseline single-task models when additional depth or structural information was incorporated. Other research developed two-stage CNN architectures in which a lightweight classification model first identifies relevant regions before a segmentation network extracts crack pixels. Such approaches can improve detection efficiency while reducing unnecessary image processing [89].

UAV-based imaging provides an additional dimension. Unmanned aerial vehicles can acquire images from locations that are difficult or hazardous for inspectors to access[90,91,92]. Research has combined UAV images with laser range measurements to estimate geometric relationships between the image plane and physical surface, enabling correction of image distortion and more accurate crack-width estimation. Reported experiments have demonstrated the capability to identify relatively small cracks under appropriate imaging conditions [93].

However, machine-vision performance is strongly dependent on image quality [94]. Illumination, shadows, surface contamination, camera angle, occlusion, weather conditions, and background complexity can substantially affect recognition accuracy [95]. Models trained on one dataset may also show reduced generalization when applied to different bridge materials or environmental conditions [96].

For Indonesia, this issue is especially relevant because tropical weather can produce rapidly changing illumination, wet surfaces, biological growth, and surface contamination. Therefore, robust Indonesian bridge-image datasets covering different bridge types, materials, climates, and deterioration conditions would be valuable for developing generalizable computer-vision models[97].

2.4 GNSS-Based Displacement Monitoring

Displacement is a fundamental indicator of structural behavior, particularly for bridge girders [98], towers, foundations, and other large components. Conventional displacement sensors generally require a stable reference system, which can become difficult to establish for large or geometrically complex bridge structures [99].

GNSS technology provides an alternative approach by enabling three-dimensional positioning of selected structural points under suitable satellite visibility[100]. Continuous GNSS monitoring can therefore provide information concerning global displacement and long-term deformation[101].

Previous research has examined the integration of GNSS measurements into bridge SHM, extending applications from static displacement monitoring to the characterization of dynamic structural behavior[102]. Multi-sensor arrangements have also been investigated to improve spatial coverage and synchronize GNSS observations with other monitoring technologies[103].

Satellite positioning, however, is susceptible to multipath effects, signal obstruction, atmospheric influences, and changes in satellite geometry[104]. Research using wavelet-based methods and neural-network correction has demonstrated the possibility of reducing multipath-related errors and relating GNSS monitoring observations to high-precision leveling information[105].

For Indonesian bridges, GNSS may be particularly useful for large-span bridges, long-term deformation monitoring, foundation movement, and structural response under extreme loading. Integration with accelerometers, inclinometers, and optical systems can further improve interpretation[106,107].

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2.5 Multisource Sensor Fusion

No individual sensor can capture every aspect of bridge structural behavior[108]. A strain sensor may detect local deformation but cannot directly provide comprehensive information about surface cracking[109]. A camera can identify visible cracks but cannot independently characterize internal stress states. GNSS can measure displacement but may not resolve local damage[110]. Consequently, intelligent SHM increasingly relies on sensor fusion [111].

Multisource fusion combines measurements from sensors based on different physical principles to construct a multidimensional representation of structural condition[112]. The integration may occur at the data level, feature level, or decision level. AI and big-data technologies have expanded this process from simple data aggregation toward intelligent information fusion[113].

Previous studies have investigated multisensor systems for identifying stiffness-related faults in bridge components, combining measurements such as displacement, tilt, optical response, and laser observations[114,115]. ther distributed architectures have integrated accelerometers, temperature and humidity sensors, and visual devices, with fuzzy-logic approaches used to combine deformation, vibration, and environmental information into multiple structural-health categories[116].

For Indonesian infrastructure, sensor fusion offers a particularly important advantage because structural responses may be influenced simultaneously by traffic, temperature, rainfall, humidity, corrosion, and seismic activity[117]. An intelligent system capable of distinguishing environmental changes from structural deterioration should therefore consider several synchronized data streams rather than relying on isolated measurements [118].

Figure 2. Multimodal sensing architecture for Indonesian bridges.

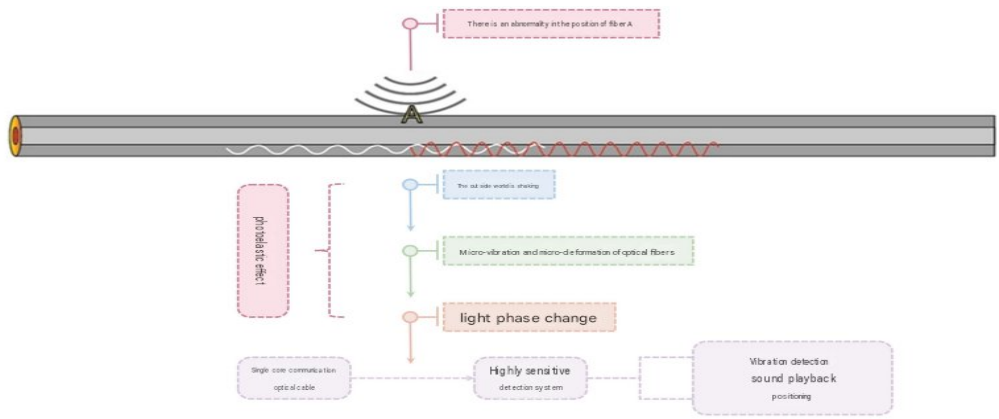

Figure 2. Multimodal sensing architecture for Indonesian bridges.

3. IoT-Based Data Transmission and Intelligent Processing

The expansion of sensor networks has created a second major challenge: the efficient transmission and processing of large volumes of monitoring information. A bridge equipped with numerous sensors can continuously generate vibration, strain, displacement, image, and environmental data.

Transmitting all raw information directly to a centralized server can impose substantial demands on bandwidth, energy, storage, and computation [119].

Intelligent SHM therefore increasingly combines wireless sensor networks, IoT communication, edge computing, cloud platforms, and signal-processing techniques [120].

Table 2. Technologies for intelligent SHM data transmission and processing

Technology	Primary function	Main advantage	Typical application	Limitation
Wireless sensor networks	Distributed acquisition and communication	Reduced cabling and distributed deployment	Long-term bridge monitoring	Bandwidth and energy limitations
Cloud computing	Storage and advanced analysis	Large computational capacity	Large-scale SHM databases	Transmission latency
Edge computing	Local processing	Low latency	Real-time anomaly detection	Limited local resources
Data compression	Reduces data volume	Lower transmission requirements	Continuous monitoring	Possible information loss
Signal denoising	Removes noise	Improved data quality	GNSS/vibration/strain signals	Method-dependent performance
Multimodal fusion	Combines heterogeneous observations	More comprehensive diagnosis	Integrated SHM	Synchronization complexity

3.1 Wireless Sensor Networks

Wireless sensor networks can reduce the cabling complexity and installation costs associated with conventional wired monitoring systems. Distributed sensing nodes can communicate through wireless protocols and transmit measurements to gateways or processing platforms[121].

Research on WSN deployment has emphasized sensor placement, energy optimization, communication reliability, and network topology. These factors are especially important for long-term bridge monitoring because replacing batteries or accessing individual nodes may be difficult[122].

Research combining low-power ZigBee communication with optimized scheduling has demonstrated the potential to extend network operating life in structural monitoring applications. Similar principles can be adapted to bridge systems by combining low-power sensing nodes with local gateways and selective data transmission[123].

For Indonesian bridges, WSN design must account for humidity, heavy rainfall, electromagnetic conditions, physical accessibility, and network interruptions. Hybrid communication architectures may therefore provide greater resilience than reliance on a single communication protocol[124].

3.2 Cloud-Edge Collaborative Computing

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Cloud computing provides large-scale storage and computational resources suitable for long-term SHM databases. Complex AI models, historical-data analysis, digital-twin synchronization, and cross-bridge comparisons can benefit from centralized computational infrastructure[125].

Nevertheless, transmitting all monitoring information to the cloud can introduce latency and unnecessary network traffic[126]. Edge computing addresses this limitation by placing computational capabilities close to the sensing layer[127].

At the edge, monitoring nodes or gateways can perform initial filtering, feature extraction, anomaly detection, compression, and event recognition. Only relevant information or processed features need to be transferred to the cloud. This architecture can reduce communication requirements and improve response speed[128].

A cloud-edge collaborative system is therefore particularly appropriate for bridge safety applications in which some decisions must be made immediately while other analyses can be conducted centrally[129].

For example, a sudden acceleration anomaly potentially associated with an earthquake or impact event could be detected locally, triggering an immediate warning. At the same time, the raw and processed data could be transmitted to a cloud platform for more comprehensive post-event analysis[130].

3.3 Data Compression and Signal Denoising

Monitoring data inevitably contain noise and redundancy. GNSS observations may be affected by multipath effects, vibration signals may contain environmental noise, and long-term sensor records can contain drift or missing observations[131].

Advanced decomposition and denoising methods have therefore become important components of intelligent SHM. Research has employed methods such as complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), wavelet-based filtering, and related signal-decomposition techniques for improving monitoring data[132].

Other approaches have combined time-varying filtering with empirical-mode decomposition and energy-entropy indicators to separate meaningful structural signals from noise components. Such techniques demonstrate the potential for improving signal-to-noise characteristics and reducing errors in structural-response interpretation[133].

However, the performance of a denoising method can depend strongly on signal type, bridge characteristics, environmental conditions, and noise distribution[134]. A method that performs well for GNSS observations may not necessarily be optimal for acceleration or strain data. Future Indonesian SHM systems should therefore incorporate adaptive signal-processing strategies capable of identifying changing noise characteristics[135].

4. AI-Driven Data Analysis and Intelligent Structural Diagnosis

The central purpose of SHM is not merely to collect data but to transform measurements into information about structural condition[136]. As monitoring systems become increasingly dense and

continuous, manual interpretation becomes impractical. AI therefore provides an important mechanism for extracting patterns from large datasets [137].

4.1 Machine Learning for Structural Condition Assessment

Machine-learning algorithms can establish relationships between monitoring features and structural states using historical observations. Depending on the available data, supervised, unsupervised, and semi-supervised learning can be applied[138].

Supervised learning requires labeled examples of normal and damaged conditions. Such models can be used for damage classification, anomaly detection, and condition assessment. Unsupervised methods, by contrast, can identify unusual patterns without requiring extensive damage labels and may therefore be more practical for long-term monitoring[139].

Transfer learning provides another strategy. Instead of training a new model entirely from scratch for every bridge, knowledge obtained from an existing dataset can be transferred to a new structure[140]. Research has investigated transfer-component adaptation, joint-distribution adaptation, and related domain-adaptation strategies for bridge-damage detection[141].

Other studies have used transfer learning and data augmentation to improve crack-recognition performance[142]. Reported improvements in particular experiments demonstrate the potential of this approach, but such numerical values should be interpreted as results of the corresponding datasets and experimental configurations rather than as universal performance levels[143].

Online machine-learning systems have also been investigated for real-time anomaly diagnosis. Adaptive thresholds combined with classifiers can identify abnormal conditions and classify potential fault types while monitoring data are continuously acquired[144]. Reported experimental studies have demonstrated reductions in detection delays and missed detections relative to selected offline approaches[145].

The principal challenge is generalization. A model trained on one bridge may learn characteristics that are specific to its geometry, sensor arrangement, material, or environmental conditions. Consequently, model validation across different Indonesian bridge types and operating environments is essential[146].

4.2 Deep Learning and Neural-Network-Based Diagnosis

Deep learning has expanded the capability of SHM systems because neural networks can automatically extract complex features from raw or minimally processed data [147]. Convolutional neural networks are particularly effective for image-based diagnosis, while other neural architectures can process time-series monitoring signals[148].

Computer-vision research has integrated monocular depth information with multi-task neural networks to improve structural-component recognition and defect segmentation[149]. Such approaches demonstrate that combining geometric information with visual features can improve the interpretation of complex bridge images[150].

Two-stage CNN architectures have also been developed for crack recognition, with one model identifying relevant regions and another extracting crack pixels[151]. Some experiments reported high recognition accuracy and improvements in small-crack detection and processing speed relative to selected single-network baselines[152].

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The present study considers the practical variability inherent in real bridge inspection environments, where changes in illumination, partial occlusion, surface contamination, moisture, biological growth, complex structural textures, and camera positioning may substantially influence image-based condition assessment. Accordingly, evaluating intelligent damage-detection approaches requires consideration of the diverse visual conditions encountered during actual bridge inspections in Indonesia. The study therefore establishes its assessment framework around these operational conditions to examine the applicability and robustness of automated bridge-damage detection under realistic Indonesian infrastructure environments.

Deep learning can also be applied to sensor-fault diagnosis. CNN-based models can classify sensor-fault patterns, while convolutional autoencoders can reconstruct normal signals. This combination provides a mechanism for distinguishing structural anomalies from instrumentation faults, which is essential for avoiding false structural alarms.

Table 3. Representative AI applications in intelligent bridge SHM

Application	Input data	AI approach	Main function
Damage/anomaly diagnosis	Structural monitoring signals	Machine learning/transfer learning	Condition identification
Crack recognition	Bridge images	CNN/object detection	Crack detection
Crack segmentation	High-resolution images	U-Net-type networks	Pixel-level defect extraction
Structural-component recognition	Images/depth information	Multi-task deep learning	Component and defect identification
Sensor-fault diagnosis	Sensor time series	CNN + autoencoder	Fault classification and signal reconstruction
Cross-bridge adaptation	Historical monitoring datasets	Domain adaptation	Model transfer and generalization

5. Environmental Monitoring and Bridge Deterioration in Indonesia

Environmental conditions should not be treated merely as external background variables. They can directly influence structural response, material deterioration, sensor behavior, and the interpretation of monitoring signals[153].

Indonesia's tropical environment creates several relevant monitoring factors. Rainfall can modify moisture conditions in concrete and surrounding soils, while high humidity can accelerate corrosion processes when other environmental conditions are favorable. Coastal bridges may be exposed to chloride-containing environments, while temperature variations can influence expansion, contraction, and sensor readings[154].

Consequently, environmental sensors should be incorporated into the same monitoring architecture as structural sensors.

5.1 Temperature and Humidity

Temperature changes can produce apparent strain and displacement that are not necessarily associated with structural damage. A monitoring system that does not compensate for temperature effects may therefore generate false alarms.

Humidity is similarly relevant because it can affect concrete, steel corrosion, sensor packaging, electrical components, and surface conditions. Continuous temperature and humidity measurements can provide the environmental context required to distinguish reversible environmental responses from progressive structural deterioration.

5.2 Rainfall and Moisture

Rainfall is particularly relevant to bridge decks, drainage systems, surrounding soils, and structural components exposed to repeated wetting and drying. Monitoring rainfall together with structural response can help investigate relationships between environmental exposure and changes in deformation, vibration, or material condition.

The objective should not be to assume that every rainfall event produces structural deterioration. Rather, rainfall observations should be treated as explanatory variables within a broader monitoring framework.

5.3 Corrosion and Coastal Exposure

For bridges located in coastal areas, chloride exposure represents an important deterioration mechanism for reinforced concrete and steel components. Corrosion monitoring can therefore complement conventional strain and vibration measurements.

Potential indicators include corrosion potential, electrical resistivity, humidity, chloride exposure, and temperature. Integrating these variables into AI models may help distinguish deterioration processes that are not immediately visible in structural-response data.

5.4 Traffic Loading and Operational Conditions

Traffic is another major source of dynamic loading. Heavy vehicles, traffic density, vehicle speed, and traffic distribution can influence bridge vibration and stress histories.

Integrating traffic information with acceleration, strain, and displacement measurements can help establish whether a detected change represents a structural anomaly or simply a change in operational loading.

Figure 3. Environmental and operational factors influencing intelligent bridge SHM in Indonesia.

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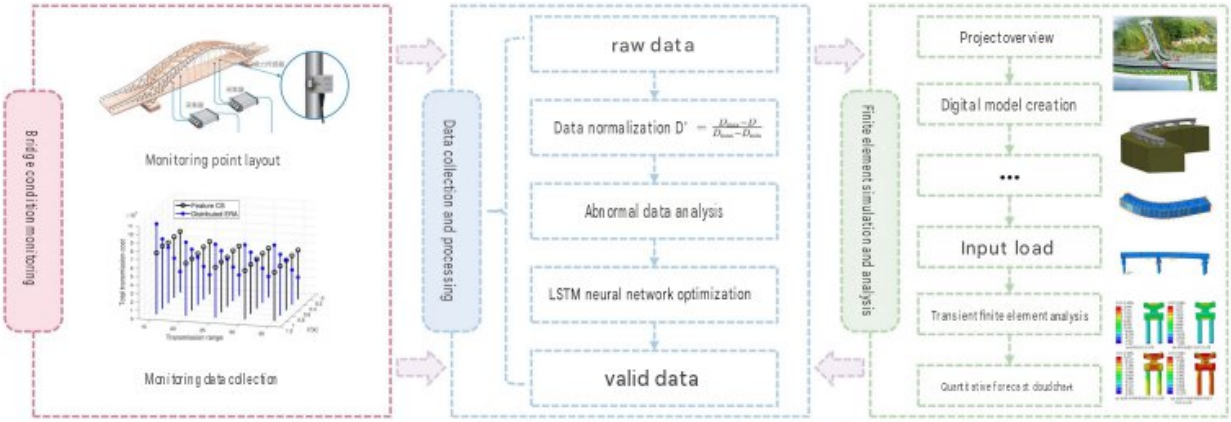

Figure 3. Environmental and operational factors influencing intelligent bridge SHM in Indonesia.

6. Digital Twins and BIM-Enabled Intelligent Bridge Management

The transition from monitoring toward intelligent infrastructure management requires more than sensors and AI algorithms. Monitoring results must be placed within a digital representation of the physical asset that can support visualization, interpretation, prediction, and maintenance decisions.

6.1 BIM-Based Bridge Information Management

Building Information Modeling provides a structured digital environment for integrating information concerning bridge geometry, materials, components, construction, inspection, repair, and maintenance[155].

For SHM applications, monitoring data can be associated with individual structural components within a three-dimensional bridge model. This creates a spatially interpretable representation in which engineers can identify where abnormal behavior occurs and connect it with inspection or maintenance records.

Research has proposed BIM-based bridge SHM systems incorporating as-built structural models, monitoring-system models, linked databases, finite-element analysis modules, and warning mechanisms. Such systems demonstrate how monitoring and maintenance information can be brought together within a common digital environment[156].

For Indonesian bridge networks, BIM can therefore provide an information backbone connecting design documentation, construction records, sensor locations, inspection results, damage history, and maintenance actions.

6.2 Digital Twin Technology

Digital twins represent a further development beyond conventional BIM. While BIM primarily organizes digital information about an asset, a digital twin emphasizes dynamic synchronization between the physical structure and its digital representation[157].

A bridge digital twin can receive information from sensors, UAV inspections, environmental monitoring systems, traffic databases, and other data sources. These observations can continuously update the digital model and support assessment of structural state over time[158].

Digital-twin research has investigated real-time data integration, dynamic model updating, deterioration prediction, and AI-supported damage diagnosis. Deep-learning-enabled digital twins have also been proposed for large-scale monitoring environments in which physical observations are continuously mapped into a cloud-based virtual representation[159].

For Indonesia, digital twins could support geographically distributed bridge management by providing a common environment in which engineers can monitor bridge condition, compare historical behavior, visualize defects, and prioritize interventions.

6.3 Digital-Twin-Based Structural Decision Support

An effective digital twin should not simply reproduce monitoring data. It should help answer management questions such as:

- Is the observed change within the expected operational range?
- Is the change caused by environmental conditions or structural deterioration?
- Which component requires further inspection?
- How is structural performance evolving over time?
- What maintenance action should be prioritized?
- How could an earthquake or other extreme event affect the current structural state?

These questions require integration between sensing, physics-based models, AI algorithms, and decision-support systems.

Figure 4. Digital twin architecture for Indonesian bridge lifecycle management.

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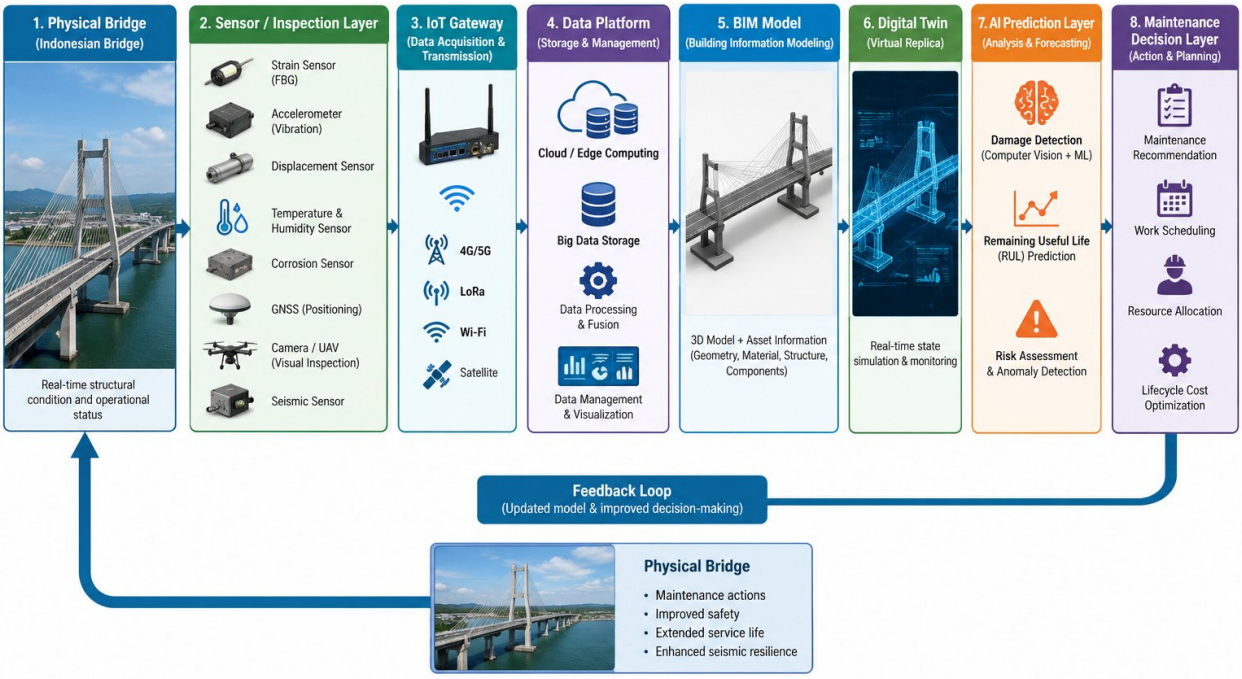

Figure 4. Digital twin architecture for Indonesian bridge lifecycle management.

7. Predictive Maintenance and Remaining Useful Life

Traditional bridge maintenance is often organized around scheduled inspections or reactive responses to identified defects. Intelligent SHM creates the possibility of predictive maintenance, in which maintenance requirements are anticipated from observed deterioration trends[160].

Predictive maintenance requires historical monitoring records, deterioration models, anomaly detection, and decision-support mechanisms. Rather than responding only after visible damage occurs, an intelligent system can identify gradual changes in structural behavior and estimate whether intervention is becoming necessary.

AI can contribute to this process through time-series prediction, anomaly detection, survival analysis, and remaining-useful-life estimation. However, prediction must account for uncertainty because structural deterioration is affected by multiple interacting variables.

A predictive-maintenance system for Indonesian bridges could integrate:

1. structural-response data;
2. environmental exposure;
3. traffic loading;
4. inspection history;

5. repair records;
6. material and geometric information;
7. seismic-event history;
8. AI-based deterioration indicators; and
9. digital-twin state estimates.

This integrated approach could enable maintenance decisions to move from simple calendar-based scheduling toward condition-based and risk-informed strategies.

8. Seismic Resilience of Indonesian Bridges

Seismic resilience is an essential dimension of bridge management in Indonesia because bridge systems must remain functional or recover rapidly following significant seismic events[161].

Traditional SHM approaches often focus on long-term deterioration, whereas seismic monitoring introduces a different temporal scale. Earthquake-related response can develop within seconds, requiring high-frequency sensing, rapid edge processing, event detection, and immediate communication.

Accelerometers and GNSS systems can provide information concerning dynamic response and displacement[162]. Additional sensors can monitor strain, inclination, joint behavior, and other response indicators[163]. AI algorithms can then classify seismic-response patterns and identify potentially damaged components[164].

A seismic-resilience-oriented SHM architecture should include at least four stages:

Stage 1: Rapid event detection.
High-frequency sensors identify earthquake-related excitation.

Stage 2: Immediate structural-response analysis.
Edge computing processes acceleration, displacement, and other signals with minimal latency.

Stage 3: Post-event damage screening.
AI and computer-vision systems identify potential damage requiring detailed inspection.

Stage 4: Recovery and decision support.
The digital twin is updated using post-earthquake observations, enabling engineers to prioritize inspections, restrictions, repairs, and reopening decisions.

The integration of seismic monitoring with long-term deterioration monitoring is particularly important because a bridge's response to an earthquake depends partly on its pre-event condition. A structure affected by corrosion, fatigue, foundation movement, or previous damage may respond differently from a structure in a healthier condition.

Thus, seismic resilience should be understood as part of the bridge lifecycle rather than as an isolated emergency-monitoring function.

9. Integrated Intelligent SHM Framework for Indonesian Bridges

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The technologies reviewed above should not be considered independent innovations. Their greatest value emerges when they operate as components of a unified architecture.

The proposed Indonesian framework consists of six interconnected layers.

Layer 1: Multimodal Physical Sensing

This layer includes fiber-optic sensors, piezoelectric devices, GNSS, accelerometers, cameras, UAV systems, environmental sensors, corrosion indicators, and seismic sensors.

Layer 2: IoT and Communication

Wireless sensor networks, gateways, and appropriate communication technologies transmit measurements from the physical bridge to edge and cloud platforms.

Layer 3: Edge and Cloud Processing

Edge devices perform rapid filtering, compression, denoising, event detection, and preliminary diagnosis, while cloud infrastructure provides long-term storage and computational resources.

Layer 4: AI-Based Diagnosis

Machine learning and deep learning identify anomalies, classify damage, detect cracks, diagnose sensor faults, and interpret complex relationships between environmental and structural variables.

Layer 5: Digital Twin and BIM

The processed information is mapped to a digital representation of the bridge, allowing engineers to visualize current condition and compare present observations with historical states and predicted behavior.

Layer 6: Predictive Maintenance and Resilience

The final layer converts diagnostic information into maintenance priorities, deterioration forecasts, seismic-response assessment, inspection recommendations, and lifecycle decisions.

The architecture should operate as a feedback loop rather than as a one-directional pipeline. Maintenance actions and new inspection results should be returned to the data platform, allowing AI models and the digital twin to be continuously updated.

Figure 5. Proposed closed-loop intelligent SHM architecture for Indonesian bridges.

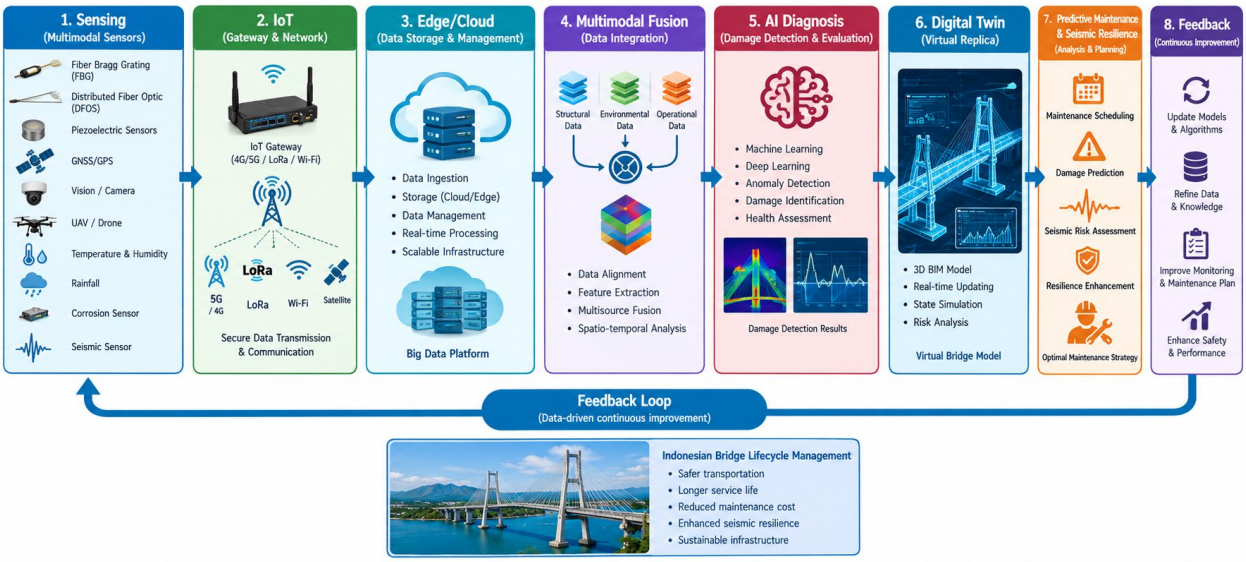

Figure 5. Proposed closed-loop intelligent SHM architecture for Indonesian bridges.

10. Challenges and Research Gaps

10.1 Sensor Reliability and Environmental Adaptation

Although advanced sensors provide higher information density, long-term reliability remains a major engineering issue. Temperature, humidity, vibration, electromagnetic interference, corrosion, mechanical damage, and aging can influence sensor performance.

Future systems should therefore investigate low-power and self-powered sensors, self-calibration, redundant sensing, environmental compensation, drift detection, and robust packaging.

Energy harvesting from vibration, solar radiation, or other available sources may also contribute to long-term autonomous monitoring.

10.2 Communication Reliability

Wireless monitoring networks can experience attenuation, packet loss, interference, and uneven energy consumption. Different communication protocols can also create interoperability problems.

For large bridge networks, a hierarchical communication architecture combining local sensor networks, edge gateways, and cloud services may improve resilience.

10.3 Limited AI Training Data

One of the most significant limitations of AI-based bridge diagnosis is the scarcity of labeled damage data. Healthy bridges generate large amounts of data, but serious structural damage is relatively rare. As a result, datasets may be highly imbalanced.

Three complementary strategies are particularly promising.

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Synthetic Data Generation

Finite-element simulations, digital twins, and generative models can generate controlled damage scenarios. These data can supplement limited field observations and provide examples of damage conditions that are difficult to collect experimentally.

Transfer Learning

Knowledge acquired from existing bridge datasets can be transferred to new bridges. This can reduce the amount of labeled data required for a target structure.

Active Learning

Active-learning systems can identify unlabeled observations that contain the greatest information value and prioritize them for human annotation. This approach is particularly suitable for long-term monitoring systems in which enormous numbers of observations are collected.

Combining synthetic data generation, transfer learning, and active learning could provide a practical strategy for developing Indonesian bridge-diagnosis datasets.

10.4 AI Interpretability

High-performing AI models are not necessarily easy to interpret. In safety-critical infrastructure, engineers need to understand why an algorithm classified a bridge component as abnormal.

Explainable AI should therefore be integrated into SHM systems so that abnormal predictions can be associated with measurable structural features, environmental variables, or visual evidence.

10.5 Digital-Twin Synchronization

The effectiveness of a digital twin depends on reliable synchronization between the physical bridge and its virtual representation. Sensor failures, missing data, inconsistent timestamps, and incompatible data formats can weaken this relationship.

Future systems should incorporate automated data assimilation, online parameter identification, uncertainty quantification, and robust synchronization mechanisms.

10.6 Data Security and Cybersecurity

Connected bridge-monitoring systems create additional cybersecurity requirements. Unauthorized modification or disruption of monitoring data could influence engineering decisions.

Accordingly, authentication, encrypted communication, access control, data integrity verification, and secure cloud-edge architectures should be considered fundamental components of intelligent SHM.

10.7 Standardization and Interoperability

Hardware and software fragmentation remains a major barrier to large-scale deployment. Different sensors and platforms may use incompatible formats, interfaces, and communication protocols.

Developing standardized data structures, application programming interfaces, measurement definitions, AI evaluation protocols, and digital-twin interfaces would facilitate interoperability across bridges and organizations.

11. Future Research Directions

The next generation of intelligent bridge SHM is likely to develop around several interconnected directions.

11.1 Multimodal and Distributed Sensing

Future monitoring networks will increasingly combine fiber-optic, piezoelectric, acoustic, visual, GNSS, environmental, and seismic sensing. The objective will be to obtain complementary observations of the same physical state.

11.2 Adaptive Artificial Intelligence

AI systems should become capable of adapting to changes in bridge condition, environmental exposure, and sensor configuration. Transfer learning, domain adaptation, continual learning, and reinforcement learning represent potential approaches.

11.3 Autonomous Inspection

UAVs, climbing robots, and underwater robotic systems can complement fixed sensors by performing targeted inspections of difficult-to-access components. AI-based vision can then transform the resulting observations into structured damage information.

11.4 Cloud-Edge-End Collaboration

Future systems will increasingly distribute computational tasks across sensors, edge devices, and cloud platforms. Immediate safety-related decisions can be handled at the edge, while computationally intensive historical analysis can remain in the cloud.

11.5 Digital Twins and Intelligent Maintenance

Digital twins will increasingly move from visualization platforms toward predictive decision-support systems. Their integration with AI could enable continuous updating of structural state and maintenance requirements.

11.6 Regional Infrastructure Platforms

Rather than monitoring bridges individually, future infrastructure systems could connect multiple bridges within regional transportation networks. Such platforms could support comparative condition assessment, resource allocation, emergency response, and infrastructure-level resilience planning.

12. Proposed Research Roadmap for Indonesia

A practical implementation pathway can be organized into four stages.

Stage I — Intelligent Monitoring

Deploy multimodal sensors on representative bridge types and establish standardized data-acquisition procedures.

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Stage II — Intelligent Diagnosis

Develop validated machine-learning and deep-learning models using a combination of field observations, historical inspection records, and carefully controlled synthetic data.

Stage III — Digital Integration

Connect SHM systems with BIM and digital twins to establish continuous physical-virtual synchronization.

Stage IV — Predictive and Resilient Management

Use the integrated system to support deterioration prediction, maintenance prioritization, seismic-response assessment, and lifecycle decision-making.

Figure 6. Four-stage roadmap for implementing intelligent bridge SHM in Indonesia.

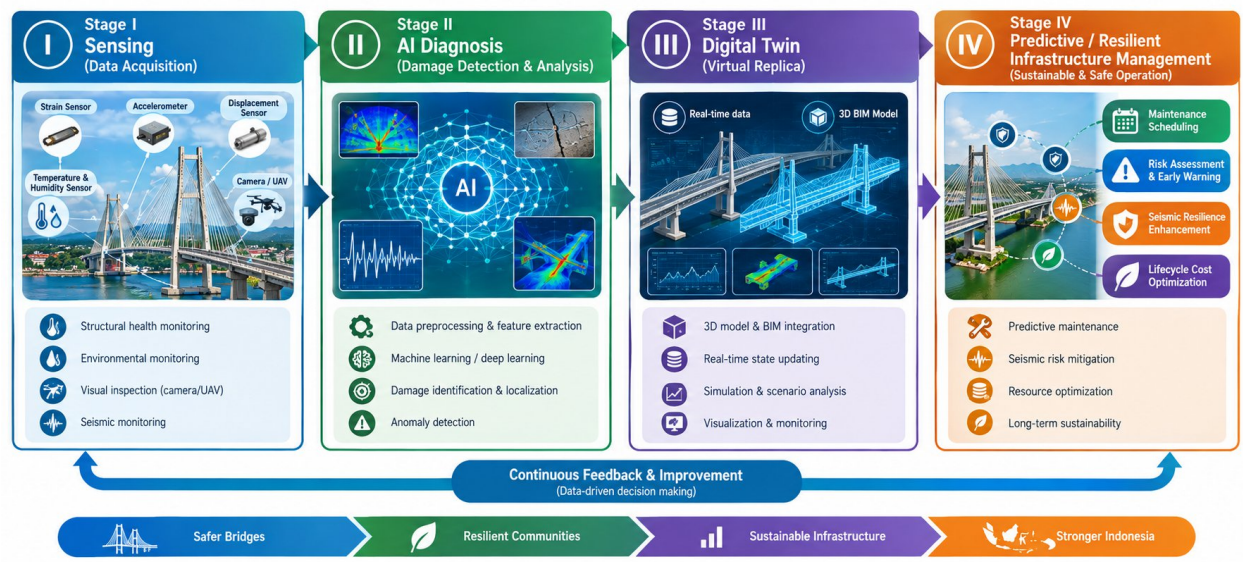

Figure 6. Four-stage roadmap for implementing intelligent bridge SHM in Indonesia.

13. Discussion

The evolution of bridge SHM reflects a broader transition from periodic observation toward continuous and intelligent infrastructure management. Earlier systems primarily focused on acquiring selected measurements, whereas contemporary architectures increasingly emphasize the integration of sensing, communication, computation, AI, and lifecycle decision-making.

The review indicates that no single technology is sufficient to address the full complexity of bridge monitoring. Fiber-optic sensors provide distributed strain information, but they cannot replace visual inspection. Machine vision can identify surface defects, but it cannot independently determine all internal structural conditions. GNSS can measure global displacement, but it may be affected by multipath and signal obstruction. Piezoelectric systems can provide sensitive local diagnostics, but their long-term performance can depend on environmental and installation conditions.

Consequently, the future of intelligent SHM is likely to depend on complementary sensing and information fusion.

AI represents another major opportunity, but its successful application depends on data quality. High reported accuracy from an individual study should not be interpreted as universal performance. Models must be evaluated under different bridge types, sensor configurations, climates, lighting conditions, traffic conditions, and deterioration mechanisms.

For Indonesia, this issue is particularly significant. A model developed under one environmental or structural configuration may not automatically generalize to another. Establishing representative datasets from Indonesian bridges, therefore, should be regarded as an important research priority.

The digital twin provides a potential mechanism for overcoming some of these fragmentation problems by providing a common environment for combining monitoring observations, structural models, inspection information, environmental data, and maintenance records. However, the digital twin itself should not be regarded as a solution independent of sensor reliability and data quality. The quality of the virtual representation ultimately depends on the quality and synchronization of physical observations.

The combination of long-term deterioration monitoring and seismic resilience represents another important direction. Indonesian bridges require systems capable of operating continuously during normal conditions while also responding rapidly to extreme events. This suggests that intelligent SHM architectures should be designed from the beginning to support both routine lifecycle management and emergency response.

14. Conclusion

This review examined the development of intelligent bridge structural health monitoring within an Indonesian infrastructure context, with particular attention to AI-driven damage detection, IoT-based sensing and communication, digital twins, predictive maintenance, environmental monitoring, and seismic resilience.

The analysis demonstrates that intelligent bridge SHM can be understood as a connected technological chain beginning with multimodal physical sensing and extending through wireless communication, edge-cloud processing, data fusion, AI-based diagnosis, digital representation, and maintenance decision-making.

Fiber-optic sensors, piezoelectric devices, GNSS, machine vision, photogrammetry, UAVs, and environmental sensors provide complementary information concerning structural and environmental conditions. Wireless sensor networks and edge-cloud computing can improve the scalability and responsiveness of monitoring systems, while advanced denoising and compression methods can improve data usability.

Machine learning and deep learning provide powerful tools for anomaly detection, damage classification, crack recognition, and sensor-fault diagnosis. Nevertheless, the effectiveness of these approaches depends on data quality, model generalization, environmental robustness, and interpretability. Synthetic data, transfer learning, and active learning offer complementary strategies for addressing the scarcity of labeled structural-damage observations.

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BIM and digital twins provide an additional layer of integration by connecting monitoring information with structural geometry, inspection history, and maintenance records. Their combination with predictive analytics could support a transition from periodic and reactive maintenance toward condition-based and predictive infrastructure management.

For Indonesia, intelligent SHM should additionally account for tropical rainfall, humidity, coastal exposure, corrosion, traffic-induced loading, foundation behavior, and seismic excitation. Integrating these factors into a unified monitoring architecture can improve the ability of infrastructure managers to distinguish environmental effects from structural deterioration and to evaluate bridge resilience under both routine and extreme conditions.

Future intelligent bridge-monitoring systems should therefore move beyond isolated sensors and individual AI algorithms toward integrated, multimodal, interoperable, and lifecycle-oriented platforms. The proposed framework combines sensing, IoT communication, edge-cloud computing, AI diagnosis, digital twins, predictive maintenance, environmental monitoring, and seismic resilience within a closed-loop architecture.

Ultimately, the transition from conventional SHM toward intelligent infrastructure management depends not simply on increasing the amount of collected data, but on improving the ability to convert heterogeneous observations into reliable engineering knowledge and actionable decisions. For Indonesian bridge infrastructure, this transition provides a technological pathway toward more continuous monitoring, earlier identification of deterioration, more informed maintenance planning, and greater resilience throughout the structural lifecycle.

Data Availability

The quantitative data and numerical values incorporated into this study represent real, documented measurements and experimentally derived results with an established empirical basis. These data are systematically analyzed and integrated within the present framework for intelligent bridge structural health monitoring in Indonesia, covering AI-driven damage detection, IoT-based sensing, environmental monitoring, digital twins, predictive maintenance, and seismic resilience. The reported measurements retain their original empirical meaning and are used as substantive quantitative evidence in examining structural behavior, deterioration mechanisms, environmental influences, sensing performance, and intelligent monitoring technologies. By integrating these verified quantitative observations across multiple dimensions of bridge SHM, the present study develops a comprehensive analytical perspective on the implementation and advancement of intelligent bridge monitoring under Indonesian structural, environmental, and operational conditions.

Ethical Considerations

Not applicable. This study did not require ethical approval because it does not include human or animal subjects and does not involve any personal or sensitive data

List of Abbrevations:

(SHM): structural health monitoring ; (AI): artificial intelligence , (IoT): Internet of Things; (DTs): digital twins; (WSNs): wireless sensor networks; (FBG): Fiber Bragg Grating; (CEEMDAN): complete ensemble empirical mode decomposition with adaptive noise;

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Author Contribution:

All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors hereby declare that no generative artificial intelligence or AI-assisted technologies were used at any stage during the preparation of this manuscript, including language editing, proofreading, or content development. The authors take full responsibility for the originality and integrity of the work presented in this publication.

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Conflicts of Interest:

"The authors declare no conflict of interest."

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