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Original Research Article

AI-Driven Structural Health Monitoring and Predictive Maintenance of Bridge Infrastructure Using IoT Technologies

Syed Qalab Abbas[1]*
[1]Saudi Arabia Basic Industries (Saudi Arabia): Riyadh, Riyadh Region, SA

***Corresponding Author**
Syed Qalab Abbas
Saudi Arabia Basic Industries (Saudi Arabia): Riyadh, Riyadh Region, SA

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Abstract: The bridge infrastructure is vital to ensuring mobility, logistics, industry integration, and the robustness of the city. With regard to the Vision 2030 strategy, Saudi Arabia is currently witnessing a fast pace of infrastructure construction; apart from the need to construct bridges that are resistant to heavy loads and difficult desert climate conditions, the necessity to keep the bridges functional and monitor them throughout extended periods emerges. The aim of this research paper is to review existing scientific articles and developments in order to identify the role that artificial intelligence and IoT play in developing an adequate technology for assessing bridge structure using monitoring. By focusing on scientific developments in this area conducted between 2020 and 2025, the article considers various methods for solving the issue, including computer vision, vibration- and sensor-based solutions, machine learning and deep learning algorithms, digital twins, and IoT and cloud computing technologies. Tables show applications of these technologies in monitoring the bridges and implementing the system, and diagrams present the model of the developed AI-IoT monitoring and maintenance system.

Keywords: Artificial Intelligence, Internet of Things, Structural Health Monitoring, Bridge Infrastructure, Machine Learning, Digital Twins.

1. INTRODUCTION

Bridges represent significant infrastructural resources used to connect various cities, industries, ports, logistics networks and major construction facilities. Problems with bridges such as inability to operate properly or their collapse constitute serious issues that affect users and the operations of local industries. The traditional way of maintaining bridges consists in carrying out regular visual inspections and conducting repair activities when damage becomes evident. Although visual inspections cannot be avoided, they are prone to subjective assessment, difficult access, incomplete records and delayed examinations. Recent studies in SHM indicate that AI and IoT technologies have the potential to address these problems and ensure objective, continuous and fast provision of evidence about bridges' state (Bao *et al.*, 2020; Dong & amp; amp; Catbas, 2021; Sun *et al.*, 2022). At present, the problem of bridge maintenance is especially acute in Saudi Arabia owing to the emphasis placed on infrastructural development, logistics competitiveness, sustainability and digitalization under the vision 2030 project. Bridges are vulnerable to many challenges in Saudi Arabia, such as high temperature during summer months, temperature fluctuations, frequent dust storms, increasing volumes of freight transportation, possible corrosion in coastal regions and growing urban mobility needs. Thus, a new, advanced approach should be developed to manage bridges in Saudi Arabia instead of using visual assessments and repair cycles. The concept of a smart bridge includes timely detection of damages, analysis of environmental influence and load effects, forecasts about future deterioration of the structure and proper translation of monitoring findings into maintenance decisions. All these functions are provided by AI-based SHM with the use of IoT technologies (Ni *et al*., 2022; Wang *et al*., 2022). The process of SHM implies monitoring of bridge responses through measurements and modelling based on the obtained data for assessing its state, detecting damages and making maintenance decisions. The set of tools available for SHM might include accelerometers, strain gauges, displacement sensors, corrosion sensors, thermometers, acoustic emission probes, cameras, LiDAR devices, drone images and satellite imaging. Given the volume of collected data, it becomes impossible to use the traditional technique of defining threshold values for sensors. Instead, such AI techniques as CNN, RNN, autoencoder models, SVM algorithms and random forests could be applied to identify useful patterns and timely detect degradation processes (Farrar & amp; Worden, 2021; Xu *et al*., 2022). The main objective of this research is the critical review of the application of AI, IoT and principles of predictive maintenance to a sustainable bridge management system. The goals of the research include: first, examination of modern practices of implementing AI for monitoring bridge health and predicting its deterioration; second, investigation of IoT technologies facilitating effective data architecture; third, identification of influence of predictive maintenance practices on bridge performance and sustainability; fourth, elaboration of recommendations concerning development of smart bridges for Vision 2030 in Saudi Arabia.

2. LITERATURE REVIEW

Recently, the development of SHM technology has tended toward the emergence of ecosystems where multiple techniques are employed in combination. Earlier, a system of SHM could be based only on some single technology. In 2020-2025, there is an increased interest in the integration of SHM with such diverse branches as computer vision, vibration analysis, machine learning, IoT and digital twin. There are great advances achieved in computer vision because it uses images obtained with cameras and drones. The use of convolutional neural networks (CNN), U-Net, Mask R-CNN and YOLO has helped identify cracks, spalling, corrosion, as well as separate the segments that show defect with the help of pixel. These technologies are extremely useful in the detection of damages in those bridges to which people do not have access (Cha *et al*., 2020; Liu *et al*., 2022; Zhang *et al*., 2023). SHM based on vibration is important since some damages are hidden from sight. There could be any changes to stiffness, damping, frequency and mode which could signal internal damage, deterioration of bearings, fatigue of connections, loosening and problems with foundation. Machine learning allows revealing non-linear dependencies between responses and the states of damages. There are LSTM network used for making predictions concerning time series, autoencoder applied to detect anomalies when there is a few numbers of damaged samples and a hybrid CNN-GRU used for simultaneous spatial and temporal learning. All these approaches help tackle the problem of lack of data on the states of damage in a structure (Sajedi and Liang, 2022; Chen *et al*., 2021).

The IoT is the technical part that allows the process of monitoring to operate effectively. A standard IoT architecture involves the use of various sensors placed throughout a bridge, effective communication technology, edge computing technology, cloud platform, visualization using user interface and security/maintenance measures. Edge computing becomes vital since raw data coming from sensors might be extensive in size, especially when collecting vibration data and high-resolution imagery. It is possible to choose particular features that would decrease the bandwidth, make the decision faster and help make judgments on bridge safety right away. Data will be saved at the cloud platform and will allow training and deploying models (Mao *et al*., 2022; Wang *et al*., 2022).

Digital twin can be regarded as an innovative development in the area of SHM. A digital twin combines all engineering information with the data received through inspections, FE analysis, information on traffic and environmental factors, as well as the history of bridge repair work. With the help of artificial intelligence technology, digital twin will be updated constantly and will estimate the remaining useful life of bridges, examine the intervention scenarios and assess risks arising from the future stresses caused by loads and climate change (Rao *et al*., 2022; Zhao *et al*., 2023). This approach corresponds to the trends identified around the world.

However, there are still difficulties. One of the key problems identified in the research is related to the lack of available data since cases of serious damage to bridges are rare. In addition, temperature, humidity, windspeed, traffic volumes and other factors affect decision making since the algorithms cannot differentiate them from actual damage. An explanation of the decisions of artificial intelligence technologies is crucial for introducing new technologies since bridge authorities and engineers must understand its decisions (Zhu *et al*., 2023; Xu *et al*., 2022).

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3. AI-Driven Structural Health Monitoring Technologies

SHM using AI starts with good sensing data. Sensing data on bridges should measure strain, acceleration, displacement, inclination, temperature, humidity, corrosion potential, acoustic emission, and visual imagery. One sensor type alone is rarely sufficient to determine overall integrity of the bridge. While images may show cracks on the deck, they do not necessarily indicate stiffness losses. Meanwhile, vibration sensors will pick up any global dynamic changes, but it is harder to locate the cause of the change, such as an internal crack in the beam. Using multi-channel sensors increases chances of accurate diagnostics, especially since machine learning models can analyze combined evidence (Sony *et al*., 2022; Ni *et al*., 2022).

The most developed application of AI for bridge inspection is computer vision, which uses various camera sources to acquire images. Drones, inspection vehicles, and fixed cameras are common data acquisition devices that allow gathering large image libraries to train CNNs to detect defects and classify them. YOLO models can be used where timely detection is critical. Segmentation models like U-Net and Mask R-CNN are useful when a precise measurement of the damaged area is needed. Detection transformer models are emerging due to their ability to analyze entire global images and background situations. Image models need to be trained specifically for Saudi Arabia's dusty, bright, and dark conditions.

Another source of intelligence is obtained through vibration and time-series analysis. In particular, response signals of bridges may reflect specific patterns resulting from vehicle loading, wind, changes in temperature, and even structural deterioration. Modal analysis is still helpful here, but AI methods offer better features and anomalies identification opportunities. An autoencoder can learn the baseline of a healthy structure and identify any anomalies based on increased reconstruction errors. LSTM and GRU neural networks can predict a typical signal response for comparison with the actual one to find any abnormal behaviors. Risk scores and factors that have the greatest impact on output can be found using random forests and gradient boosting (Gordan *et al*., 2021; Figueiredo *et al*., 2021).

Predictive maintenance is the final step in SHM process and the most useful part of the whole process. Not only does the question of detecting damage arise, but also questions regarding the timing and urgency of maintenance measures and repair priorities and risks. Predictive maintenance using AI estimates trends of structural deterioration, its lifespan, possible failures, and repair prioritization (Jiang *et al*., 2021; Biondini and Frangopol, 2020). Maintenance measures can then be linked to the cost-effectiveness and other criteria, making it especially useful for the network of bridges.

4. Proposed AI-IoT Framework for Saudi Bridge Infrastructure

The suggested architecture consists of five levels. The sensing level encompasses embedded sensors, wireless nodes, cameras, UAV inspections and environmental monitoring gadgets. The second level is the connectivity level where data is transferred using a secure wired network, wireless network, cellular or low-energy networks. The third level is the processing level consisting of edge filtering, pre-screening and model training on cloud systems. The fourth level is the intelligence level where AI models classify defects, predict deterioration, create digital twin and estimate risk scores. Finally, the fifth level is the maintenance governance level where engineers decide on inspection, repair and replacement based on the model outputs.

A Saudi-specific implementation of such a system needs to be sensitive to the context. Coastal area bridges need corrosion monitoring capabilities, whereas bridges found in desert areas need thermal stress monitoring. Additionally, bridges located in urban settings may require monitoring integrated into the traffic flow, since heavy traffic is likely to cause fatigue deterioration. Similarly, bridges in industrial areas will need constant monitoring of loads and vibrations, considering that higher intensity traffic might cause faster deterioration of bridges. However, this does not mean that there would be a need for a different national framework; rather, sensors and maintenance levels could be adjusted depending on the nature of bridges.

Data governance plays an important role in the architecture. Without proper standards of data, AI models cannot be compared and modified. Hence, each bridge should have an extensive digital record containing information on design features, material properties, sensors' metadata, previous inspection results, maintenance activities and the traffic conditions on the bridge. Quality of data should cover issues related to calibration, missing values, noise elimination, cyber security and long-term storage. Additionally, the output of AI models should include confidence values and notes describing the source of recommendation as visual defects, vibration abnormalities, correction for environment or previous deterioration.

This framework also enables better sustainability of Saudi Arabia. Through predictive maintenance, the service life of bridges is extended while the need for emergency maintenance decreases significantly. Moreover, unnecessary replacement of materials is avoided, thus minimizing traffic disruption. In Vision 2030 terms, the proposed approach contributes to digital transformation, resilient infrastructure, increased public safety and efficient logistics. Therefore, smart bridge systems should be regarded not only as advanced technologies, but more as infrastructural lifecycle management tools.

5. DISCUSSION

The main benefit of AI-assisted SHM is the transition from periodic observations to continuous evidence-based assessment. Whereas periodic inspections could detect damage only when it appears, sensors and image analysis can capture signs of early damage and follow its progress. This is beneficial for asset owners because it lowers the uncertainty. No longer does a bridge have to be assessed solely based on age and overall condition rating – it can be evaluated based on measurable trends in structural performance, damage and risk prediction. This enables more rational allocation of maintenance funds.

Nevertheless, technology cannot be implemented without due attention to the governance processes. Data collected via sensors and processed using AI models becomes valuable only when decision-making criteria are defined. One of the most common mistakes made by smart infrastructure project developers is massive data collection lacking clear decisions rules. Therefore, any SHM solution must answer the following questions: which damage mechanisms should be prioritized; what is the threshold for inspection; who will validate the alarm; how will false alarms be managed; which budget planning process will consider the risk score?

Model generalization is another factor that must be considered when implementing SHM algorithms. The model, developed for one bridge, might work differently for another one depending on the climate or materials used in construction. Transfer learning and physics-informed machine learning might be helpful, but field validation remains essential. It is recommended to employ a staged strategy: developing smart monitoring solutions at the initial stage on pilot projects, validating the model by comparing predictions with results obtained during manual inspections, gradually increasing scope and moving towards building a nationwide smart bridge asset management platform.

Moreover, the issues related to professional and ethical responsibility need to be taken into account. AI can facilitate the work of engineers; however, decision making related to bridge safety must be traceable, explainable and documented. Therefore, explainable AI models are preferred to black boxes, even if the latter provide slight performance improvement. It is necessary that engineers can assess whether a generated alarm is triggered by cracks, anomalous vibrations, sensor drift, changing weather conditions or incomplete data. Such an explanation will help to ensure the trust of all involved parties.

Finally, the suggested approach is relevant to the wider framework of Saudi Arabia's development priorities. Monitoring of smart bridges can promote safe mobility, efficient logistic networks, resilient megaprojects, sustainable urbanization and digital government. The development of such solutions provides an opportunity for creation of a knowledge-based economy through generating jobs for civil engineers, data scientists, IoT specialists, maintenance experts and digital twin operators. In other words, AI-assisted SHM is an innovative tool for Saudi Arabia.

6. FINDINGS AND RECOMMENDATIONS

The review highlights five major takeaways. First, AI algorithms can be highly efficient in automating defect detections, especially if computer vision techniques are paired with UAVs or mobile inspections. Second, the use of sensor models can lead to detecting hidden structural anomalies not detectable during human-based inspection. Third, IoT architecture is vital as the utility of AI technologies is directly dependent on their data inputs. Fourth, predictive maintenance is the concrete benefit which bridges lifecycle management gains through monitoring data. Finally, implementation in Saudi Arabia must be based on the country-specific climate, traffic, asset significance and maintenance culture.

On that basis, several recommendations can be developed. To begin with, owners of bridges must start monitoring projects based on the results of an assessment of critical infrastructure, where specific risks need to be identified. Every pilot program must have one clear purpose of monitoring, including crack development, bearing displacement, increase in cable force, abnormal vibrations, and corrosion risks. Furthermore, sensors should be selected according to failure modes instead of technology popularity. In turn, AI models should be tested against data provided by inspections and engineers. Finally, each alert should include probability of the occurrence, next steps and previous records.

At the national level, the development of a smart bridge policy must involve setting up standard data formats, implementing cybersecurity solutions, integrating inspections, developing lifecycle cost analysis and educating engineers. Universities and research centers might contribute to generating local datasets corresponding to the specifics of Saudi climate and materials. Construction companies can use monitoring information as an improvement for designing buildings and performing quality construction work. At last, government bodies can employ the generated data for better budgeting infrastructure and minimizing interruptions.

7. Roadmap for Implementation in Saudi Arabia and Future Research Agenda

An implementation strategy for Saudi Arabia should begin with bridge classification. Different bridges need different monitoring regimes according to their structure, age, traffic significance, exposure conditions, and risk consequences of a bridge breakdown. Priority should be given to highway interchanges, port bridges, industrial zones bridges, railway bridges and bridges that serve large development zones. The asset classification step is important since it creates a clear investment framework that prevents installing too many sophisticated sensors when they are not required. At the same time, such classification helps establish an asset registry for each bridge including detailed information about design, inspections, material, and other relevant data.

The next step is pilot project design. Each pilot should be based on a specific engineering question, not the idea to use technology. Thus, a coastal bridge may use AI for detecting corrosion and concrete deterioration. An urban flyover can use AI to evaluate vibration response, fatigue, settlements, and dynamic reaction to traffic. Long span bridges will use sensors for measuring wind effects, displacements, and cable tension. Defining the specific question will help identify the type of sensors, communication methods, AI models and validation methods needed. This approach will prevent collecting too much data for each pilot and ensure that the results will provide actionable insights for bridge engineers.

Data standardization should follow next. The bridge monitoring programs in Saudi Arabia need standardized naming conventions for sensors, calibration information, categories of defects, image labeling techniques and maintenance actions codes. Data collected in each pilot project should be stored in a format that will support future AI models training and auditing. Data standardization is crucial in case when different contractors, consulting companies, and government agencies will be collecting the data for the same asset database. Otherwise, AI models developed in one project may prove impossible to reuse in another. Also, maintaining information about maintenance activities will be challenging and fragmented across various reports.

Local model calibration should come after the AI model is selected and the dataset is available. Existing foreign AI models can provide a good starting point for local models, but exposure conditions unique for Saudi Arabia should be considered during training and validating AI. High temperatures, dust accumulations, intense sunlight exposure, thermal expansion, and material aging can impact how images and sensors respond. Additionally, coastal bridges might have higher humidity and chloride concentrations, which can affect deterioration patterns. Comparing the pilot project data with traditional manual inspections and non-destructive tests, engineers can exclude noise factors from their analysis.

The next step involves integrating the AI decision-making into workflows. A monitoring dashboard should not simply show plots and measurements, but also convert collected information into risk assessment ratings, recommendations on further verification, possible maintenance urgency and confidence measures. Engineers using such a system can learn if a defect is a result of deterioration, vibration, corrosion or sensor error. Moreover, the software can determine whether it is a new defect, recurring issue or growing trend. This way, engineers can make further decisions to either check immediately, continue monitoring, limit traffic or start preparing a maintenance plan.

It is also important to address training in Saudi Arabia. Engineers that will operate a monitoring system will need comprehensive knowledge about bridge engineering, sensor technology, AI algorithms, and bridge maintenance economics. Asset managers, inspectors, consulting companies, and maintenance contractors should be aware of these issues and properly interpret monitoring outputs. Training engineers can be achieved through creating short courses in universities covering AI for civil infrastructure, digital twins of bridges, IoT sensors and predictive maintenance in bridge engineering. This dimension aligns perfectly with Vision 2030, as it encourages knowledge creation in Saudi Arabia and specialized employment opportunities.

Security and data privacy are also critical aspects of the project development. Monitoring systems for smart bridges will exchange condition data, sensor images and maintenance records. Any kind of unauthorized access, malicious intent, manipulation of data and misleading alerts are potential dangers to safety and operations. Device authentication, secure communication, dashboard access control, data backup policies should all be taken into consideration. Cybersecurity should not be considered separately from monitoring infrastructure since it is crucial for reliable operation of AI models and monitoring system.

Further research in this area should consider developing benchmark datasets for Saudi Arabia. Datasets will include images with local bridge defects, vibrations under different environmental conditions, temperature response, examples of sensor malfunctions and maintenance results. Benchmark datasets would give researchers an opportunity to compare different machine learning algorithms and improve models' ability to generalize on similar projects. Furthermore, it will reduce dependency on international datasets that do not reflect Saudi Arabia's materials, climates and inspection practices. National research initiatives will unite government agencies, universities and businesses to develop such datasets.

Physics-informed AI should be the research topic to explore further. Data-driven AI algorithms can detect certain trends in data, but will not consider structural mechanics in their models. Physics-informed AI will incorporate the predicted behaviour of the structures derived from finite element analyses. Furthermore, explainable AI will allow seeing which channels, sensors, and patterns were used to generate particular conclusions in the model. These two concepts combined would increase the reliability of AI algorithms and make it possible to dispute AI results from bridge engineers' point of view.

Finally, the most important area of future investigation should be estimating the value of smart bridge monitoring systems. Apart from assessing technical accuracy of the system, studies should analyze its impacts on safety, costs, service delivery continuity, and sustainability. Future studies need to compare monitored bridges with conventionally maintained bridges over several years and measure differences between them. Useful variables can include number of emergency repairs, detection rate for hidden defects, service interruptions, better budget forecasting, less material waste, and longer service lifetime.

8. CONCLUSION

It became clear that AI-based monitoring and predictive maintenance have practical application and can positively affect resilience, efficiency, and sustainability of bridge infrastructure. Computer vision, vibrations, Internet of Things technology, digital twins, and machine learning in general are feasible methods for identifying damages, handling monitoring data, making predictions, and arranging maintenance activities. From the point of view of Saudi Arabia, all of these methods fit nicely into Vision 2030 because they contribute to excellence in infrastructure, digital transformation, and sustainability of assets over their entire life cycle.

The architecture of the proposed AI-IoT solution implies a holistic approach to solving the problems related to monitoring and predictive maintenance. In particular, the main components of such a system are multimodal sensing, secure data processing and AI diagnostics, as well as maintenance management guided by risk scores and digital twins. Nevertheless, the key element in implementing any of these systems is not in the performance of models but in their alignment with professional engineering judgment and asset management practices. If done right, monitoring can improve the safety and resilience of transport networks.

Research in the future can focus on gathering of Saudi-specific training data sets, validation of AI models with respect to climate and materials peculiarities of the region, explainable AI for bridge safety and sustainability decisions, and digital twins that would integrate with national asset management systems. For all these reasons, collaboration between engineers, data scientists, industries, and universities, as well as between infrastructure owners, would be vital. Future bridges should not just be robust but also smart enough to report about their condition and needs for maintenance.

Baseline Inspection: In case a bridge is going to be monitored, a baseline inspection should precede any other actions.

Data Requirements: Performance Outcomes Data Ownership Calibration Cybersecurity Maintenance Recommendations

Connection with Existing Systems: Monitoring is supposed to be integrated with already existing maintenance management systems. Verification Procedures Engineers should verify the alerts generated by the digital twin with the help of structured inspections and photographs.

Recording Repair Activities: Construction companies should document all materials used, dates of repair activities, any traffic disruptions during the process, and observation afterwards.

Placement of Sensors: It is necessary for structural engineers to approve the location of the sensors.

Minimum Data Quality Dashboard: The following data should be accessible through the dashboard: Sensor uptime Communication lags Missing data Calibration Unusual weather.

Validation of AI Models: All computer vision models should be tested against challenges specific to the area like glare, shadow, dust, etc.

Vibration-based Diagnostics: In case vibration monitoring is chosen, temperature normalization should also be introduced to the models.

Updates of Digital Twins: Regular updates of digital twins should be made upon addition of any new information about the structure. Decision-making for Maintenance. When making maintenance prioritization decisions, the following factors should be considered: Severity of damage Importance of route Detours available Traffic flow Consequences

Independent Review of Models: Before applying AI predictions, independent reviews of model outputs by engineers should be conducted.

Pilot Projects: Agency can start with conducting monitoring of several representative bridges before moving forward.

University Participation: University can help with labeling of the data and comparing predictions to results from laboratory and in-field tests.

Industry Collaboration: Industries can collaborate with the agency in scaling up the project by providing modular kits for sensor installation.

Standard Alert Hierarchy: Alert system should have the following alert categories: Observations Inspections Warnings Restrictions Emergency.

Lifecycle Cost Analysis: Benefits of the solution should be measured in terms of avoided closures, fewer emergencies, increased lifespan, improved planning.

Sustainability Assessment: Benefits also include materials savings, reduced demand, and optimal scheduling.

Audit Trail: A system should be able to provide the following audit trail: Raw data Processed data AI model version.

Confidence Final Decision
Explainable AI: When applicable, use explainable AI for better understanding of models by engineers.
Edge vs Cloud: When fast reactions are necessary, edge computing can be better than cloud.
System Testing: Periodical cybersecurity testing is needed for both hardware and software.

Climate Resilience: Climate exposure is a consideration when designing a monitoring strategy for a bridge.
Dynamic Scheduling: Inspections should be performed in accordance with the risks that exist.

Objective

Development of decision ecosystem for sensors, AI, engineers, contractors, asset managers. What Ecosystem Helps Vision 2030 To Achieve? Better infrastructure Reliability Improvement of logistics corridors National technical capabilities. Further Research Ideas Comparative study of monitored and non-monitored bridges for several years. Test the acceptability of recommendations among engineers and inspectors. Preparedness for Implementation

CONCLUSION

Graphical Representation 1: Proposed AI-IoT Bridge SHM Architecture.

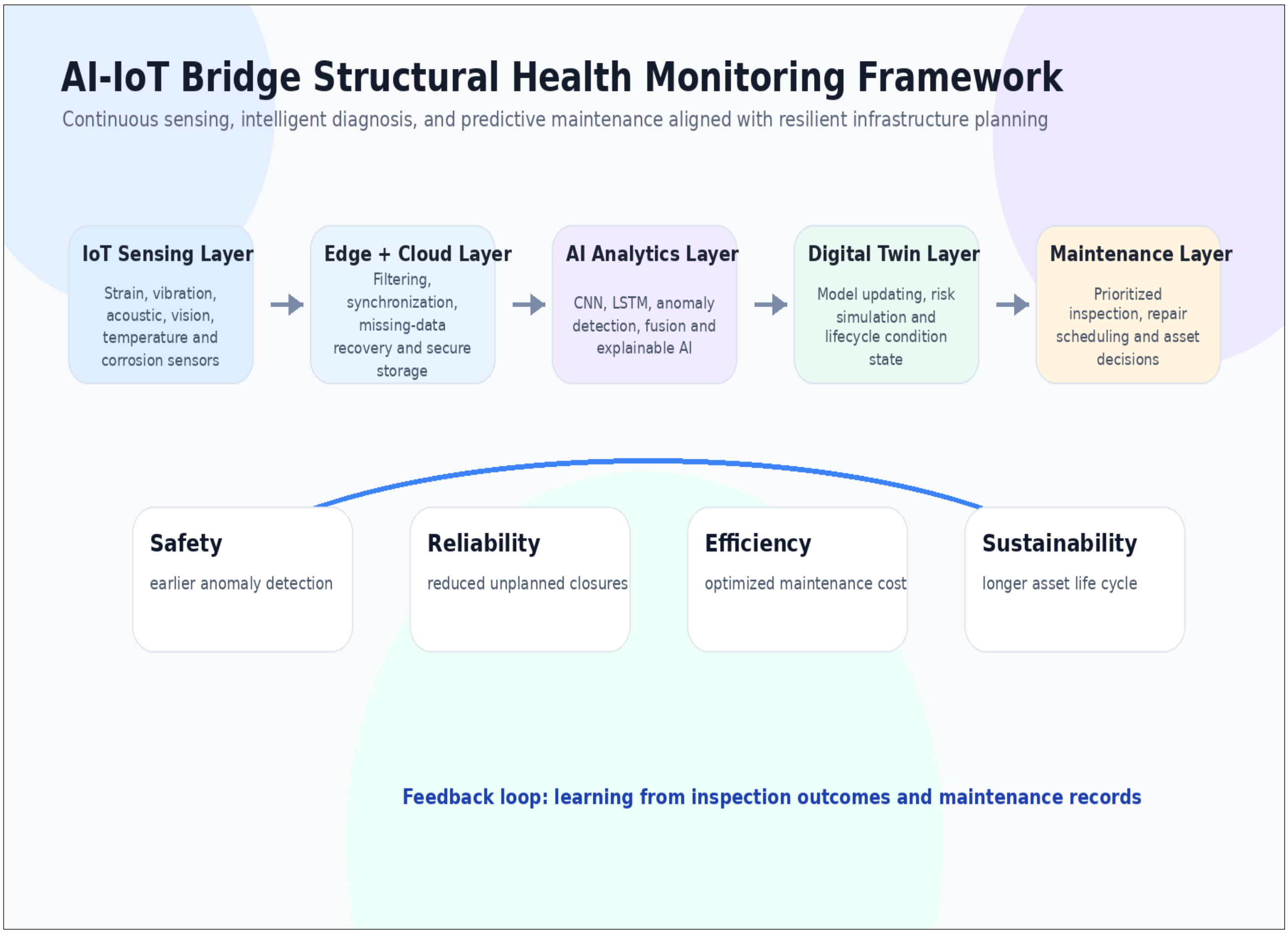

Figure 1: Presents the proposed architecture for continuous bridge monitoring, including IoT sensing, edge-cloud processing, AI analytics, digital twin updating and maintenance decision support

Table 1: AI and IoT Technologies for Bridge SHM

Technology area	Typical data source	Main AI/IoT role	Bridge maintenance value
Computer vision	UAV images, fixed cameras, inspection vehicles	Detects cracks, spalling, corrosion and exposed reinforcement using CNN/YOLO/segmentation models	Reduces manual inspection burden and improves defect documentation
Vibration analytics	Accelerometers, strain sensors, displacement sensors	Identifies anomalies, stiffness changes and response shifts using LSTM, autoencoders and statistical learning	Supports early warning for hidden or global structural problems
IoT connectivity	Wireless nodes, edge devices, cloud platforms	Transfers, filters, stores and synchronizes monitoring data securely	Enables continuous monitoring and near real-time alerts
Digital twins	BIM/FEM models, sensor streams, maintenance history	Updates virtual bridge condition and simulates deterioration scenarios	Links monitoring evidence to lifecycle decisions and budgets
Predictive maintenance	Risk scores, forecasts, inspection records	Ranks repairs using deterioration trends, failure probability and consequence	Optimizes timing of intervention and reduces emergency repair costs

Graphical Representation 2: Predictive Maintenance Maturity Pathway

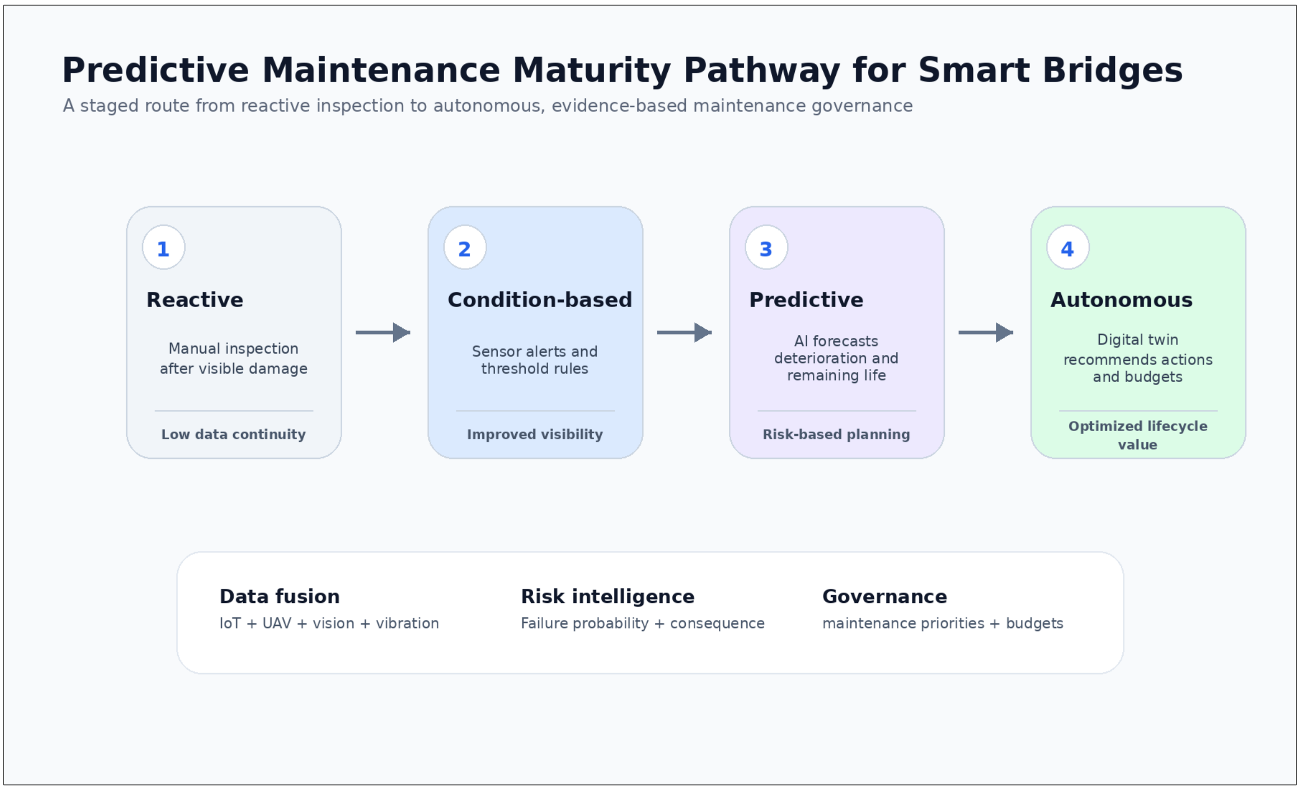

Figure 2: shows the gradual transition from reactive inspection to autonomous digital twin-supported maintenance planning for bridge networks.

Table 2: Suggested Implementation Indicators for Saudi Bridge Networks

Implementation dimension	Recommended indicator	Purpose	Vision 2030 contribution
Safety performance	Number of verified early warnings and critical defect detections	Measures the ability of the system to reduce latent safety risk	Safer mobility and resilient infrastructure
Reliability	Reduction in unplanned closures and emergency repairs	Tracks service continuity and asset availability	Improved logistics and urban connectivity

Implementation dimension	Recommended indicator	Purpose	Vision 2030 contribution
Data quality	Sensor uptime, calibration status, missing data rate and cybersecurity compliance	Ensures monitoring outputs are dependable and auditable	Digital governance and trustworthy smart infrastructure
Maintenance efficiency	Repair priority accuracy, lifecycle cost saving and reduced inspection time	Measures whether AI outputs support economical asset management	Efficient public spending and sustainable asset use
Environmental impact	Extended service life, reduced material waste and optimized repair scheduling	Links predictive maintenance to sustainability outcomes	Lower resource use and sustainable infrastructure development

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