International Journal of Scientific Research and Engineering Development-– Volume 9 Issue 6, Nov – Dec 2026
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

An Integrated IoT and Vision-Based Framework for Bridge Health and Environmental Monitoring

[1]Mr. T. Raghavendra Gupta, [2]P. Komal Kelly
[1]Associate Professor, Department of CSE
[2](Department of Computer Science and Engineering, Hyderabad Institute of Technology and Management, Hyderabad, Telangana, India
Email: komalkelly2006@gmail.com)

----------**********----------

Abstract:

Bridges are exposed to environmental changes and dynamic loading from road traffic. Periodic inspection alone may not capture short-term changes in vibration behaviour or nearby water conditions. This paper presents an integrated prototype framework for infrastructure monitoring that combines camera-based observation of a water-level reference, vibration sensing, auxiliary environmental measurement, edge processing and a local warning interface. The framework is organised into sensing, edge analysis, wireless communication and alert-actuation stages. Image observations are processed to support water-level estimation, while vibration measurements are summarised using statistical descriptors to support condition monitoring. A separate embedded controller operates visual and audible indicators in response to configured monitoring states. The contribution of this work is the integration of complementary monitoring channels within a low-cost, edge-oriented prototype. The paper intentionally omits implementation-sensitive information, including detailed hardware configurations, circuit assignments, model artefacts, internal parameter values and communication settings. The current work demonstrates the design and functional integration of the prototype; quantitative field validation, calibrated reference measurements and long-duration reliability testing remain necessary. No numerical detection-accuracy or structural-damage-classification claim is made.

Keywords — **Bridge monitoring, infrastructure health, Internet of Things, computer vision, water-level estimation, vibration analysis, edge computing, wireless alert system.**

----------**********----------

I. INTRODUCTION

Bridges are critical transportation assets that experience continuous environmental exposure and dynamic loading. Vehicle movement produces time-varying structural responses, while rainfall, river flow and rising water levels can create additional risks to bridge approaches, foundations and surrounding infrastructure. A monitoring arrangement that observes both vibration behaviour and nearby water conditions can provide useful information for maintenance personnel and traffic-management systems.

Conventional bridge inspection is commonly based on scheduled visual checks and periodic measurements. Such methods can miss transient events occurring between inspection intervals. Sensor-based structural health monitoring can provide continuous measurements, but the cost and complexity of large-scale instrumentation may limit deployment, particularly in small-scale or budget-constrained monitoring projects. Camera-based observation offers a complementary, non-contact method for monitoring visible environmental indicators such as a staff gauge.

Recent computer-vision research has investigated staff-gauge localisation, waterline detection and deep-learning-based water-level estimation. The supplied reference study describes image-based estimation across multiple water bodies and discusses challenges associated with reflections, illumination changes and site-specific calibration

 ©IJSRED: All Rights are Reserved

[1]. Other studies have explored image processing, object detection and segmentation for water-level monitoring [2]–[5]. These developments motivate the use of camera imagery as one input to a broader infrastructure-monitoring framework.

The present work develops an integrated prototype in which an edge-processing unit acquires and analyses image and sensor observations, while a separate embedded controller operates external warning indicators through a wireless link. The vibration channel provides acceleration measurements, and the visual channel captures staff-gauge scenes for image-based water-level estimation. An auxiliary environmental sensing channel is also included. The system is intended as a monitoring and alert-support prototype; it is not presented as a certified bridge-safety instrument or as a substitute for structural inspection.

A. Problem Statement

A low-cost monitoring prototype is required to observe two different but related conditions: dynamic vibration behaviour associated with traffic loading, and changes in water level near a bridge. These measurements are typically acquired through separate systems. The problem addressed in this work is the integration of camera-based water-level estimation, accelerometer-based vibration acquisition and a local warning mechanism into a single edge-oriented architecture.

B. Objectives and Contributions

The objectives are: (i) to acquire vibration measurements from the monitored structure; (ii) to capture staff-gauge imagery and estimate water level through an image-processing and learning-based workflow; (iii) to collect an auxiliary environmental measurement; (iv) to derive interpretable statistical descriptors from vibration observations; (v) to communicate monitoring states to a separate controller; and (vi) to provide visual and audible indication when configured alert conditions are met.

The principal contribution is the integration of heterogeneous sensing channels, edge-side analysis and a local alert mechanism in a single prototype. The paper describes the functional methodology and system-level design while withholding implementation-specific information that is not required to understand the research contribution.

II. RELATED WORK AND TECHNICAL BACKGROUND

A. Camera-Based Water-Level Monitoring

Camera-based water-level measurement uses visible references, commonly staff gauges, to infer the position of the water surface. Earlier image-processing methods used edges, colour thresholds and waterline extraction. Their performance can degrade under shadows, reflections, low contrast, perspective distortion and changes in camera position. The supplied reference paper notes that these issues motivate more robust learning-based approaches and reviews methods including gauge detection, segmentation and deep-learning-based recognition [1].

The supplied reference study proposes a classification-based approach for staff-gauge readings and compares feature-aggregation strategies. It also describes the use of a site-specific lookup mapping to convert predicted classes into physical water-level values. This paper uses that work as technical context. The present prototype does not claim to reproduce the reference study's dataset, model architecture or reported accuracy [1].

B. Deep Learning and Image Segmentation

The Segment Anything Model (SAM) introduced a general-purpose promptable image-segmentation framework [6]. Subsequent work has investigated combining waterline detection with SAM for image-based water-level monitoring [7]. During project development, segmentation workflows were studied and a small-scale implementation exercise was carried out to understand the roles of image encoding, prompt representation, attention operations and mask decoding. This activity is described as model-development study; it is not reported as a validated segmentation result in the integrated monitoring prototype.

C. Vibration-Based Monitoring

An accelerometer provides time-series acceleration measurements that can be examined for changes in amplitude and temporal behaviour. Statistical descriptors such as RMS, standard

 ©IJSRED: All Rights are Reserved

deviation, maximum absolute magnitude and peak-to-peak amplitude provide compact summaries of a measurement window. These features can support threshold-based event indication, but they do not independently establish the presence, location or severity of structural damage. Reliable bridge assessment requires sensor calibration, baseline characterisation, repeatable loading conditions and engineering interpretation.

D. Research Gap

The project addresses an implementation gap between isolated sensing functions and an integrated, low-cost monitoring prototype. Camera-based water-level observation and vibration measurement are combined with edge processing and a separate wireless alert controller. The current work focuses on system-level integration and functional operation. A larger field dataset, reference instrumentation and controlled structural tests remain necessary for performance validation.

III. SYSTEM OBJECTIVES, SCOPE AND ASSUMPTIONS

A. System Overview

The architecture is organised into four functional blocks: (1) image and sensor acquisition; (2) edge-side processing and monitoring-state evaluation; (3) wireless communication between independent processing and control units; and (4) alert actuation through visual and audible indicators. This functional separation allows sensing and analysis to operate independently from the external alert interface.

TABLE I
FUNCTIONAL BLOCKS OF THE PROTOTYPE

Functional block	General description	Purpose
Image observation	Camera-based image acquisition	Observe a visible water-level reference
Vibration monitoring	Accelerometer-based sensing	Acquire dynamic response measurements
Environmental context	Auxiliary environmental sensing	Record contextual environmental observations
Edge analysis	Embedded edge-processing unit	Perform image and signal processing
Wireless control	Independent embedded controller	Receive monitoring states
Alert interface	Visual and audible indicators	Communicate configured alert conditions

B. Scope

The scope includes image acquisition, image enhancement, learning-based water-level estimation, vibration data acquisition, statistical feature extraction, auxiliary environmental sensing, wireless message exchange and alert actuation. The paper reports these activities at a functional level and intentionally excludes detailed component specifications, acquisition schedules, wiring information, model files, software dependencies and communication configurations.

The work does not establish a validated structural-damage classifier, a bridge-specific finite-element model, a calibrated relationship between acceleration and damage severity, or a certified flood-warning threshold. It also does not claim that a traffic-light response is safe for public-road deployment without independent verification and fail-safe design.

C. Design Assumptions

The monitoring logic assumes that the vibration sensor is securely mounted and that its orientation remains consistent during a measurement session. Vibration descriptors are calculated over defined observation windows. Water-level estimates depend on the visibility and geometry of the reference gauge and on the quality of the estimation model and its site mapping. Alert conditions are configurable system settings; their values and engineering derivation are not disclosed. The auxiliary environmental measurement is treated as contextual information and is not used here as a direct indicator of structural damage.

IV. PROPOSED METHODOLOGY

A. Overall Processing Workflow

The monitoring workflow begins with parallel acquisition of image and sensor observations. The image stream is enhanced and passed through a trained estimation workflow to obtain a water-level output. In parallel, vibration measurements are grouped into analysis windows and converted into statistical descriptors. The processing unit evaluates the available monitoring values against configured conditions. A wireless message communicates the resulting monitoring state to a separate controller, which operates the appropriate visual or audible indicator.

 ©IJSRED: All Rights are Reserved

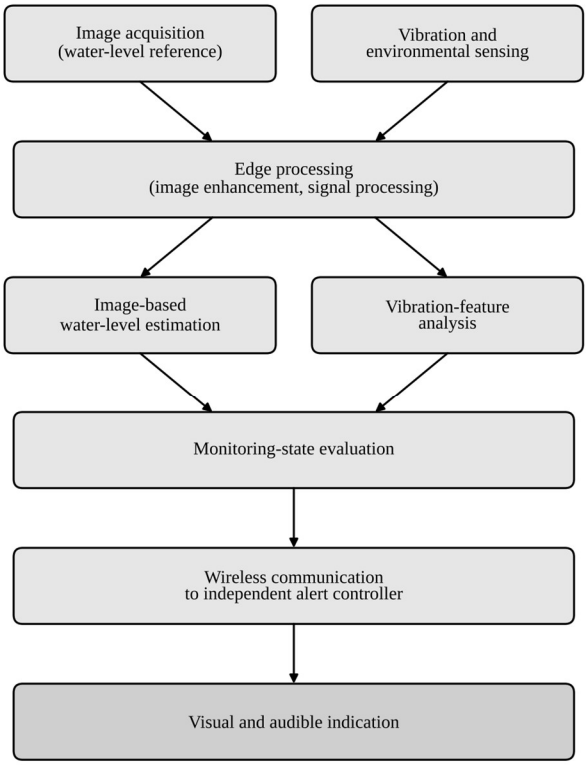


Fig. 1 Functional sequence: image and sensor acquisition → edge processing → image-based water-level estimation and vibration-feature analysis → monitoring-state evaluation → wireless communication → independent alert controller → visual and audible indication.

B. Image Acquisition and Preprocessing

Outdoor images may be affected by low illumination, uneven lighting, reflections and local contrast variation. An image-enhancement stage is therefore used to improve the visibility of relevant gauge features before estimation. The preprocessing approach combines intensity adjustment with local contrast enhancement. Exact processing parameters and implementation settings are withheld because they are specific to the project configuration and are not necessary to explain the method.

The enhanced image is passed to the project's trained water-level estimation workflow. The output is interpreted through a site-dependent mapping that relates model predictions to physical water-level readings. The model artefacts, internal architecture details, training configuration, class definitions and deployment-specific settings are not disclosed. The paper does not attribute the reference study's architecture or reported metrics to the present prototype.

C. Mini-SAM Development Activity

As part of the research preparation, the SAM architecture and the Adaptive-SAM water-level monitoring approach were studied. A basic Mini-SAM model was implemented in PyTorch to examine the functional roles of the image encoder, prompt encoder, attention-based interaction and mask decoder. This activity provided an implementation-level understanding of segmentation workflows. It is distinct from the integrated water-level inference pipeline described above and is not used to claim a measured segmentation accuracy for the bridge-monitoring prototype.

D. Vibration Data Acquisition

Vibration measurements are collected as a time series and grouped into analysis windows. For a window containing N samples x_1, x_2, …, x_N, descriptive features are calculated to summarise signal magnitude and variation. These include the mean, root-mean-square value, standard deviation, peak-to-peak amplitude and peak magnitude:

$$\mu = (1/N)\,\Sigma_{i=1}^{N} x_i \quad (1)$$

$$x_{RMS} = \sqrt{[(1/N)\,\Sigma_{i=1}^{N} x_i^2]} \quad (2)$$

$$\sigma = \sqrt{[(1/N)\,\Sigma_{i=1}^{N} (x_i - \mu)^2]} \quad (3)$$

$$x_{pp} = \max(x_i) - \min(x_i) \quad (4)$$

$$x_{peak} = \max(|x_i|) \quad (5)$$

These features summarise the vibration window and can be compared with a baseline or configured monitoring condition. A single fixed threshold is not sufficient to diagnose structural damage because measured acceleration depends on sensor mounting, orientation, traffic characteristics, structural response and environmental noise.

E. Temperature Measurement

An auxiliary environmental sensor is included to provide contextual measurements alongside vibration and image observations. The present paper does not define an environmental-variable-based structural-condition model or claim a causal relationship between the auxiliary measurement and bridge damage.

F. Decision Logic and Wireless Alerting

The processing unit combines the water-level estimate and vibration descriptors to determine a

 ©IJSRED: All Rights are Reserved

monitoring state according to configured conditions. The state is transmitted wirelessly to an independent embedded controller. The controller operates the external visual and audible indicators through an electrically isolated switching interface. Detailed pin assignments, relay-channel mappings, supply specifications and controller firmware details are withheld.

The communication architecture uses a wireless link because the processing and alert-control functions are implemented on separate devices. Messaging and direct-control approaches were examined during integration and testing. Protocol settings, message formats, network credentials and device-specific communication details are not included in this paper.

V. IMPLEMENTATION

A. Hardware Integration

The prototype consists of an edge-processing unit, an image-acquisition device, vibration and auxiliary environmental sensors, a separate embedded control unit, and external visual and audible indicators. The processing unit performs acquisition and analysis, while the control unit handles alert actuation. Exact hardware models, electrical ratings, wiring diagrams and component-level integration details are intentionally omitted.

B. Embedded Software

The edge software is organised around sensor acquisition, image capture, preprocessing, model inference, vibration-feature calculation, data logging and communication. The embedded controller receives a monitoring command and activates the corresponding alert output. Source code, file paths, model checkpoints, software versions, timing configurations and other implementation-specific settings are excluded.

C. Image Processing Implementation

The image-processing stage improves visibility in challenging illumination conditions before the image is passed to the water-level estimation workflow. A site-dependent mapping translates the model output into a physical reading where the relevant calibration is available. Specific enhancement parameters, model identifiers, checkpoint names and internal inference settings are not disclosed.

D. Functional Integration and Troubleshooting

The implementation work covered sensor interfacing, image acquisition, image enhancement, vibration logging, embedded control development, wireless communication and alert operation. Integration required coordination between the processing unit and the independent alert controller. The development process also involved addressing software compatibility and resource constraints associated with edge computing. Detailed troubleshooting records and deployment configurations are withheld.

VI. RESULTS AND DISCUSSION

A. Implemented System Functions

The available project records support reporting the following implementation outcomes at a system level: image acquisition and enhancement were implemented; a trained water-level estimation workflow and site-dependent output mapping were prepared; vibration acquisition and statistical feature extraction were developed; an auxiliary environmental sensing channel was incorporated; and a separate embedded controller was integrated wirelessly with visual and audible alert outputs.

TABLE II
IMPLEMENTATION STATUS AND EVIDENCE BOUNDARY

Function	Implementation status	Evidence boundary
Image observation	Image acquisition and enhancement workflow implemented	No image-availability or objective image-quality metric supplied
Water-level estimation	Trained estimation workflow and site-dependent output mapping prepared	No independently verified error metric supplied
Vibration monitoring	Sensor acquisition and statistical feature extraction developed	No calibrated benchmark or controlled loading results supplied
Environmental sensing	Auxiliary environmental measurement incorporated	No accuracy comparison supplied
Alert actuation	Wireless controller integrated with visual and audible outputs	No end-to-end latency or reliability result supplied

B. Interpretation of Vibration Features

RMS describes the effective magnitude of an acceleration signal over an observation window, while peak and peak-to-peak values highlight transient excursions. Standard deviation describes

 ©IJSRED: All Rights are Reserved

dispersion around the mean. These measures can support comparison between baseline observations and periods of increased dynamic activity. However, the available project records do not establish a controlled vehicle-pass dataset, a calibrated reference measurement or a statistically validated baseline. Consequently, no numerical claim about vehicle classification, damage detection or structural condition is made.

C. Interpretation of Image-Based Water-Level Estimation

Staff-gauge imagery enables non-contact observation and can reduce the need for a water-level transducer at the observation point. Image enhancement is intended to improve visibility in challenging scenes, while the trained estimation workflow and site mapping provide a structured water-level output. Reliability depends on camera stability, gauge visibility, perspective, reflections, occlusion and the representativeness of the training data. The reference paper reports results for its own experiments across multiple water bodies [1]; those results are not results of the present prototype.

D. Alert-System Behaviour

The wireless alert architecture separates data processing from physical indication. The processing unit evaluates monitoring values, while the independent controller performs alert actuation. For operational deployment, the alert-state logic must define normal, warning, critical and communication-failure conditions, including safe behaviour if messages stop or a sensor becomes unavailable. These fail-safe behaviours require explicit testing before the system can be considered for live traffic-management use.

E. Limitations

The current paper documents a prototype implementation rather than a completed field-validation study. The evidence available for this paper does not include a controlled dataset of vibration under known vehicle loads, calibrated reference water-level measurements paired with image estimates, independently verified model-performance metrics, engineering-derived alert thresholds, end-to-end communication measurements or long-duration outdoor reliability results. The system must not be interpreted as a validated structural-damage detector until these evaluations are completed.

VII. CONCLUSION AND FUTURE WORK

This paper presented an integrated IoT- and vision-based framework for bridge and environmental monitoring. The prototype combines image-based water-level observation, vibration measurement, auxiliary environmental sensing, edge processing, wireless communication and independent alert actuation. The work demonstrates the integration of complementary monitoring channels within a common workflow while intentionally withholding project-specific implementation details.

The main outcome is a system-level sensing and alert architecture that brings visual environmental monitoring and vibration observation into a common workflow. The available evidence establishes prototype integration but does not establish quantitative detection performance or structural-damage diagnosis. Future work should include controlled baseline and traffic-loading observations, calibrated reference water-level measurements, independent evaluation of estimation error, measurement of edge-processing performance, assessment of wireless reliability and verification of fail-safe alert behaviour. Thresholds should be derived from site-specific observations and engineering assessment. Long-duration field trials are required before operational deployment.

REFERENCES

[1] "Deep Learning for Image-Based Water Level Estimation Across Multiple Water Bodies," supplied reference manuscript, 2026.
[2] Z. Wu, Y. Huang, K. Huang, K. Yan, and H. Chen, "A review of non-contact water level measurement based on computer vision and radar technology," *Water*, vol. 15, no. 18, 2023.
[3] L. Sabbatini, L. Palma, A. Belli, F. Sini, and P. Pierleoni, "A computer vision system for staff gauge in river flood monitoring," *Inventions*, vol. 6, no. 4, 2021.
[4] G. Qiao, M. Yang, and H. Wang, "A water level measurement approach based on YOLOv5s," *Sensors*, vol. 22, no. 10, 2022.
[5] L. Hashemi-Beni, M. Puthenparampil, and A. Jamali, "A low-cost IoT-based deep learning method of water gauge measurement for flood monitoring," *Geomatics, Natural Hazards and Risk*, vol. 15, no. 1, p. 2364777, 2024.
[6] A. Kirillov et al., "Segment anything," in *Proc. IEEE/CVF International Conference on Computer Vision (ICCV)*, 2023, pp. 4015–4026.
[7] C. Fang, K. Duan, Z. Lv, J. Huang, Q. Zhong, J. Chen, and D. Long, "Improving image-based water-level monitoring by coupling water-line detection techniques and the segment anything model," *Environmental Modelling & Software*, vol. 192, p. 106566, 2025.

 ©IJSRED: All Rights are Reserved