

AI-IoT Smart Infrastructure Crack Detection System

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Abstract: Ageing infrastructure requires continuous monitoring to identify early signs of structural damage and prevent potential failures. Conventional inspection methods rely primarily on manual observation, making them time-consuming, costly, and difficult to perform frequently. This paper presents an Artificial Intelligence and Internet of Things (AI-IoT)-based structural health monitoring system that integrates computer vision and vibration sensing for automated crack detection and abnormal vibration identification. A camera captures images of the monitored structure, and a lightweight MobileNetV2-based deep learning model classifies surface conditions as crack or no-crack. Simultaneously, an L3G4200D gyroscope interfaced with a Raspberry Pi provides angular velocity readings, which are analysed using a calibrated threshold-based method to identify deviations from baseline vibration conditions. A rule-based fusion engine combines the visual and sensor outputs to classify the overall structural condition into three severity levels: LOW, MEDIUM, and HIGH. An RGB LED provides local status indication, while a secure web dashboard enables remote monitoring of structural conditions. When a HIGH-severity condition is detected, the system generates an automated email alert to facilitate timely inspection and corrective action. The proposed system demonstrates the integration of AI-based vision, IoT sensing, severity assessment, and automated alerts for structural condition monitoring. Further quantitative evaluation and real-world validation are required to establish its reliability and practical applicability.

Key Word: Structural Health Monitoring, Crack Detection, MobileNetV2, Internet of Things (IoT), Raspberry Pi, Vibration Monitoring, Sensor Fusion.

I. INTRODUCTION

Civil infrastructure such as bridges and dams requires continuous monitoring to detect early signs of structural damage and ensure timely maintenance. Traditional inspection methods rely on periodic manual assessment, which can be time-consuming and labour-intensive. To address these limitations, this paper presents an Artificial Intelligence (AI) and Internet of Things (IoT)-based Structural Crack Detection and Vibration Monitoring System that integrates computer vision and inertial sensing using low-cost embedded hardware. The system captures surface images using a camera and classifies them as crack or no-crack using a MobileNetV2-based Convolutional Neural Network trained through transfer learning. An L3G4200D gyroscope connected to a Raspberry Pi measures angular velocity, while a calibration-based threshold method identifies abnormal vibration conditions. A rule-based fusion engine combines the visual and sensor outputs to determine the overall structural severity as LOW, MEDIUM, or HIGH. The detected status is indicated through an RGB LED and displayed on a password-protected web dashboard containing camera images, sensor readings, crack status, and historical data. For HIGH-severity conditions, an automated HTML email alert containing the triggering image is generated to support timely inspection and corrective action. The proposed system integrates AI-based image classification, IoT sensing, embedded computing, and remote monitoring into a unified framework. The prototype aims to support early identification of potential structural distress through automated assessment and alerts. Further quantitative testing and real-world validation are required to establish its reliability for practical structural monitoring applications.

II. SCOPE OF THE PROJECT

The scope of this project is limited to a proof-of-concept prototype demonstrated on a small physical test rig (a beam or board with a visible crack) rather than deployment on an actual in-service bridge. The vision pipeline performs binary crack/no-crack classification with a heuristic, contour-based visual severity estimate rather than precise crack width or depth quantification. The sensor pipeline uses a single gyroscope's angular velocity magnitude as a vibration proxy rather than a full inertial measurement suite. The fusion logic is intentionally rule-based rather than a trained multimodal neural network, keeping the severity decision explainable and verifiable within the scope of an academic project. Communication between the Raspberry Pi and the dashboard is assumed to occur over a local Wi-Fi network rather than a wide-area cellular

link. The project covers model training, sensor interfacing, fusion logic, LED control, dashboard development, and automated alerting, along with testing and evaluation of the assembled system.

III. EXISTING SYSTEM AND PROPOSED SYSTEM

Existing System: Currently deployed structural monitoring approaches fall into two broad categories. The first is manual visual inspection performed periodically by qualified engineers, which is subjective, infrequent, and dependent on inspector accessibility and expertise. The second is dedicated wired SHM sensor networks installed on high-value infrastructure, which provide accurate, continuous data but at high installation and maintenance cost, restricting their use to a small fraction of structures in service. A smaller body of low-cost, student and hobbyist-accessible prototypes has explored either vision-based crack detection or IoT-based vibration monitoring individually. However, these existing systems generally address only one sensing modality at a time and rarely fuse both into a single, unified severity assessment communicated through both a physical indicator and a remote dashboard with automated alerting.

Proposed System: The proposed system addresses this gap using a Raspberry Pi that fuses two independent senses: a USB camera classified by a MobileNetV2 crack detector, and an L3G4200D gyroscope monitored by a calibrated anomaly detector. A rule-based fusion engine combines both into a LOW/MEDIUM/HIGH severity level. The result drives a physical RGB LED indicator, a secure multi-page Streamlit dashboard, and an automatic HTML email alert (with the triggering photo embedded) fired only on HIGH severity. The system's fast, independent fusion loop (running every 0.25 seconds) is decoupled from the slower camera-and-inference loop (every 2 seconds), ensuring vibration anomalies are reflected on the dashboard almost instantly rather than being limited by camera inference latency.

IV. SYSTEM DESIGN

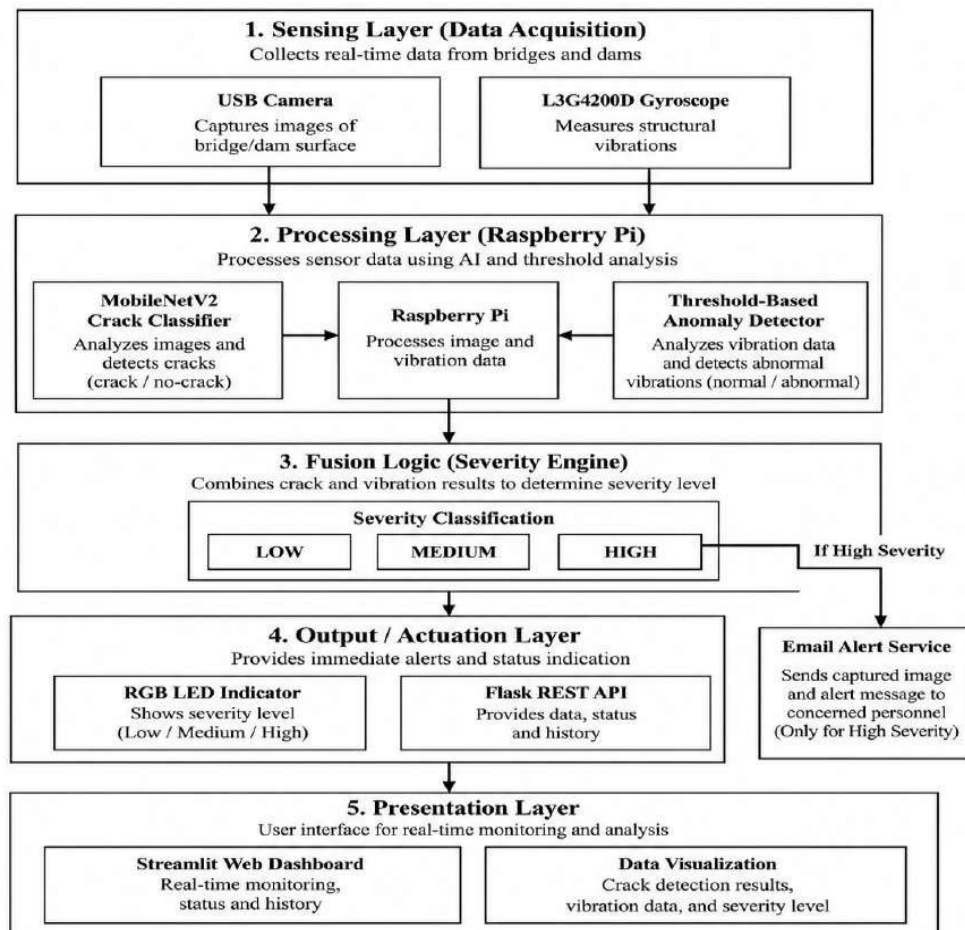


Figure 1: System Design

1. Sensing Layer / Data Acquisition: The system first collects real-time data using two sensors. A USB camera captures images of the concrete surface, while the L3G4200D gyroscope measures structural vibrations. These inputs provide the data required for crack and vibration monitoring.
2. Processing Layer /Raspberry Pi: The collected data is processed by the Raspberry Pi. The camera images are given to the MobileNetV2 crack classifier, which identifies whether a crack is present. At the same time, the gyroscope readings are analyzed using a threshold-based anomaly detector to identify abnormal vibrations.

3. Fusion Logic / Severity Engine: The results from crack detection and vibration analysis are combined by the fusion logic. Based on these results, the system determines the overall structural condition as Low, Medium, or High severity.
4. Output / Actuation Layer: The severity level is indicated using an RGB LED. The system also uses a Flask REST API to provide the current status and historical data to other components. If the severity is High, the system automatically triggers an email alert with the captured image and alert message.
5. Presentation Layer: Finally, the information is displayed through a Streamlit web dashboard. The dashboard provides real-time monitoring, crack detection results, vibration data, severity status, and historical information, allowing the user to monitor the structural condition easily.

The system was developed using Python, Raspberry Pi, MobileNetV2, OpenCV, the L3G4200D gyroscope, and Streamlit for web-based monitoring. It integrates AI-based crack classification, threshold-based vibration detection, rule-based severity assessment, RGB LED indication, and automated email alerts. Functional testing was conducted to evaluate crack detection, sensor operation, severity classification, dashboard authentication, LED indication, and email alert behaviour.

V. RESULTS

The implemented AI-IoT Smart Infrastructure Crack Detection System integrates the major stages of structural health monitoring into a unified monitoring platform. The system captures surface images using a USB camera and classifies them as crack or no-crack using a MobileNetV2-based deep learning model. Simultaneously, the L3G4200D gyroscope monitors angular velocity, and a threshold-based detection mechanism identifies abnormal vibration conditions.

The fusion engine combines the outputs of the image classification and vibration monitoring modules to determine the structural severity level as LOW, MEDIUM, or HIGH. The RGB LED provides local status indication, while the Streamlit dashboard displays crack detection confidence, vibration readings, severity status, and historical monitoring data. The monitoring system also supports sensor disconnection handling and resumes combined monitoring after sensor reconnection and recalibration. The automated email notification module generates an HTML-formatted alert containing the triggering image when a HIGH-severity condition is detected. Functional testing covers crack classification, vibration detection, dashboard authentication, LED indication, and email alert behaviour. The prototype demonstrates the integration of AI-based crack detection, vibration monitoring, severity classification, and remote notifications. However, the current implementation is a proof of concept tested on a small physical test rig, and further quantitative evaluation and real-world validation are required to establish its reliability for practical structural health monitoring.

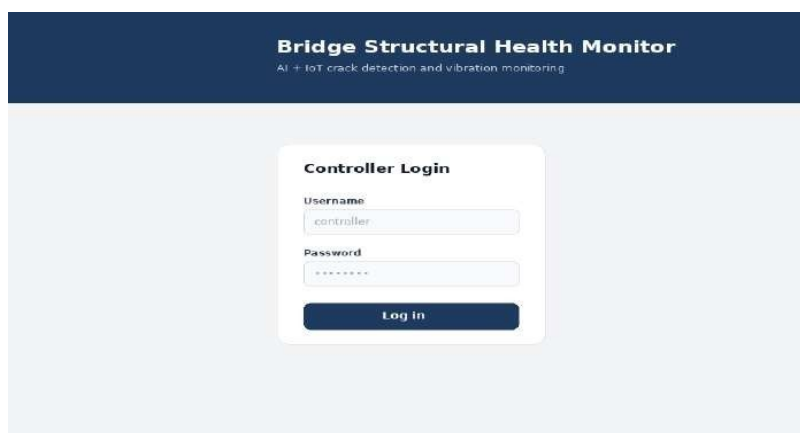


Figure 1: Controller Login Page

The controller login page provides password-protected access to the structural monitoring dashboard. It restricts access to authorized users before they can view the camera feed, sensor information, and monitoring analytics.

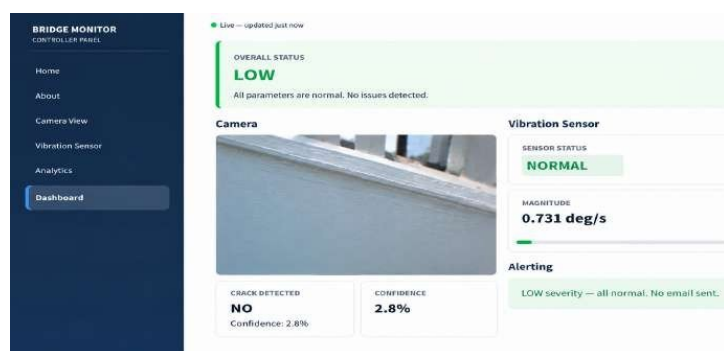


Figure 2: Dashboard Overview – LOW Severity State

The dashboard displays the monitored condition when the system classifies the structural status as LOW severity. It presents the camera feed, crack detection result, confidence value, gyroscope status, and vibration readings, allowing users to observe the current monitoring condition.

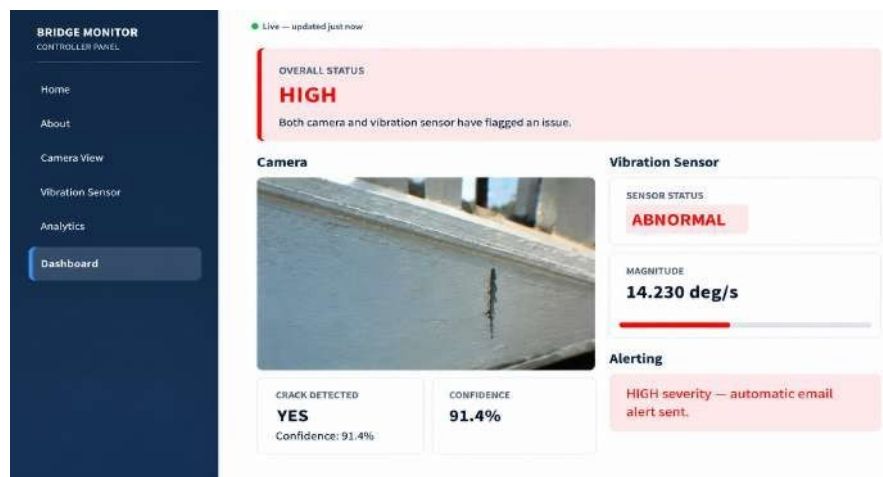


Figure 3: Dashboard Overview – HIGH Severity State

This dashboard view represents a HIGH-severity condition identified by the fusion engine. It displays the crack detection output and abnormal vibration status. When a crack and abnormal vibration are detected together, the system assigns HIGH severity and triggers an automated email alert.

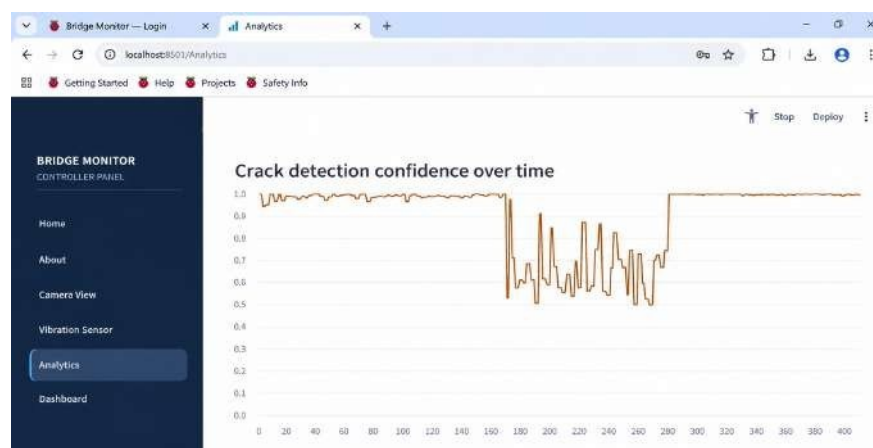


Figure 4: Crack Detection Confidence Over Time

This graph illustrates changes in the confidence values produced by the crack detection module over time. It helps users observe the output of the MobileNetV2 classifier during image analysis and review variations in its predictions.

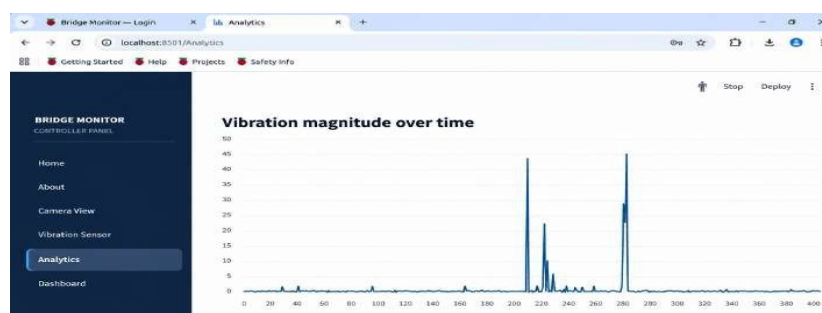


Figure 5: Vibration Magnitude Over Time

The vibration monitoring graph presents changes in the gyroscope readings over time. Peaks in the graph indicate periods of increased measured angular velocity, helping users observe sensor activity and identify readings that exceed the calibrated anomaly threshold.



Figure 6: Severity Level over Time

This visualization presents variations in the system's severity classification during monitoring. It helps users review changes in the LOW, MEDIUM, and HIGH states determined by the fusion engine from the available image and sensor results.



Figure 7: Recent Readings

The recent readings module displays historical monitoring records, including sensor information and associated status values. It allows users to review previous readings and examine the recorded monitoring history through the dashboard.

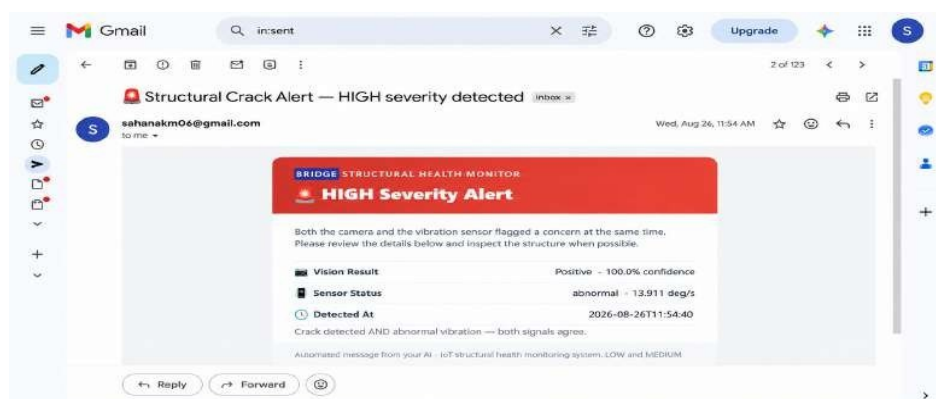


Figure 8: Automated HIGH-Severity Email Alert

The email alert module generates an HTML-formatted notification when the system detects a HIGH-severity condition. The notification includes information about the detected event and the triggering photograph, enabling the recipient to review the condition and arrange further inspection.

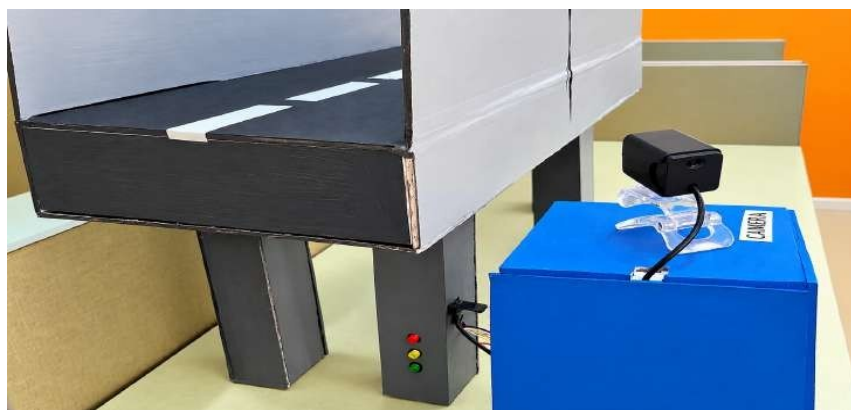


Figure 9: Physical Prototype of the AI-IoT Smart Infrastructure Crack Detection System

The physical prototype demonstrates the integration of the Raspberry Pi, camera, gyroscope, LED indicators, and test structure. It illustrates the implementation of the proposed monitoring framework and its ability to combine visual crack detection, vibration sensing, severity assessment, and alert generation.

VI. DISCUSSION

The proposed AI-IoT Smart Infrastructure Crack Detection System integrates MobileNetV2-based crack classification and L3G4200D gyroscope-based vibration monitoring into a unified structural health monitoring framework. The rule-based fusion engine combines both outputs to classify the structural condition as LOW, MEDIUM, or HIGH severity, providing a combined assessment of visual defects and abnormal vibration conditions.

The system provides multiple monitoring features, including RGB LED indication, a password-protected Streamlit dashboard, historical data visualization, and automated email alerts for HIGH-severity conditions. The dashboard presents crack detection confidence, vibration magnitude, severity trends, and recent sensor readings. These features support remote observation and help communicate potentially abnormal conditions to the concerned personnel.

Functional testing demonstrated the operation of the individual modules and their integration. The test cases covered crack and no-crack classification, sensor calibration, abnormal vibration detection, LED indication, sensor disconnection and reconnection, dashboard authentication, and automated email alerts. The system also demonstrated a fallback to vision-only monitoring when the gyroscope was disconnected, with normal fusion operation resuming after reconnection and recalibration.

Despite these capabilities, the prototype has certain limitations. Crack detection is limited to binary classification with a heuristic visual severity estimate rather than precise crack width or depth measurement. The fusion mechanism uses predefined rules instead of a trained multimodal model, and vibration monitoring relies on gyroscope readings as a proxy for structural vibration. Furthermore, the system was demonstrated on a small physical test rig rather than an operational bridge or dam, and dashboard connectivity depends on a local Wi-Fi network.

Overall, the prototype demonstrates the feasibility of integrating AI-based image classification, low-cost vibration sensing, severity assessment, and automated notifications in a single monitoring system. Further quantitative evaluation, testing under varied environmental conditions, and validation on real infrastructure are required to establish its reliability and practical applicability.

VII. CONCLUSION

The project successfully developed a low-cost AI and IoT-based system for structural crack detection and vibration monitoring using Raspberry Pi. It combines MobileNetV2-based crack detection and gyroscope-based vibration monitoring with

rule-based fusion to determine LOW, MEDIUM, and HIGH severity levels. The system provides real-time status through an LED indicator, web dashboard, and email alerts. The system also improves monitoring response by separating the sensor-fusion loop from the camera-processing loop. Future work includes TensorFlow Lite optimization, additional sensors, crack size measurement, improved fusion techniques, and testing on real structures.

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