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Embedded Edge Ai-Based Smart Dam and Bridge Structural Health Monitoring with Predictive Flood Analytics and Iot System

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Abstract
Dams and bridges require continuous monitoring to ensure safety and long-term performance, yet conventional inspection relies on periodic manual measurements that can delay the detection of abnormal behavior. This paper presents an embedded Edge AI-based smart dam and bridge structural health monitoring system with predictive flood analytics and IoT connectivity. ESP32-based monitoring units acquire temperature, humidity, rainfall, water level, load, vibration, acceleration, gyroscope, strain and tilt-related parameters from prototype dam and bridge models, while an ESP32-CAM provides live visual surveillance. Feed-forward artificial neural networks developed with TensorFlow/Keras, using 17 input features for the dam and 15 for the bridge with StandardScaler normalization, classify each structure as NORMAL, WARNING or CRITICAL; the dam model is converted to TensorFlow Lite for edge deployment. A Flask backend connects the units to a web dashboard, and critical conditions trigger LED, buzzer and siren alerts, an automated motor/gate response and e-mail notification. Dashboard outputs, logged sensor records and time-wise event analyses from the prototype demonstrate continuous, low-cost and real-time condition assessment that reduces dependence on manual inspection.

Keywords: *Embedded system, Structural health monitoring, Edge AI, ESP32, Artificial neural network, TensorFlow Lite, IoT, Flood analytics.*

1. Introduction
Dams and bridges are critical civil infrastructure that support water management, transportation and economic development. Their safety depends on continuous observation of vibration, acceleration, tilt, strain, load, temperature, humidity, rainfall and water level. Traditional inspection relies mainly on periodic physical inspection and manual measurements, which demand considerable human effort and may not capture rapidly changing conditions, so abnormal structural behavior can go unnoticed between inspections. Advances in embedded systems, sensors, the Internet of Things (IoT), edge computing and Artificial Intelligence (AI) now make continuous, automated structural health monitoring (SHM) practical. Sensors collect structural and environmental data, Edge AI models classify the condition close to the monitoring hardware, and IoT communication delivers the results to a central dashboard, local alarms and e-mail. This paper presents an ESP32-based smart dam and bridge SHM system with predictive flood analytics. Separate monitoring units are used for the dam and the bridge. Feed-forward Artificial Neural Network (ANN) models trained with TensorFlow/Keras take 17 input features for the dam and 15 for the bridge and classify the condition as NORMAL, WARNING or CRITICAL. The dam unit also measures water level with an ultrasonic sensor and operates an automated motor-driven gate, while an ESP32-CAM streams live video of the monitored setup. The rest of the paper is organized as follows: Section 1.1 reviews related work, Section 1.2 states the objectives, Section 2 describes the methodology, Section 3 presents the results and discussion, and the final section concludes the work.

1.1.Related Work

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Recent research has applied IoT, edge computing and machine learning to infrastructure monitoring. Al-Ali et al. (2024) developed a low-cost road-bridge health monitoring and warning system that combines edge computing, machine learning and deep learning with a fuzzy-logic algorithm to grade bridge condition, while Navaz et al. (2024) proposed an energy-efficient clustering strategy to extend the lifetime of large-scale wireless sensor networks. Saravanan et al. (2024) showed that low-cost MPU6050-based wireless nodes can monitor laboratory-scale structures with an average difference of less than 6% from a conventional accelerometer. Yang et al. (2024) reviewed the calibration of bridge SHM sensing systems, stressing the importance of reliable sensor data, and Yaghoubzadehfard et al. (2024) applied ensemble learning to bridge monitoring with an interferometric radar system. Bhatta and Dang (2024) surveyed IoT for SHM of civil structures and highlighted the benefits of remote, continuous monitoring. Edge-oriented work includes the low-cost, low-power edge computing system of Hidalgo-Fort et al. (2024), which achieved more than ten years of autonomy and a modal-frequency error below 1.72% against commercial systems, and the lightweight edge prototype of Wang et al. (2025a), which gives faster local AI inference with reduced power consumption. Moser et al. (2024) reviewed fiber-optic sensing for concrete dams, and Khan et al. (2025) identified IoT combined with AI/ML as a promising route for dam SHM. For flooding, de Melo et al. (2025) combined neural networks with process-based models to predict flood discharge up to 36 hours ahead. Other studies explored deep learning with low-cost accelerometers (Emadi et al., 2025), adaptive edge intelligence on wireless smart sensor networks (Yang et al., 2025), cloud–edge collaborative optimization for bridge monitoring (Wang et al., 2025b) and deep-learning data fusion for predictive maintenance of bridge decks (Hakimi et al., 2025).

Although these studies show the value of IoT and edge intelligence, most address bridges or dams separately, concentrate on model performance or on individual parameters, and rely on centralized processing; few connect the AI output directly to local alerts, e-mail notification and physical actuator response. The present work addresses this gap by integrating multi-parameter dam and bridge monitoring, water-level-based flood analysis, ANN condition classification with TensorFlow Lite deployment, alerts, actuator response and a real-time dashboard on one low-cost platform.

1.2.Objectives

The main objective is to develop an automated, real-time and cost-effective smart infrastructure monitoring unit for continuous SHM of dams and bridges. The specific objectives are: (i) to acquire dam and bridge structural and environmental parameters continuously with ESP32-based units; (ii) to develop ANN-based Edge AI models with 17 and 15 input features that classify NORMAL, WARNING and CRITICAL conditions, and to prepare the dam model for TensorFlow Lite deployment; (iii) to monitor dam water level with an ultrasonic sensor and provide an automated motor/gate response; (iv) to provide LED, buzzer, siren and LCD alerts and e-mail notification for abnormal or critical conditions; and (v) to provide Wi-Fi/HTTP-based communication between the ESP32 units, a Flask backend and a web dashboard with live ESP32-CAM streaming.

2. Methodology

2.1.System Architecture and Working

The system is organized into sensor, edge-processing, backend and AI, display, actuator and user-interface layers, as shown in Fig. 1. Dam sensors (ultrasonic, DHT22, load cell with HX711, MPU6050, DS18B20 and rain sensor) and bridge sensors (MPU6050, DHT22, strain, vibration, tilt and load) form the sensor layer. The ESP32 dam and bridge nodes perform data acquisition and local control and send readings to the Flask backend over Wi-Fi using HTTP. The backend hosts the Edge AI engine and an SQLite database, the actuators and alert devices form the output layers, and the web dashboard and e-mail alerts form the user interface. As shown in Figure 1 Layered architecture of the proposed system[1 – 10].

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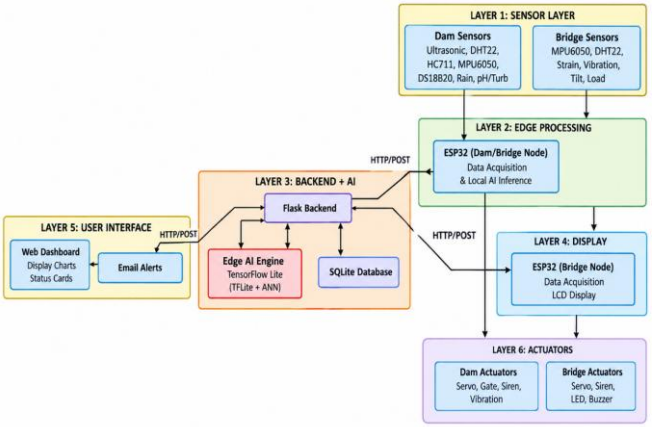


Figure 1 Layered architecture of the proposed system

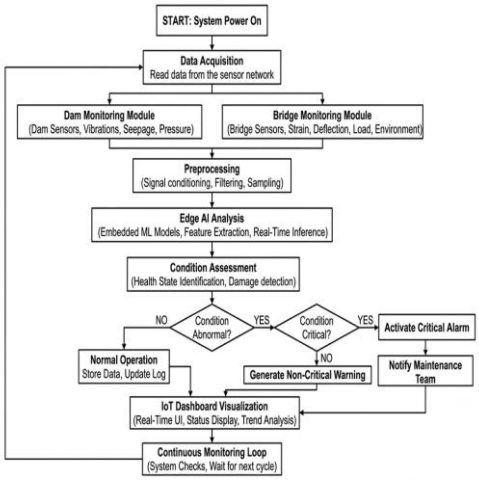


Figure 2 Flow chart of the proposed system

The operating sequence is shown in Fig. 2. The readings of each node are arranged into the feature vector of the corresponding model, normalized with StandardScaler and passed to the ANN, which outputs NORMAL, WARNING or CRITICAL with a confidence value. A WARNING condition raises a dashboard and buzzer indication, whereas a CRITICAL condition additionally activates the siren, the configured motor/gate response and an e-mail notification. Results and history are stored in the database and displayed on the dashboard together with the live ESP32-CAM stream. As shown in Figure 2 Flow chart of the proposed system.

2.2.Hardware Description

Both monitoring units are built around ESP32 development boards, and an ESP32-CAM provides visual surveillance of the dam setup. The components and their roles are listed in [11] Table 1. An SMPS supplies the system, and a buck converter steps the voltage down to the levels required by the two ESP32 boards, the ESP32-CAM and the other modules (Fig. 3). As shown in Table 1. Main components of the dam and bridge units, Figure 3 Circuit diagram of the dam and bridge monitoring units.

Table 1 Main components of the dam and bridge units

Component	Unit	Purpose
ESP32 board	Both	Data acquisition, processing and communication
ESP32-CAM	Dam	Live visual surveillance
MPU6050	Both	Acceleration, gyroscope, tilt and vibration-related movement
DHT22	Both	Temperature and humidity
Load cell + HX711	Both	Structural load/strain
Vibration / piezo sensor	Both	Abnormal structural vibration
DS18B20	Dam	Water temperature
HC-SR04	Dam	Water level (ultrasonic distance)
Rain sensor	Dam	Rainfall for flood-related

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		monitoring
28BYJ-48 + ULN2003	Dam	Stepper-motor gate response
Servo motor	Bridge	Mechanical movement in bridge prototype
Siren / buzzer	Dam / Bridge	Audible warning
16×2 I²C LCD	Bridge	Display of values and condition
SMPS	Both	Main DC power supply

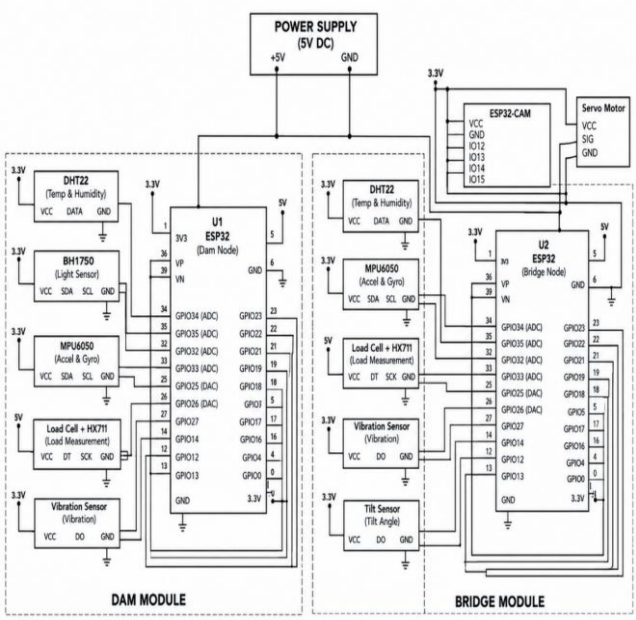


Figure 3 Circuit diagram of the dam and bridge monitoring units

2.3.Edge AI Model Development

Separate feed-forward ANN models were developed with TensorFlow/Keras for the dam and the bridge. The dam dataset has 17 input features: temperature, humidity, X-, Y- and Z-axis acceleration and its magnitude, X-, Y- and Z-axis gyroscope values and their magnitude, load, vibration, rainfall, water level, water-level change, a pressure/structural-load parameter and a structural-condition parameter. The bridge dataset has 15 input features, including temperature, humidity, acceleration, gyroscope values and magnitudes, strain, load, piezoelectric vibration, tilt status and tilt angle. The target is the condition class NORMAL, WARNING or CRITICAL. Inputs are normalized with StandardScaler. Both networks (Table 2) use two hidden Dense layers with ReLU activation and a three-neuron Softmax output layer, and are trained with the Adam optimizer and sparse categorical cross-entropy loss. The dam model uses an 80:20 stratified train–test split; the bridge model uses early stopping that monitors [12] validation loss and restores the best weights. The trained models are stored in Keras format with their scalers and class configuration, and the dam model is converted to TensorFlow Lite for lightweight edge inference. As shown in Table 2. ANN architecture of the dam and bridge models.

Table 2 ANN architecture of the dam and bridge models

Layer	Dam model	Bridge model
Input	17 features	15 features
Hidden 1	Dense, 32, ReLU	Dense, 32, ReLU
Hidden 2	Dense, 16, ReLU	Dense, 16, ReLU
Output	Dense, 3, Softmax	Dense, 3, Softmax
Optimizer / loss	Adam / sparse categorical cross-entropy	Adam / sparse categorical cross-entropy

2.4.Software and Communication

The backend is written in Python using Flask, NumPy and scikit-learn, with TensorFlow/Keras for model development; the ESP32 firmware is developed in the Arduino IDE. The ESP32 units and the backend exchange data over Wi-Fi using HTTP/REST, the ESP32-CAM supplies a live video stream shown on the dashboard, and e-mail alerts are sent through SMTP to the authorized recipient. The dashboard is implemented in HTML, CSS and JavaScript and

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shows sensor values, AI prediction and confidence, alert status, actuator status and the camera feed [13 – 15].

3. Results And Discussion

3.1.Results

Fig. 4 shows the developed prototype with the dam and bridge models and their ESP32-based controller. The controller manages sensor acquisition, AI-based condition analysis and alert/actuator response, and its LCD displays the current condition together with messages for sensor errors, sensor failures and critical events. As shown in FIGURE 4. Hardware prototype of the smart infrastructure monitoring system. The web dashboard (Fig. 5) presents the dam and bridge AI predictions with confidence and class probabilities, key sensor values and actuator status on a single page. A WARNING status is displayed when abnormal variations are detected and DAM IN CRITICAL when critical dam conditions occur; separate alerts for the dam and the bridge show the condition, timestamp and relevant sensor information. As shown in Figure 5 System overview dashboard of the dam and bridge.

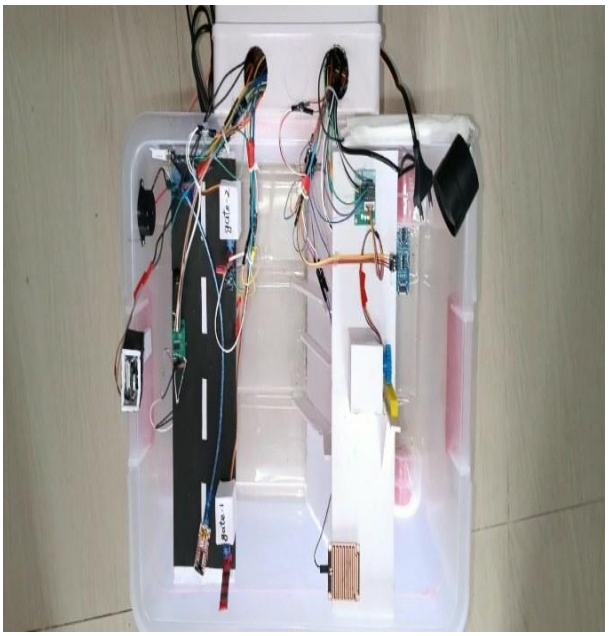


Figure 4 Hardware prototype of the smart infrastructure monitoring system

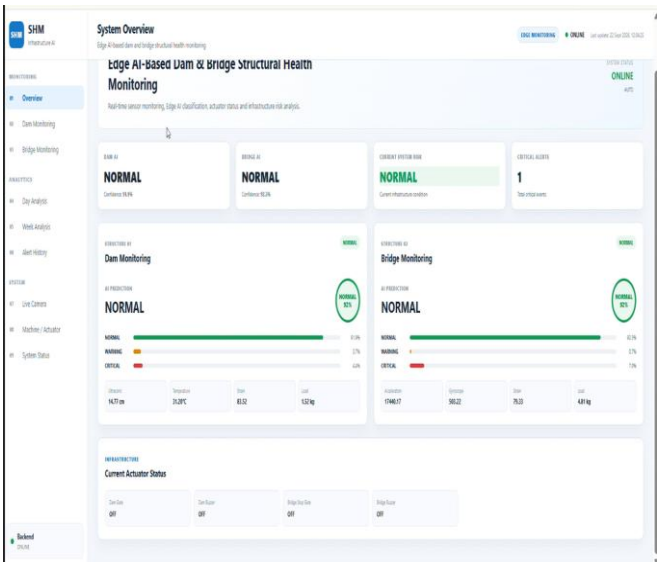


Figure 5 System overview dashboard of the dam and bridge

The dam monitoring page (Fig. 6) shows the AI state, confidence, risk level and gate status together with ultrasonic distance, rainfall, temperature, humidity, water temperature, vibration, acceleration, strain and load, and plots their real-time variation. Representative logged records are given in Table 3; during critical conditions the motor, gate and buzzer are activated automatically, and every record carries a timestamp and the dam status. As shown in Figure 6 Real-time dam structural health monitoring. As shown in Table 3 Sample dam monitoring records.

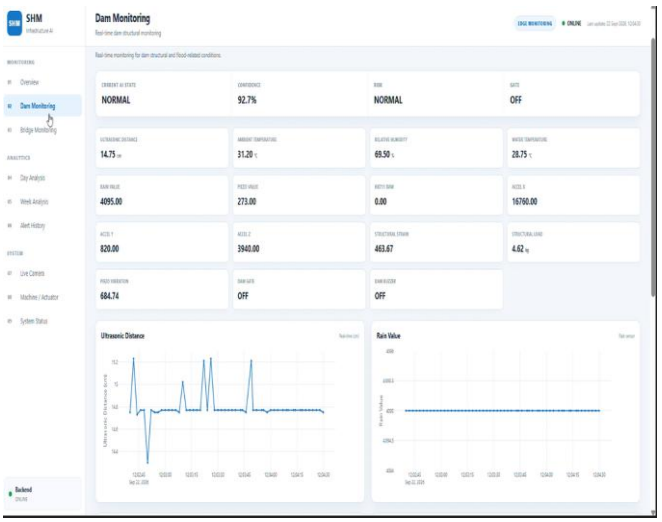


Figure 6 Real-time dam structural health monitoring

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Table 3 Sample dam monitoring records

Timestamp	Dist (cm)	Temp (°C)	Hum (%)	Rain	Piezo	Gate
2026-09-26 05:30:05	20.51	29.1	67.5	0	1272	ON
2026-09-25 19:57:05	5.63	31.4	63.6	1	3131	ON
2026-09-22 17:51:11	18.28	30.7	72.2	3	1792	ON
2026-09-22 17:49:44	18.28	30.8	74.8	0	1510	ON
2026-09-22 13:46:36	5.09	33.3	67.5	2	320	OFF

The bridge monitoring page (Fig. 7) tracks acceleration, gyroscope values, vibration, tilt, strain, load, temperature and humidity and classifies the bridge as NORMAL, WARNING or CRITICAL. Critical conditions activate the disturbance indicator, stop gate and buzzer, and each record stores the timestamp, status, sensor readings and actuator state. As shown in Figure 7 Real-time bridge structural health monitoring.

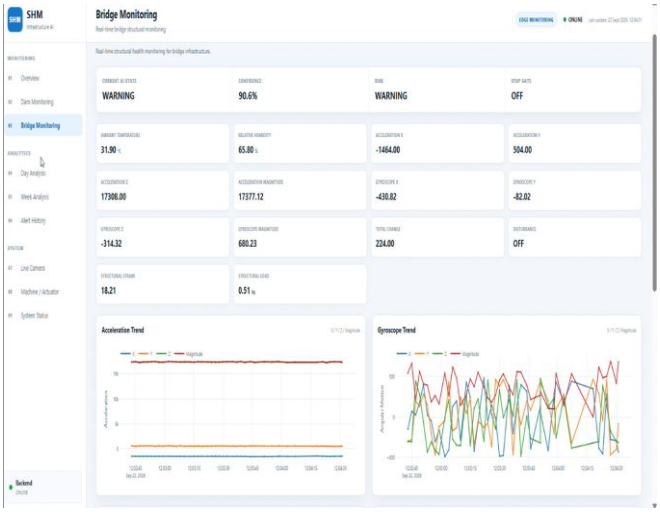


Figure 7 Real-time bridge structural health monitoring

Time-wise analysis at 5-minute intervals (Table 4) counts the NORMAL, WARNING and CRITICAL dam events. The busiest slot is 05:25 with 120 events, and 10 CRITICAL events occur in the 05:30 slot. The bridge shows a similar pattern, with 108 events at 05:25 and four CRITICAL events at 05:30. Weekly totals (Table 5) show that most activity was logged from Sunday to Tuesday, with Monday highest for both structures (2,722 dam and 2,516 bridge events); no events were logged on Wednesday and Thursday. As shown in Table 4. Dam daily analysis (5-minute slots).

Table 4 Dam daily analysis (5-minute slots)

Time	NORMAL	WARNING	CRITICAL	Total
04:30	31	31	0	62
05:20	1	2	0	3
05:25	60	60	0	120
05:30	21	21	10	52
09:20	12	11	0	23
09:25	29	29	0	58

Table 5 Weekly event counts of the dam and bridge

Day	Dam total	Dam critical	Bridge total	Bridge critical
Sunday	806	72	659	10
Monday	2722	72	2516	51
Tuesday	1225	43	1097	26
Friday	75	10	379	20
Saturday	318	10	0	0

Alert-history, live camera, actuator and e-mail pages complete the interface. The ESP32-CAM streams live video of the dam setup for remote visual inspection, the stepper motor responds to critical dam conditions with its status shown on the dashboard, and separate e-mail alerts for the dam and the bridge carry the infrastructure status, AI prediction, timestamp and real-time sensor values.

3.2.Discussion

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The results show that the three-class ANN output can drive a complete monitoring workflow. NORMAL keeps regular monitoring, WARNING raises a dashboard and buzzer indication, and CRITICAL activates the siren, the motor/gate response and e-mail notification, while the LCD and dashboard show the same state, so an operator does not have to interpret several raw readings. Including rainfall and ultrasonic water level with vibration, load and acceleration in the dam model links flood-related and structural observations in one classification. Functional testing of sensor acquisition, ANN inference with 17 and 15 features, StandardScaler preprocessing, water-level measurement, motor response, local alerts, e-mail generation, camera streaming and dashboard updates confirmed that these functions work together in the integrated system. Under continuous operation, repeated predictions, camera streaming, dashboard updates and actuator operation proceeded without disturbing the monitoring process. Critical events formed a small share of the events logged during prototype operation: 207 of 5,146 dam events (about 4.0%) and 107 of 4,651 bridge events (about 2.3%). The evaluation was carried out on prototype-scale dam and bridge models with a simulated dam environment; validation with larger real-world datasets and under varied environmental conditions remains future work.

Conclusion

This paper presented an ESP32-based embedded Edge AI system for smart dam and bridge structural health monitoring with predictive flood analytics and IoT connectivity. Multi-parameter sensing, StandardScaler preprocessing and feed-forward ANN models with 17 (dam) and 15 (bridge) input features classify the structural condition as NORMAL, WARNING or CRITICAL, and the dam model is converted to TensorFlow Lite for edge deployment. Ultrasonic water-level monitoring with an automated motor/gate response, local LED, buzzer, siren and LCD alerts, e-mail notification, ESP32-CAM surveillance and a real-time Flask-based dashboard are combined in a single low-cost platform that reduces dependence on periodic manual inspection and supports timely inspection and maintenance planning. Future work includes larger real-world datasets, more advanced AI architectures, additional strain, displacement and crack sensors, multiple camera units with AI-based visual analysis of cracks and surface damage, larger-scale gate and valve systems, historical rainfall and weather data for improved flood prediction, and configurable multi-level notification rules.

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