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Smart IoT Based Comprehensive Analysis of Infrastructure Health, Damage Prevention and Detection

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Abstract

Bridges and highways are essential to modern transportation, and maintaining their structural condition is important for ensuring safe and uninterrupted travel. In many cases, infrastructure is still inspected manually at regular intervals, which requires considerable time and effort and does not provide continuous information about the condition of the structure. To overcome these limitations, this project presents a Smart Monitoring System that combines IoT-based sensing with intelligent data analysis. The proposed system enables continuous observation of infrastructure health and helps identify abnormal conditions at an early stage, supporting timely maintenance and improving overall structural safety. The proposed model employs multiple sensors to measure important structural parameters such as vibration, tilt, load, and stress. These sensors are connected to an ESP32 controller, which collects and transfers the data to a cloud platform using lightweight communication methods like MQTT. The cloud environment stores and processes the incoming data for continuous monitoring and analysis. Machine learning is integrated into the proposed system to analyze sensor data and identify unusual patterns that may indicate potential structural problems. Along with this, rule-based conditions are applied to interpret changes in sensor measurements and provide an indication of possible crack-related damage. The collected information is presented through a web-based dashboard, where users can view live sensor readings, historical trends, overall structural condition, and warning notifications when the monitored parameters reach unsafe levels. The proposed system transfers processed sensor readings rather than continuous raw signals, helping to lower data traffic and maintain reliable communication when network connectivity is limited. During testing, the system was able to monitor structural parameters with minimal delay and identify abnormal changes in the collected data. Overall, the solution provides a cost-effective and practical method for improving infrastructure safety, assisting maintenance planning, and reducing the need for frequent manual inspections.

Keywords: *Smart Infrastructure Monitoring, Internet of Things (IoT), Structural Health Assessment, ESP32, MQTT-Based Communication, Edge Computing, Machine Learning, Anomaly Detection, Sensor Data Analysis, Real-Time Monitoring, Predictive Maintenance, Cloud Data Storage, Infrastructure Safety, Low-Bandwidth Communication.*

1. Introduction

Bridges and road networks are important parts of modern transportation infrastructure, supporting the movement of people, goods, and services. These structures are exposed to continuous traffic loads, weather conditions, environmental effects, and gradual material deterioration. Over a period of time, such factors can weaken structural components and affect their stability. At present, infrastructure condition is often evaluated through scheduled inspections carried out by personnel. Although these inspections are useful for identifying obvious defects, they do not provide continuous information about how a structure behaves between inspection periods. As a result, small changes in vibration, load distribution, or inclination may remain unnoticed and can develop into more serious structural problems. Manual inspection also requires considerable time, manpower, and maintenance expenditure, particularly when a large number of structures need to be monitored. Conventional visual inspection has further limitations when dealing with changes that are difficult to identify from the surface. Variations in vibration, excessive loading, or small changes in tilt may provide early indications of structural deterioration, but these conditions may not always be visible during a routine inspection. Since assessments are normally performed at predetermined intervals, there can be significant gaps between two inspections. This makes it difficult for maintenance teams to respond immediately to unexpected changes and often results in corrective maintenance being carried out only after a problem becomes noticeable.

The development of IoT devices and embedded controllers provides an opportunity to improve this process through continuous data collection. Sensors connected to an ESP32 can be used to obtain measurements related to vibration, load, tilt, and other structural parameters. The collected readings can then be transferred to a cloud platform using MQTT, which is well suited for lightweight communication between IoT devices and remote services. However, some existing monitoring solutions require specialized equipment or generate large amounts of data, which can increase implementation and communication costs. These limitations can make such systems difficult to deploy across large infrastructure networks or in locations where network connectivity is limited. To address these concerns, the proposed Smart Monitoring System combines IoT-based sensing, cloud storage, and intelligent data analysis for continuous infrastructure monitoring. Multiple sensors collect structural measurements, while the ESP32 performs initial processing before forwarding the relevant information to the cloud. Instead of continuously transmitting raw sensor signals, the system sends processed readings, thereby reducing unnecessary data transfer and improving communication efficiency. Machine learning is incorporated to identify unusual patterns in the collected measurements, while predefined rules are used to evaluate conditions associated with excessive load, abnormal tilt, vibration, stress, and possible crack development. The proposed system also provides a web-based monitoring interface through which users can view current sensor readings, historical trends, structural status, and warning notifications. By combining continuous sensing with automated analysis, the system can provide an early indication of potentially unsafe conditions and assist maintenance personnel in making timely decisions. The approach is intended to reduce dependence on periodic manual inspections while providing a practical and relatively low-cost method for monitoring infrastructure. Overall, the system demonstrates how IoT, cloud technologies, and intelligent data analysis can be combined to support safer, more reliable, and more efficient infrastructure management.

2. Literature Survey

Research in infrastructure health monitoring has increasingly moved toward the use of sensor networks, IoT platforms, and automated data analysis[1]. Recent work has explored the continuous measurement of structural parameters such as vibration, load, and tilt to understand the condition of bridges and roadway structures. IoT-based monitoring systems allow[3] data from sensors placed at different locations to be collected and transferred to a central platform, reducing the need to depend entirely on periodic physical inspections and improving the availability of structural information [4][6]. Traditional structural monitoring techniques generally relied on individual sensors and predefined threshold values to identify unusual behaviour. Such approaches typically examined characteristics of signals such as vibration, strain, or displacement. However, sensor readings can be influenced by environmental conditions and variations in operating conditions, which can make simple threshold-based techniques less reliable. The use of machine learning has therefore become an important research direction, with classification and anomaly detection methods being explored to identify unusual structural behaviour more effectively [1]. Researchers have also investigated the use of multiple types of sensors within a single monitoring framework. Combining measurements from different sensors can provide a broader view of structural behaviour and help identify relationships between different physical parameters. Despite these developments, the availability of suitable datasets remains a challenge. Many studies use limited, laboratory-generated, or simulated data, which can make it difficult to determine how well the developed models will perform when applied to different structures and real-world conditions [4]. Real-time monitoring has become another important area of research. Several proposed systems provide continuous sensor acquisition together with dashboards and warning mechanisms so that users can observe structural conditions remotely. Although these features improve accessibility, many implementations still depend mainly on fixed threshold values for generating alerts. Such approaches may provide warnings after a parameter crosses a predefined limit but offer limited capability for identifying developing problems or predicting future structural conditions [6][8]. Communication efficiency is also an important consideration in IoT-based infrastructure monitoring. Systems that continuously transmit large quantities of raw sensor information can place additional demands on network bandwidth and processing resources. This becomes particularly challenging when monitoring infrastructure in remote locations or areas with unreliable connectivity. Therefore, efficient processing and transmission of relevant sensor information are important for developing monitoring systems that can operate under practical network constraints [7]. Another limitation observed in existing approaches is the relatively limited integration of different analytical methods and monitoring functions. In some systems, data collection, anomaly detection, visualization, and alert generation are implemented as separate or basic functions. As a result, the available information may not always provide a complete picture of the infrastructure's condition. Improving the connection between sensor measurements, intelligent analysis, and user-oriented visualization can make monitoring systems more useful for maintenance and decision-making. The proposed system addresses these limitations by combining continuous IoT-based sensing with local data processing, cloud storage, and intelligent analysis. Rather than transferring unnecessary raw sensor streams, the system processes the measurements and communicates structured sensor information, thereby helping to reduce network traffic [2]. Machine learning is used to identify abnormal patterns in the collected data, while rule-based analysis evaluates conditions associated with excessive load, unusual vibration, tilt, stress, and possible crack development. In addition, the proposed system provides a web-based dashboard that brings together real-time measurements, historical graphs, structural status, and automated alerts. This allows users to monitor the infrastructure from a single interface and respond more quickly when critical conditions occur. By combining IoT sensing, efficient communication, machine learning, and real-time visualization, the proposed approach aims to provide a practical and cost-effective framework for infrastructure health monitoring while supporting timely maintenance and improved structural safety [7].

3. System Architecture

The proposed system is designed as a layered architecture that brings together sensor-based data collection, local processing, IoT communication, cloud storage, and intelligent analysis. At the first level, different sensors are placed at suitable locations on the infrastructure to measure important parameters such as vibration, tilt, load, and stress. These sensors are connected to an ESP32 microcontroller, which serves as the main interface between the sensing devices and the monitoring platform. Before the readings are transmitted, the ESP32 performs basic processing and filtering to minimize unwanted variations in the collected data [1]. After preprocessing, the sensor readings are organized into a structured data format and transferred to the cloud using MQTT. Since MQTT is designed for lightweight device-to-server communication, it helps reduce unnecessary network traffic and is suitable for applications where connectivity or bandwidth may be limited [9]. The communication layer maintains the flow of monitoring data between the ESP32 and the backend while supporting continuous data transmission with low communication overhead [10].

The backend forms the central processing and storage component of the system. A cloud-based database stores the incoming sensor measurements along with their corresponding timestamps, allowing previous readings to be retrieved for historical analysis and trend identification. Machine learning techniques are applied to the collected data to recognize patterns that differ from normal structural behavior. These

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detected abnormalities can be used as indicators of possible structural problems or increased risk [11]. In addition to machine learning, predefined rules are used to evaluate combinations of sensor readings and identify conditions that may be associated with cracks, excessive loading, abnormal vibration, or structural instability. As shown in Figure 1 Architecture Diagram - It represents the system architecure, explains us about the working of the hardware model used for the damage detection and prediction.

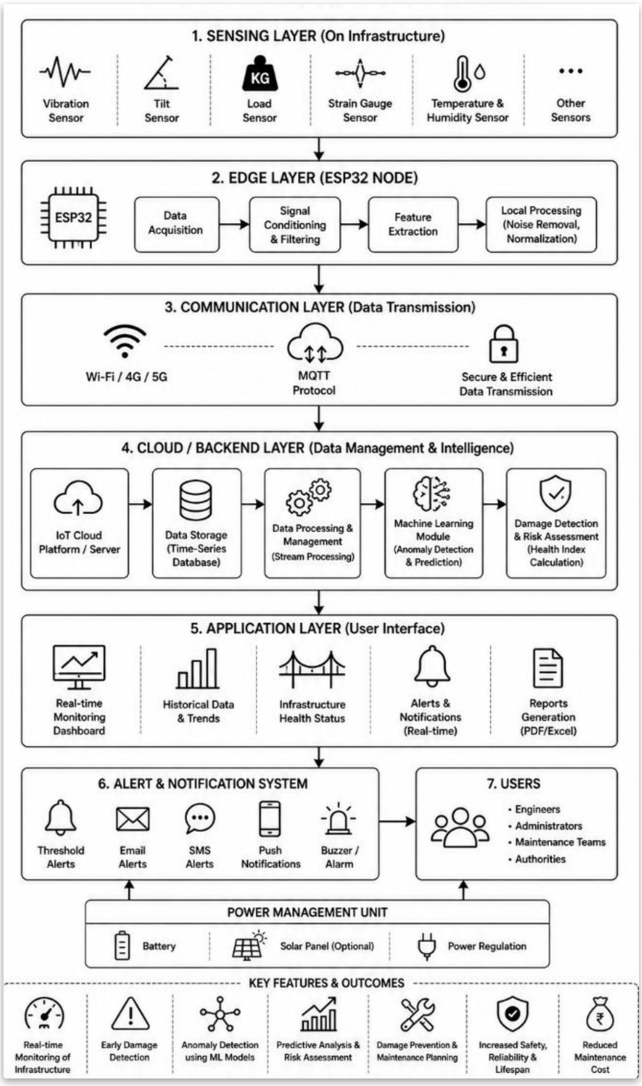

Figure 1 Architecture Diagram - It represents the system architecure, explains us about the working of the hardware model used for the damage detection and prediction

The application layer is centered around a web-based dashboard that allows users to monitor the infrastructure remotely. It presents current sensor readings along with historical data and the overall condition of the monitored structure. Graphs and tables are used to make the sensor information easier to understand, while an alert mechanism informs the user when a measured parameter crosses its specified safety limit [12]. This provides maintenance personnel with a convenient way to observe structural changes and respond to critical conditions. A server-side module, developed using technologies such as Node.js or an equivalent backend framework, coordinates communication between the monitoring devices, cloud services, and dashboard. It handles API requests, data exchange, and synchronization of information between the different layers of the system. Security features such as user authentication can also be incorporated to restrict access and protect infrastructure-related information from unauthorized users [13][14]. The architecture is structured to improve the overall efficiency of the monitoring process. Initial processing at the edge reduces the amount of unnecessary information that needs to be transmitted, while structured data communication helps control bandwidth consumption. The modular separation of sensing, communication, processing, storage, and visualization also makes it easier to expand the system in the future. This design allows additional sensors, analytical models, or monitoring features to be integrated without significantly changing the existing framework. Overall, the architecture supports continuous infrastructure monitoring and provides flexibility for deployment under different network conditions [15].

4. Implementation & Methodology

The proposed system is organized as a distributed, multi-layer framework for continuous infrastructure health monitoring and intelligent analysis. It combines sensor-based data collection with processing at the edge and cloud-based data analysis to provide timely structural information. This approach helps reduce communication delays, improves the efficiency of data transfer, and supports the early identification of abnormal structural conditions[16 – 18].

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4.1.Edge Data Acquisition and Normalization

Instead of transmitting raw sensor signals, which would increase communication overhead B_s, the system performs preprocessing at the edge device (ESP32). Let the structural state be represented as a feature set:

$$S=\{s\_i|s\_i=(v\_i,t\_i,l\_i,\sigma\_i)," " i\in T\}$$

where v_i, t_i, l_i, and σ_idenote vibration, tilt, load, and stress measurements at time instance i. To ensure consistency across varying environmental conditions and sensor ranges, Min-Max normalization is applied:

$$s_i' = \frac{s_i - s_{\min}}{s_{\max} - s_{\min}}$$

where s_minand s_maxrepresent the minimum and maximum observed values within a time window. This normalization ensures that the processed data remains scale-invariant and suitable for machine learning models [1].

4.2.Feature Extraction and Structural Mapping

To analyse the structural behaviour, the system derives additional features from raw sensor inputs. For example, the rate of change of vibration and tilt is computed to identify dynamic structural variations. The Euclidean representation of multi-sensor deviation is defined as:

$$D_i = \sqrt{(v_i - v_{ref})^2 + (t_i - t_{ref})^2 + (l_i - l_{ref})^2}$$

where v_ref,t_ref,l_refrepresent baseline values under normal conditions. A feature vector representing the structural state is defined as:

$$V_s = [v_i, t_i, l_i, \sigma_i, D_i]$$

This vector is used as input to anomaly detection models. Additionally, threshold-based logic is incorporated to detect potential crack formation when abnormal patterns are observed across multiple parameters [4].

4.3.Real-time Data Transmission & Synchronization

The communication layer employs lightweight protocols such as MQTT to ensure efficient data transfer between the edge device and the cloud server. The system separates the data plane (sensor data transmission) from the control plane (system management and configuration).

The probability of successful data delivery P(D)can be modeled as:

$$P(D)=P(C)\cdot(1\text{-}P(L))$$

where P(C)represents connectivity reliability and P(L)denotes packet loss probability. To reduce bandwidth consumption, only structured feature data is transmitted instead of raw signals, significantly lowering data size while maintaining analytical accuracy [2]. Backend services handle data synchronization, storage, and API-based access for real-time visualization.

4.4.Network Architecture and Latency Optimization

The system follows a cloud-assisted architecture where edge devices communicate with a centralized backend for processing and visualization. The end-to-end latency is defined as:

$$L\_e2e=T\_acq+T\_proc+T\_trans+T\_cloud+T\_vis$$

Where T_acq is sensor data acquisition time, T_proc is edge preprocessing time, T_trans is communication delay, T_cloud is cloud processing time and T_vis is dashboard rendering time. By performing initial processing at the edge and transmitting only optimized data, the system minimizes T_transand overall latency. This ensures near real-time monitoring performance suitable for practical deployment scenarios [6].

4.5.Machine Learning-Based Anomaly Detection

To detect unusual patterns in the collected structural data, the system uses a lightweight machine learning technique based on the Isolation Forest algorithm. The method identifies data points that differ significantly from the normal observations by examining how easily they can be separated within the generated isolation trees [4]. An anomaly score is assigned to each input feature vector according to its corresponding isolation depth in the model. If:

$$A(s) > \theta$$

where θ is a predefined threshold, the system classifies the state as anomalous. This approach enables early detection of potential failures and supports predictive maintenance strategies.

4.6.Visualization and Alert Mechanism

The processed data is visualized through the web-based dashboard that displays real-time parameters, historical trends, and system status. Alerts are generated when monitored values exceed predefined thresholds or when anomalies are detected by the machine learning model. Notification mechanisms include visual alerts, messages, and optional hardware indicators such as buzzers and indicators [7].

5. Technical Stack

The proposed system architecture is designed to balance computational efficiency, real-time responsiveness, and scalable data handling. The technical stack is organized into multiple functional layers, enabling modular development and efficient integration of sensing, communication, analytics, and visualization components.

5.1.Edge Layer & Embedded Processing

The sensing and edge processing layer is built around the ESP32 microcontroller, which interfaces with various sensors such as vibration, tilt, load, and stress sensors. This layer is responsible for real-time data acquisition, signal conditioning, and preliminary preprocessing. By performing operations such as filtering, normalization, and feature extraction locally, the system reduces unnecessary data transmission and improves response time. The use of embedded processing ensures efficient handling of sensor data with minimal power consumption, making it suitable for continuous monitoring applications [1].

5.2.Communication Layer

For real-time data transmission, the system utilizes Wi-Fi connectivity along with lightweight communication protocols such as MQTT. This layer is designed to support efficient and reliable data exchange between edge devices and the cloud backend. MQTT follows a publish-subscribe model, enabling asynchronous communication and reducing network overhead. Compared to traditional HTTP-based communication, this approach significantly lowers bandwidth consumption and improves scalability in distributed environments [2][6].

5.3.Application & Backend Layer

The backend layer is responsible for handling core application logic, data processing, and API management. Technologies such as Node.js or Python-based frameworks (e.g., Flask) are used to implement RESTful services that manage incoming data streams and provide endpoints for visualization and control. This layer also integrates machine learning models for anomaly detection and structural risk analysis. The backend ensures efficient handling of concurrent data requests and supports real-time synchronization between system components [3].

5.4.Data Persistence Layer

Data storage is managed using a database system such as MongoDB or SQL-based solutions, depending on system requirements. The database stores time-series sensor data, system logs, and historical records required for analysis and reporting. Proper indexing mechanisms are employed to optimize query performance and ensure scalability as the volume of data increases. The persistence layer maintains data integrity and supports long-term monitoring and predictive analytics [5].

5.5.Visualization & User Interface Layer

The application interface is implemented as a web-based dashboard using technologies such as HTML, CSS, and JavaScript, along with visualization libraries like Chart.js. This layer provides real-time monitoring of structural parameters, graphical representation of data trends, and tabular insights. It also includes alert mechanisms that notify users when system parameters exceed predefined thresholds. The user interface is designed to be intuitive and responsive, enabling effective decision-making for infrastructure management [7].

5.6.Intelligent Analysis Layer

The system includes an intelligent analysis layer that uses machine learning methods, including the Isolation Forest algorithm, to detect unusual patterns in the collected sensor data. The incoming measurements are examined to identify deviations

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from normal structural behavior that may indicate potential risks. In parallel, rule-based conditions are used to recognize situations such as excessive loading and possible crack development by considering multiple sensor parameters together. Combining machine learning with rule-based analysis provides a more dependable monitoring mechanism and supports remote assessment of infrastructure conditions [4].

6. Results & Discussion

The proposed Smart IoT-based infrastructure monitoring system is assessed using three main performance measures: response time, anomaly detection accuracy, and data transmission efficiency. The evaluation results indicate that the system is capable of monitoring structural conditions in real time, identifying unusual behavior through intelligent analysis, and transmitting relevant data with efficient use of network resources.

6.1.Quantitative Latency Analysis

The primary performance indicator for real-time monitoring systems is end-to-end latency (L_e2e), which determines how quickly sensor data is acquired, processed, and visualized. The proposed system, which incorporates edge processing and lightweight communication protocols, is compared with traditional cloud-dependent monitoring architectures [6].

Table 1 Network Performance and Latency Comparison

System Type	Average Latency (ms)	Jitter (ms)	Packet Loss (%)
IoT Optimized System (Proposed)	60 ± 8	3.5	< 0.2
Traditional Cloud-Based System	175 ± 20	14.2	1.4

The reduction in latency is achieved by minimizing dependency on centralized processing and eliminating redundant data transmission. The latency improvement can be expressed as:

$$\Delta L = Lcloud - Ledge \approx Tcloud + Tbuffer$$

The results indicates that Le2e remains below the 100ms, ensuring timely detection of structural abnormalities and enabling real-time decision-making [2].

6.2.Anomaly Detection Accuracy

The accuracy of the machine learning model used for structural health assessment is evaluated using sensor data collected under simulated and controlled conditions. The system employs an Isolation Forest-based anomaly detection model to identify deviations from normal structural behaviour [4].

- Normal Condition Detection Accuracy: 95.2%
- Anomaly Detection Accuracy: 91.8%
- False Positive Rate: < 5%

The application of a normalized sensor inputs improves model stability and ensures consistent performance across varying environmental conditions such as noise and temperature fluctuations [1].

6.3.Bandwidth Optimization Analysis

An important contribution of the system is the reduction in network bandwidth usage through structured data transmission. Instead of transmitting raw sensor signals continuously, the system sends processed feature data.

The bandwidth reduction is calculated as:

$$B_{red} = \left(1 - \frac{B_s}{B_r}\right) \times 100\%$$

where:

B_r = raw data transmission rate (~500 KB/s)

B_s= structured data transmission rate (~20 KB/s)

This results in an approximate 96% reduction in bandwidth usage, enabling the system to operate effectively even in low-bandwidth environments [2].

6.4.System Throughput and Backend Performance

The backend system, implemented using lightweight server frameworks and database optimization techniques, is evaluated under concurrent request conditions.

- Average Response Time (T_resp): 30 ms
- Concurrent Handling Capacity: Up to 500 requests
- Query Complexity: O(log⁡n)using indexed

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database structures

The use of efficient indexing mechanisms ensures fast data retrieval and scalability as the system grows in size and complexity [5].

6.5.Discussion of Findings

The evaluation of the proposed system indicates that it can overcome several limitations associated with conventional infrastructure monitoring, particularly the lack of continuous observation, communication overhead, and delayed response to structural changes and updates. By combining edge processing with IoT communication, the system performs preliminary analysis close to the sensing unit before forwarding the required information to the backend. This helps reduce unnecessary processing and communication delays while allowing abnormal sensor patterns to be identified at an early stage. The use of structured sensor information also helps reduce the amount of data transmitted over the network. This makes the system more suitable for locations where internet connectivity may be limited or unreliable. In addition, the combination of machine learning-based anomaly detection and rule-based assessment provides two complementary methods for evaluating the condition of the monitored structure. Machine learning can identify unusual patterns in sensor readings, while predefined conditions can be used to recognize events such as excessive loading or abnormal structural behaviour. Unlike conventional inspection procedures, the proposed system continuously records information from the infrastructure. The stored sensor readings provide a historical record that can be examined to understand how the structure changes over time. Monitoring several parameters simultaneously, including load, stress, vibration, and the tilt, gives a more detailed representation of structural behaviour than relying on a single measurement. In particular, load monitoring can indicate when the weight associated with vehicles approaches or exceeds the defined safe capacity of the structure. Vibration and tilt measurements provide additional information about unusual movement or changes in the structural condition. When a monitored parameter reaches a critical level, the alert mechanism can immediately notify the responsible personnel instead of waiting for the next scheduled inspection. This can provide additional time for inspection and corrective action, potentially reducing the severity of damage and associated maintenance costs. The web-based dashboard improves the usability of the system by presenting sensor measurements, graphs, tables, and structural status information through a single interface. Users can therefore observe current conditions as well as review previous measurements for comparison. Cloud-based data storage further allows authorized users to access the monitoring information remotely and maintain a centralized record of infrastructure conditions. Another advantage of the proposed framework is its modular structure. Additional sensors can be incorporated depending on the type and requirements of the infrastructure being monitored. This makes the approach adaptable to bridges, roadways, flyovers, and other structures where continuous condition assessment is required. The use of relatively low-cost components such as the ESP32 and commonly available sensors also makes the prototype more accessible than specialized industrial monitoring equipment. Continuous automated monitoring can reduce the amount of routine manual observation required from maintenance personnel. More importantly, identifying abnormal conditions at an early stage provides engineers with an opportunity to investigate the affected structure before the problem becomes severe. As the system collects more historical data, the machine learning component can also be refined to improve anomaly identification and support more reliable risk assessment. Overall, the results demonstrate the potential of combining IoT, edge processing, cloud storage, and the intelligent data analysis for infrastructure health monitoring. The proposed system provides a scalable and the practical approach for a continuous structural assessment, helping improve safety, support timely maintenance decisions, reduce inspection-related effort, and enhance the long-term reliability of critical infrastructures [7].

Conclusion

The proposed work presents an IoT-based approach for continuously assessing the condition of bridges and other infrastructure. The system combines ESP32-based sensing, edge processing, MQTT communication, cloud storage, and machine learning to monitor important structural parameters such as vibration, tilt, load, and stress. Processing the sensor information closer to the source helps reduce unnecessary communication and supports faster availability of monitoring data. An important feature of the system is its use of processed and structured sensor readings rather than continuously transmitting raw signals. This reduces the amount of information transferred through the network and makes the solution more suitable for locations where connectivity or bandwidth may be limited. The experimental observations also indicate that the system can provide monitoring information with low response delay, supporting its use in real-time infrastructure safety applications [2][6]. The inclusion of anomaly detection further helps identify sensor patterns that may indicate unusual structural behaviour and can assist in planning preventive maintenance activities [4]. The architecture is organized into separate sensing, communication, processing, storage, and visualization components. This modular arrangement makes it possible to modify or extend individual parts of the system without redesigning the complete framework. The web dashboard provides users with access to current measurements, historical information, graphs, and structural status, while the alert mechanism helps communicate critical conditions promptly [7]. There is considerable scope for improving the system in future developments. Deep learning models could be explored for more detailed prediction of structural damage, while computer vision techniques could be incorporated to detect visible cracks directly from infrastructure images. The system could also be extended through a combination of edge and cloud processing to improve scalability and computational efficiency. Mobile application support, weather sensors, GPS-based monitoring, and integration with larger infrastructure management platforms could further increase its practical usefulness [1]. Overall, the proposed system provides a practical, scalable, and cost-effective framework for smart infrastructure monitoring. By reducing dependence on periodic manual inspections and providing continuous information about structural conditions, it can assist maintenance teams in identifying potential problems earlier. With further development of AI-based crack detection, advanced predictive models, remote notifications, and large-scale cloud deployment, the system has the potential to become a more comprehensive solution for improving the safety, reliability, and long-term management of bridges and roadways.

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