Artificial Intelligence Based Structural Health Monitoring Of Bridges

Lieutenant Colonel Vaibhav Srivastava[1], Prof DI Narkhede[2]

[1]M-Tech (Structures), Faculty of Civil Engineering, College of Military Engineering
Pune - 411031, India
bhav623@gmail.com

[2] Professor, Faculty of Civil Engineering, College of Military Engineering
Pune - 411031, India
di_narkhede@yahoo.com

DOI: 10.29322/IJSRP.15.05.2025.p16137
https://dx.doi.org/10.29322/IJSRP.15.05.2025.p16137

Paper Received Date: 16th March 2025
Paper Acceptance Date: 18th April 2025
Paper Publication Date: 26th May 2025

Abstract

The global demand for sustainable, reliable, and resilient infrastructure has significantly increased in the face of aging bridge networks, rapid urbanization, and climate-induced stresses. Traditional inspection-based approaches to bridge maintenance, heavily reliant on manual visual checks, have proven inadequate in their ability to detect early-stage deterioration, assess real-time conditions, and forecast future failures. These methods are not only time-consuming and resource-intensive but are also vulnerable to human error and inconsistencies arising from lighting, weather conditions, and surface irregularities. In response to these limitations, this technical paper presents a comprehensive, AI-powered, and digitally integrated methodology for the structural health monitoring (SHM) of bridges and civil infrastructure. It combines the power of LiDAR-based point cloud data, deep learning techniques, digital twin modelling, simulation analytics, and real-time dashboards to establish a predictive, autonomous, and highly scalable SHM framework. The research highlights significant technological advancements and engineering practices that align with modern infrastructure safety, longevity, and cost-effectiveness [1],[5].

The research demonstrates that AI-based SHM systems, when built upon LiDAR imaging, image segmentation, digital twin simulation, and predictive modelling, can replace or augment traditional inspection methods [4],[6],[7]. The system reduces the reliance on human judgment, enhances measurement accuracy, and brings consistency to the critical task of structural monitoring. By automating detection, enabling forecast-driven planning, and integrating visual interfaces, this technical paper delivers a scalable and deployable SHM solution for infrastructure operators, especially in resource constrained or high-risk environments. The methodology is field-ready, adaptable to different bridge typologies, and primed for integration into smart city ecosystems and national infrastructure safety programs [1], [5].

As bridges around the world continue to age, such AI-driven SHM pipelines will become essential tools in the arsenal of engineers and authorities committed to maintaining public safety, reducing lifecycle costs, and modernizing infrastructure management [2],[3].

Index Terms

LiDAR, Crack Detection, Structural Health Monitoring (SHM), OpenCV, Point Cloud, Bridge Safety, Image Processing, Height Map, AI, Artificial Intelligence, AI-Based Inspection, Digital Twin, Modular Bridges, Sensor Integration, ANSYS Simulation, Real-Time Monitoring, Dashboard Visualization, Civil Infrastructure.

1. Introduction

The structural integrity of bridges is critical to public safety and economic continuity. Traditional inspection regimes, dependent on visual assessments and manual documentation, are susceptible to human error, inconsistency, and environmental dependency. Additionally, they often fail to detect minor yet progressive damage in time to prevent large-scale deterioration or collapse [8]. The increasing demand for reliability, especially in post-disaster or aging urban infrastructure, necessitates the deployment of intelligent, sensor-integrated, and AI-driven SHM systems.

This paper introduces a novel integration of **LiDAR point cloud data**, **OpenCV-based image processing**, and **automated crack segmentation** within an SHM context [4],[6]. This methodology supports real-time monitoring, automates crack detection, and quantifies geometric properties, thereby facilitating proactive maintenance and lifecycle optimization. Compared to photogrammetry-based methods, LiDAR provides centimeter-level accuracy and independence from ambient light, making it suitable for both day and night inspections [6]. The technique is evaluated on multiple bridge types and sets the stage for integration with full-scale digital twin platforms in civil infrastructure.

2. Evolution of Structural Health Monitoring (SHM)

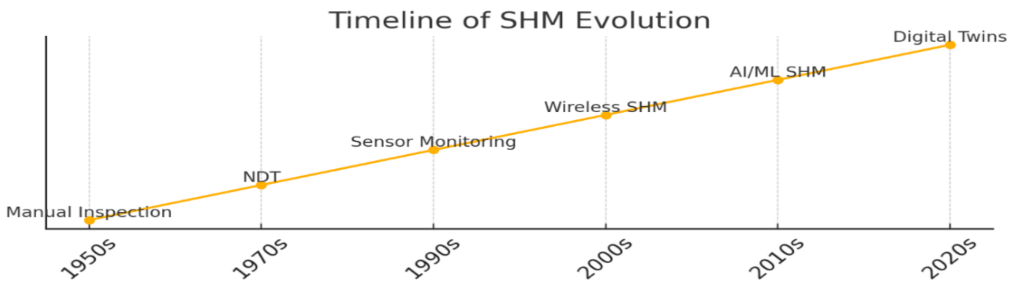
SHM has evolved from passive, periodic visual inspections to data-driven, continuous assessment systems powered by sensors and real-time analytics [8]. Initially, SHM was limited to static strain gauge systems and accelerometers affixed at known stress points. These systems, while useful, lacked spatial resolution and coverage [9]. Crack Detection and segmentation has been carried out earlier by analysing photographs using software like YOLO [15],[18] This concept also involves using AI for automatic detection and segmentation of cracks for further assessment on ground. However, the drawback of this technique is that it can often be misleading as dirt marks, paint etc can also be detected as cracks in a photograph. Also, the crack width, length and depth cannot be computed.

With the advent of wireless sensor networks, edge computing, and AI, the domain of SHM has expanded into:

(a) **Real-time vibration analysis**
(b) **Displacement and fatigue modeling**
(c) **Crack propagation prediction**
(d) **3D structural deformation tracking**

Notably, SHM has expanded its scope from isolated measurements to full-surface evaluations using optical and LiDAR technologies. LiDAR in particular allows comprehensive surface mapping, enabling anomaly detection over large surface areas and complex geometries. AI and computer vision further empower systems to automate interpretation, bypassing the subjective limitations of human inspection.

In this context, the proposed method integrates dense 3D LiDAR scanning with lightweight image processing for fast, accurate, and field-deployable structural damage analysis.



Timeline of SHM Evolution

Period	Milestone
Pre-1980	Visual inspections and manual logs
1980–1995	Introduction of wired strain and vibration sensors
1995–2010	Emergence of WSNs and basic data logging systems
2010–2017	Adoption of FEM, pattern recognition, IoT systems
2017–Present	AI models, LiDAR integration, and digital twins

Comparative Timeline of the Evolution of Inspection Practices

3. LiDAR Technology in SHM

Light Detection and Ranging (LiDAR) is a remote sensing method that emits laser pulses to measure the distance between the sensor and surrounding objects. The reflected pulses are processed to generate high-resolution 3D point clouds representing surface geometry. LiDAR systems can be terrestrial (static scanners) or mobile (mounted on drones or vehicles), offering flexibility for various SHM applications [4].

3.1 Advantages in Structural Monitoring

(a) **Precision**: Millimeter-level surface resolution suitable for micro-crack detection [6].
(b) **Speed**: Millions of points per second enable large-area scans in short durations.
(c) **Independence from lighting**: Performs well under low visibility and night-time conditions [7].
(d) **Data density**: Allows complete coverage of surfaces including bridge decks, beams, and piers.

ISSN 2250-3153

3.2 Integration with SHM Pipelines

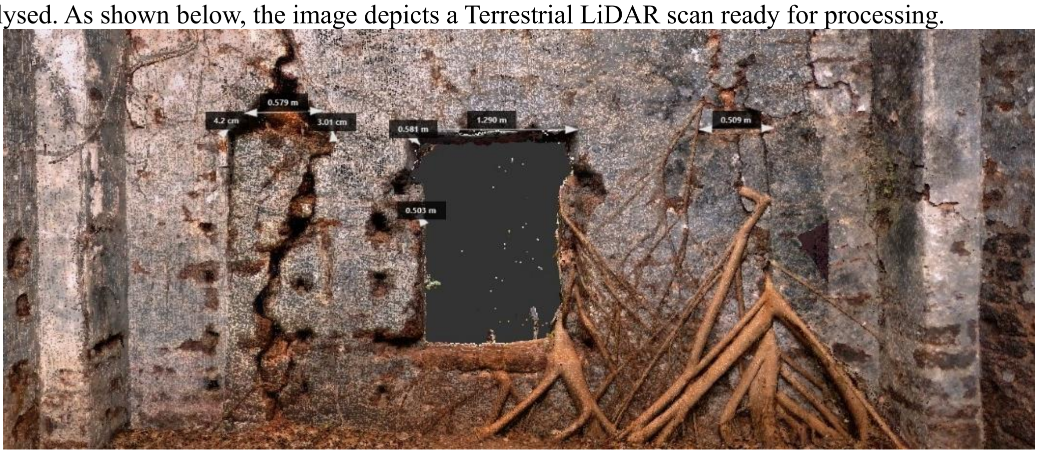
In this framework, LiDAR provides foundational geometry, which is further processed into height maps. These 2D grayscale projections retain the essential topographic features of the bridge surface, thus enabling standard image processing techniques to identify structural anomalies. For the purpose of this research paper two types of LiDAR; one was a **mobile based LiDAR** which came with its own set of limitations and challenges and the second was a **terrestrial radar**. Both systems were used separately to scan structures and detect anomalies in them. The measurement of the anomaly was also carried out. It is imperative and promising to note that with both LiDAR systems measurement of **length, width** and **depth** of any crack or anomaly were possible. The Fig below shows the LiDAR scan image of a structure captured **using a <u>low-cost</u> technology, i.e. a <u>mobile phone</u> (easily available technology)**. The same can also be done by using more powerful terrestrial or air borne radars that are more accurate with millions of points collected per second. However, the same would be a huge data set and would require powerful processors to process in a suitable time frame [4], [10].

<u>A Sample Lidar Scan of a Small Structure</u>

3.3 Crack Detection and Segmentation Using LiDAR Images

Crack detection and segmentation using Light Detection and Ranging (LiDAR) technology represent a significant advancement in structural health monitoring (SHM), particularly for bridge infrastructure. LiDAR captures high-resolution three-dimensional (3D) point clouds, enabling precise surface mapping and defect identification with superior accuracy compared to traditional imaging methods. The integration of LiDAR with machine learning (ML) and deep learning algorithms has significantly improved automated crack detection, allowing for precise localization and quantification of structural anomalies.

For the purpose of this project the LiDAR Images were taken of a isolated structure separately for development and analysis. Structures in distress were selected that could be assessed with the available LiDARs. The same was developed as a concept and successfully analysed. As shown below, the image depicts a Terrestrial LiDAR scan ready for processing.



<u>Sample Terrestrial LiDAR Scan Images ready for Processing</u>

4. Crack Detection and Segmentation Using LiDAR Images

4.1 Data Acquisition and Preprocessing

The SHM pipeline begins with scanning bridge elements using terrestrial LiDAR and exporting the data in .e57 format. The key processing steps are:

(a) **Extraction of XYZ coordinates** using the pye57 Python library.
(b) **Filtering of invalid or NaN values** to ensure point cloud integrity.
(c) **Downsampling and spatial normalization** to prepare data for 2D projection.

4.2 The crack detection process using LiDAR involves **pre-processing** steps such as noise filtering, surface smoothing, and segmentation to enhance feature extraction. Algorithms such as edge detection, and morphological operations. Generally, histogram-based thresholding is commonly applied to LiDAR-generated depth images to delineate crack patterns. **The high-density point clouds generated by LiDAR enable the measurement of crack width, length, and depth, which are critical parameters for**

assessing structural integrity. Moreover, LiDAR's capability to operate in varying lighting conditions and capture sub-millimetre details makes it ideal for inspecting hard-to-reach bridge components. The fusion of LiDAR with other imaging modalities, such as infrared thermography and photogrammetry, further enhances the robustness of crack detection frameworks. Future advancements in AI-driven LiDAR processing, coupled with edge computing, will facilitate real-time defect monitoring, predictive maintenance, and automated decision-making in SHM.

4.3 The initial phase of the crack detection study employed two distinct approaches: Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and the OpenCV (Open Source Computer Vision) library. The DBSCAN algorithm was utilized to identify clusters of points exhibiting minimal height variations, which are indicative of potential cracks. Critical parameters, such as *epsilon* (the neighborhood search radius) and *min_samples* (the minimum number of points required to form a cluster), were carefully calibrated based on the structural dimensions under investigation. The resulting clusters were visually distinguished through color coding and subsequently exported for further analysis [11]. However, a significant limitation of the DBSCAN approach was encountered, as it proved inefficient in loading and visualizing 2D point cloud data within Python's 3D visualization environments. This limitation was primarily due to high computational demands, rendering the method more suitable for high-performance computing systems with advanced hardware configurations. Consequently, the analysis transitioned to the OpenCV library to achieve the research objectives more efficiently.

Using OpenCV, the three-dimensional LiDAR point cloud data were transformed into two-dimensional grayscale height maps, where pixel intensity values encoded elevation information. This conversion facilitated the application of advanced computer vision algorithms to accurately identify surface depressions corresponding to crack formations. Each detected crack was subsequently analyzed to determine its dimensional characteristics, including length, width, and an approximate depth inferred from grayscale intensity variations. The extracted dimensional data were overlaid on the processed images for visualization and concurrently exported to Microsoft Excel to enable structured reporting and further statistical analysis [4], [6].

4.4 Height Map Generation The 3D point cloud is projected onto a 2D grid based on user-defined resolution (e.g., 1 cm/pixel). For each pixel coordinate, the **lowest Z-value (height)** is stored, creating a grayscale image where pixel intensity represents elevation. Cracks appear as localized depressions (darker pixels), distinguishable from the surrounding structure.

Python code:

```
height_map = cv2.normalize(height_map_filled, None, 0, 255, cv2.NORM_MINMAX).astype(np.uint8)
```

4.3 Image-Based Crack Detection

Using OpenCV, the height map is processed through a sequence of steps:

(a) **Gaussian Blurring**: Reduces noise and minor texture inconsistencies.
(b) **Thresholding**: Highlights potential crack regions based on intensity dips.
(c) **Morphological Opening**: Removes small artifacts and bridges gaps between crack segments.
(d) **Contour Detection**: Extracts crack geometry from the cleaned binary image.

Python code:

```
_, thresh = cv2.threshold(blurred, 30, 255, cv2.THRESH_BINARY_INV)
contours, _ = cv2.findContours(clean, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
```

4.4 Crack Measurement and Classification

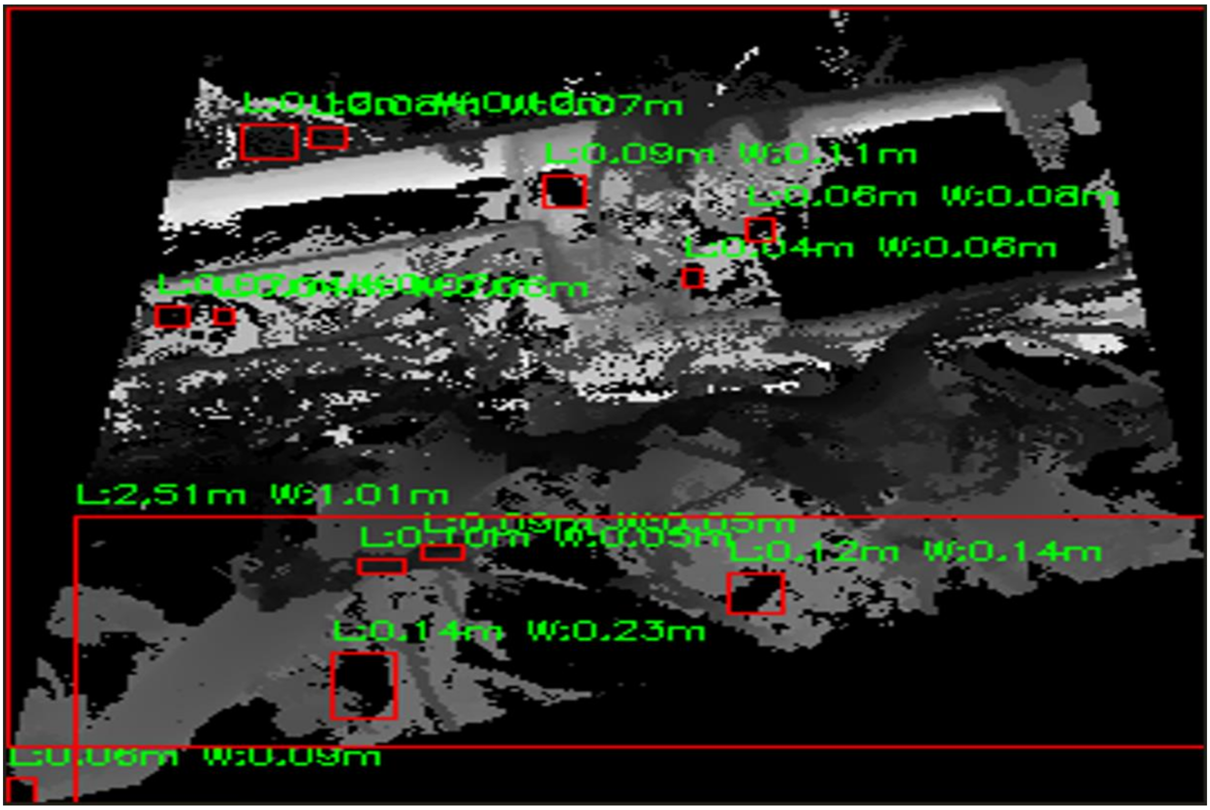
Each contour is measured for:

(a) **Length**: Width of bounding box × spatial resolution
(b) **Width**: Height of bounding box × resolution
(c) **Depth**: Mean grayscale value of the crack region (darker = deeper)

Cracks are then classified by severity:

Severity	**Length (m)**	**Width (m)**	**Depth (est.)**
Minor	< 0.5	< 0.1	< 50 intensity
Moderate	0.5–1.0	0.1–0.2	50–100
Severe	> 1.0	> 0.2	> 100

All crack data is exported to Excel and visualized on the original image with dimensional annotations.



Sample 2D output (.PNG format) using Python

4.5 3D Visualization in Open3D

To correlate detected cracks with their original 3D location, crack pixels are mapped back to the 3D point cloud. Cracks are color-coded red and overlaid on the structure using Open3D:

Python code:

```
pcd.colors = o3d.utility.Vector3dVector(colors)
o3d.visualization.draw_geometries([pcd])
```

This visual aid enhances interpretability for engineers and inspectors.

4.6 Advantages of LiDAR over Traditional Methods

Aspect	Traditional Methods	LiDAR Technology
Contact Requirement	Physical contact needed	non-contact, safe for high or hazardous locations
Resolution	Centimetre-level	Millimetre-level resolution
Data Format	2D images/manual notes	3D geospatial point clouds
Reusability	Single inspection snapshot	Repetitive, longitudinal comparison possible
Automation	Limited	Fully automatable with AI models

4.7 Challenges and Limitations

(a) While LiDAR is transformative, it has certain limitations:
(b) Data Volume: LiDAR scans can exceed hundreds of millions of points, demanding large storage and fast processing resources.
(c) Reflectivity Artifacts: Highly reflective surfaces, such as polished steel or water, can lead to noisy or missing data [10].
(d) Environmental Sensitivity: Rain, fog, and strong sunlight can affect accuracy, especially in aerial LiDAR.
(e) Cost: High-resolution LiDAR scanners and UAVs represent a significant initial investment.
(f) Despite these, advances in edge computing, cloud storage, and low-cost LiDAR units are mitigating many of these drawbacks.

5. Digital Twin Technology for Bridge Monitoring

Digital twin technology originated in aerospace and manufacturing but has recently gained traction in civil infrastructure. In bridge engineering, a digital twin is a continuously updated digital replica of a physical bridge that integrates geometry, material properties, loading scenarios, and real-time sensor inputs. It enables simulations of dynamic performance, stress distribution, and degradation prediction [12].

5.1 Conceptual Workflow

(a) **Bridge Modeling**: CAD-based geometric modeling (e.g., SolidWorks, Revit)
(b) **Structural Simulation**: Static/dynamic analysis in FEA tools (ANSYS)
(c) **Sensor Integration**: Real or virtual sensors embedded in simulation
(d) **Data Stream Mapping**: Real-time update of simulation via IoT inputs
(e) **Dashboard Display**: Visualization in web-based or standalone GUI

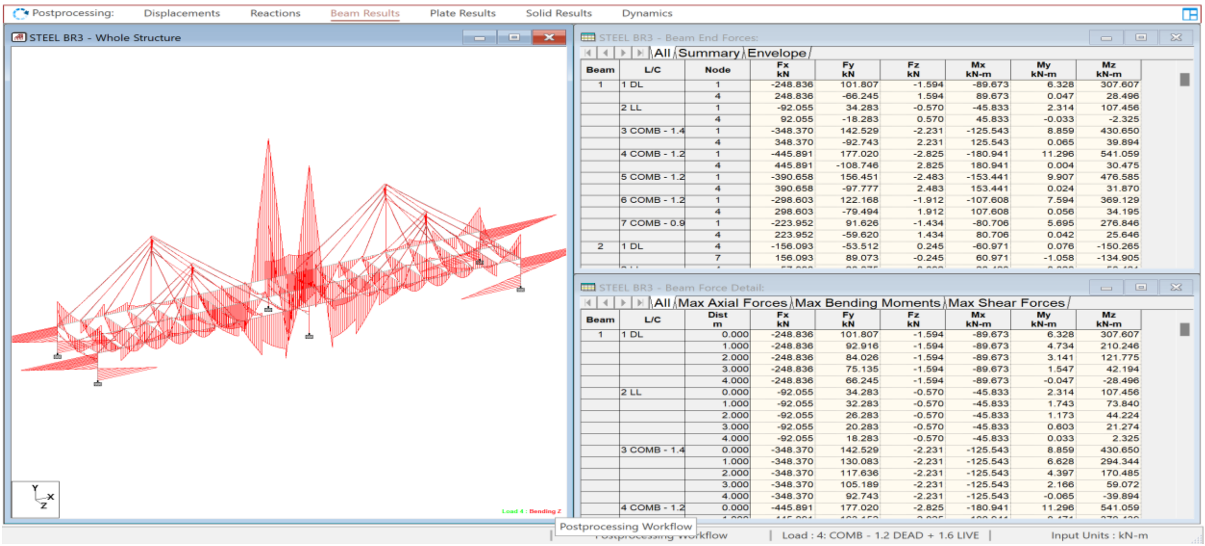
5.2 Use Cases in SHM

(a) Real-time load testing and stress tracking [1]
(b) Crack propagation forecasting [2]
(c) Seismic behavior simulation [5]
(d) Fatigue damage estimation under traffic loads

In this study, a digital twin of a number of bridges (including a Bailey bridge) was developed using SolidWorks for geometric modelling [5] and ANSYS Workbench for structural analysis. The model includes boundary conditions, loading scenarios (IRC Class 70R [13]), and virtual sensors for strain, deflection, and modal frequency.

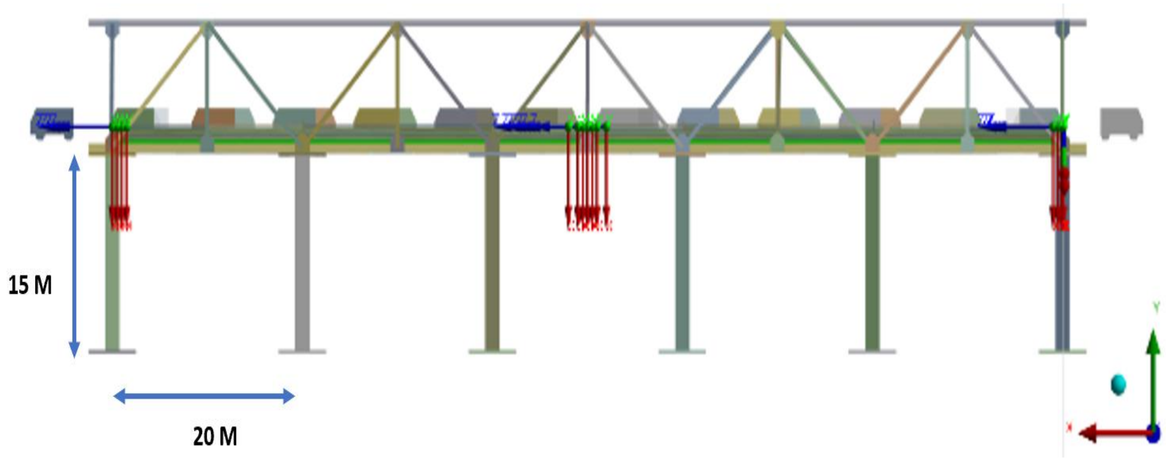
6. Digital Twin in Bridge Monitoring Systems

Digital twin technology [3]is revolutionizing bridge monitoring by creating real-time, data-driven virtual replicas of physical structures. A digital twin is a high-fidelity, continuously updated digital model that integrates real-time sensor data, historical records, and predictive simulations to assess the condition and performance of bridges. This dynamic model enhances structural health monitoring (SHM) by providing insights into potential failure points, stress distribution, and long-term deterioration patterns [12]. Fig below shows a bridge modelled in STAAD.



Analysis of a Bridge Modelled on STAAD

6.1 In order to evaluate Real World Bridges, a Bridge (Fig below) was modelled in Solid Works and exported to Ansys for analysis, as Ansys allows importing of different types of steel modelling and subsequent analysis. Ansys also allows virtual representation of sensors and analysis of the point at which the sensor is placed.



Hypothetical Bridge Modelled in Solid Works and Exported to Ansys for Analysis

6.2 Key Components of a Digital Twin in Bridge Monitoring

(a) **Real-Time Data Integration**. Digital twins incorporate data from IoT-enabled sensors, LiDAR, strain gauges, accelerometers, fiber optics, and environmental monitoring systems to continuously update the virtual model. This live data stream allows for early detection of structural anomalies and stress variations.

(b) **Advanced Computational Modelling**. Finite Element Analysis (FEA) and AI-driven predictive analytics are integrated into the digital twin to simulate stress responses, load distributions, and failure scenarios. Engineers can analyse different conditions such as traffic loads, seismic events, and extreme weather impacts in real time.

(c) **Predictive Maintenance and Anomaly Detection**. By leveraging machine learning (ML) and AI algorithms, digital twins can predict crack propagation, corrosion risks, and material fatigue before visible deterioration occurs. This allows for proactive maintenance, reducing repair costs and enhancing bridge safety.

(d) **Enhanced Structural Performance Monitoring**. The digital twin enables engineers to visualize stress-strain relationships, identify weak points, and assess structural deflections with precision. This is particularly valuable for aging infrastructure and bridges subjected to high dynamic loads.

(e) **Simulation and Scenario Testing**. Engineers can use digital twins to test "what-if" scenarios, such as simulating heavy traffic loads, extreme weather conditions, and impact forces. This helps in refining bridge design improvements and emergency response planning.

(f) **Remote Monitoring and Decision-Making**. The digital twin provides cloud-based, remote access to bridge health data, allowing authorities to monitor multiple structures simultaneously. Automated alerts and decision-support systems enable rapid response to structural risks, minimizing downtime and potential failures.

(g) **Lifecycle Management and Long-Term Sustainability**. Digital twins contribute to asset lifecycle optimization by tracking historical performance data, predicting deterioration trends, and suggesting optimal maintenance schedules. This extends bridge service life while reducing overall operational costs.

(h) **Integration with Augmented Reality (AR) and Virtual Reality (VR)**. Advanced digital twins can be integrated with AR/VR visualization tools, allowing engineers and inspectors to interact with the 3D model, inspect damage points virtually, and streamline inspection processes without physical site visits.

6.3 Digital Twin Architecture

The system architecture consists of:

(a) **LiDAR model** captured from field scans
(b) **Sensor backend** hosted on AWS EC2 using MQTT brokers
(c) **Digital twin front-end** on Unity3D visualizing the mesh
(d) **AI module** analysing input from sensors and predicting anomalies
(e) **Dashboard interface** for engineers to interact with the model

This architecture allows for **real-time updates**, **alerts**, and **inspection planning**.

6.4 Advantages of Digital Twin Technology in Bridge Monitoring

(a) Real-time structural health tracking for early damage detection
(b) Reduced maintenance costs through predictive analytics
(c) Enhanced safety and risk mitigation for critical infrastructure
(d) Improved design validation by simulating real-world stresses
(e) Remote accessibility for multi-location bridge monitoring

Predictive maintenance aims to predict when equipment or infrastructure, like bridges, will fail so that maintenance can be performed just in time to address the issue before it becomes critical. By predicting failures before they occur, predictive maintenance minimizes downtime, reduces repair costs, and extends the life of the infrastructure.

7. Real-Time Monitoring of Bridges Using Sensor Networks

Real-time monitoring bridges the gap between digital simulations and field performance. It involves embedding sensors within the bridge structure to collect data on various physical phenomena [14].

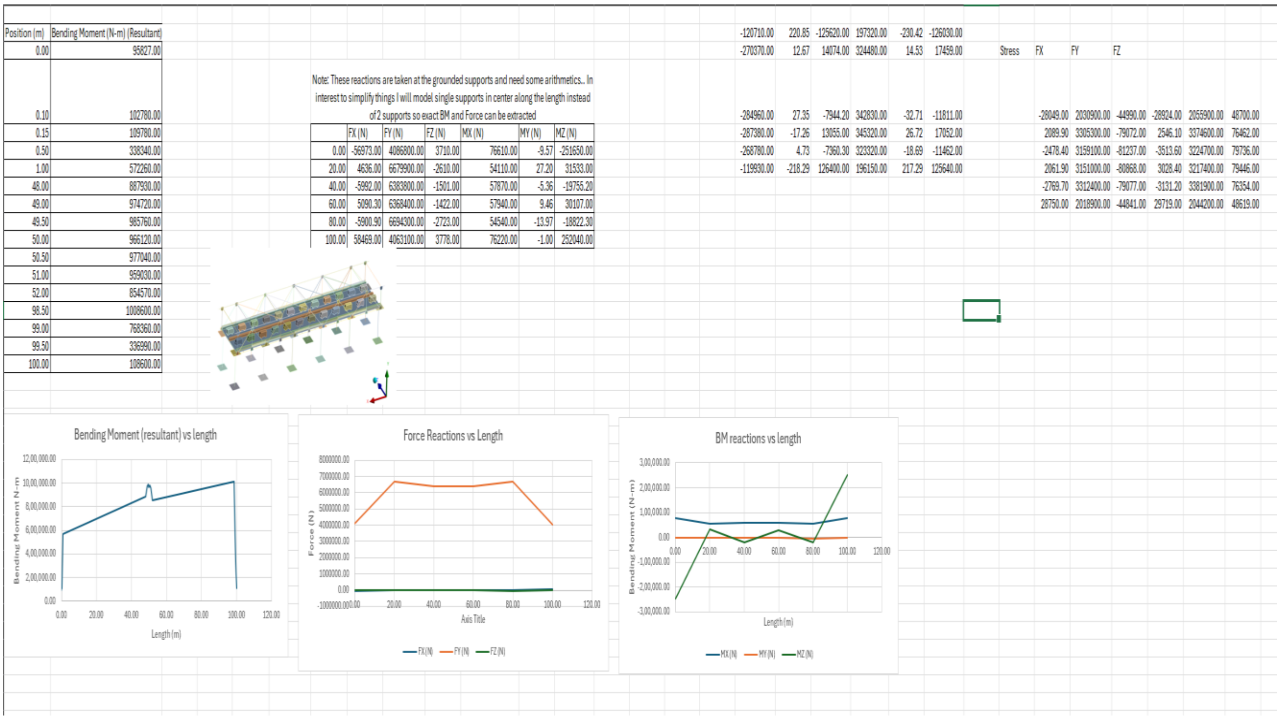
7.1 Sensor Types

(a) **Strain Gauges**: Measure axial strain in concrete and steel members.
(b) **Accelerometers**: Capture vibrations due to dynamic traffic or wind.
(c) **Displacement Sensors (LVDTs)**: Track beam deflection or pier movement.
(d) **Temperature Sensors**: Account for thermal expansion effects.
(e) **Fiber Optic Sensors**: Enable distributed sensing over long distances.

7.2 Signal Processing and Data Acquisition Data is processed using filters (e.g., Butterworth low-pass) to remove noise. Sampling rates depend on dynamic event sensitivity (e.g., 100 Hz for traffic vibration). Sensors are linked via wired or wireless nodes to a central data logger, which pushes data to the digital twin environment.

7.3 Sensor Based Computation of Data

The model of the undermentioned bridge was created digitally, for moving loads of Cl70R, each as per IRC6: 2017. However, since structural analysis software do not facilitate digital sensors and their respective sensor data in corresponding units; points were assumed on the digital model where the data was collected, and the corresponding data was derived through simulation on Ansys software. On the data set so derived the analysis and dash board was created to understand how the sensor data would work [1], [9]. The following reports represent the same.



Bridge Analysis with a Continuously Displaced Load

7.4 The following table presents the structural forces and moments recorded at various positions along the bridge. The key parameters analyzed include axial force (FX), shear forces (FY and FZ), bending moments (MX, MY), and torsional moment (MZ).

Position	FX (N)	FY (N)	FZ (N)	MX (N)	MY (N)	MZ (N)
0.00	-56973.00	4086800.00	3710.00	76610.00	-9.57	-251650.00
20.00	4636.00	6679900.00	-2610.00	54110.00	27.20	31533.00
40.00	-5992.00	6383800.00	-1501.00	57870.00	-5.36	-19755.20
60.00	5090.30	6368400.00	-1422.00	57940.00	9.46	30107.00
80.00	-5900.90	6694300.00	-2723.00	54540.00	-13.97	-18822.30
100.00	58469.00	4063100.00	3778.00	76220.00	-1.00	252040.00

7.5 Observations:

(a) Axial Force (FX):
  (i) Varies between -56973 N (compression) at position 0.00 m to 58469 N (tension) at position 100.00 m.
  (ii) Indicates alternating zones of compression and tension, typical in continuous bridge spans under dynamic loads.
(b) Shear Forces (FY & FZ):

(i) FY (Primary Shear in Y-Direction) is significantly large throughout, peaking at 6694300 N at 80 m. This suggests high vertical shear due to substantial live loads, possibly near mid-span or supports.

(ii) FZ (Shear in Z-Direction) shows smaller values, both positive and negative, indicating minor lateral shear effects, possibly from wind or minor asymmetrical loads.

(c) Bending Moments (MX & MY):

(i) MX (Bending about X-axis) varies between 54110 Nm to 76610 Nm, indicating a consistent flexural demand across the bridge.

(ii) MY (Bending about Y-axis) remains relatively small (max ±27.20 Nm), showing that lateral bending is minor compared to vertical bending, which is typical for bridges designed primarily to resist vertical loads.

(d) Torsional Moment (MZ):

(i) Significant variations observed, with a maximum of 252040 Nm at 100 m. High torsional moments at this end suggest asymmetric loading or geometric discontinuity (e.g., curvature or skewness at the end of the span).

7.6 Engineering Interpretation:

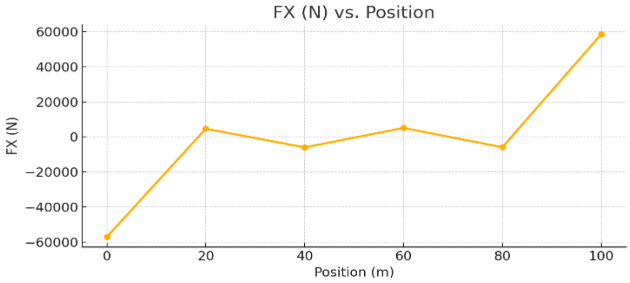
(a) The bridge experiences high vertical shear forces (FY), requiring adequate shear reinforcement or stiffening, particularly near positions 80 m and 20 m.

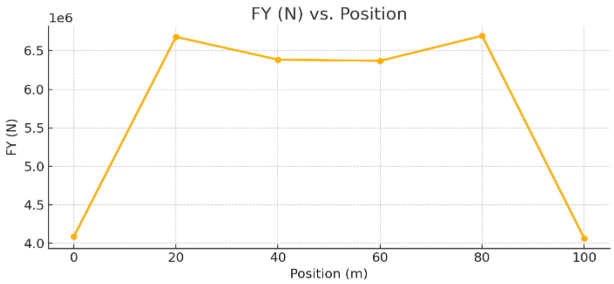
(b) Axial forces alternate between compression and tension, likely indicating the effect of moving loads and varying span supports.

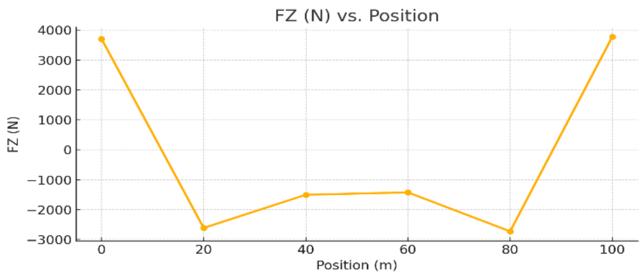
(c) Bending moments and torsional effects are within reasonable design expectations but require careful checking at critical sections (positions 0 m and 100 m) due to higher moment concentrations.

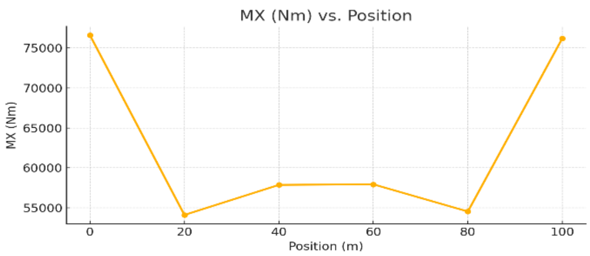
(d) High torsional effects at the ends suggest special consideration for bearing designs and lateral load resistance.

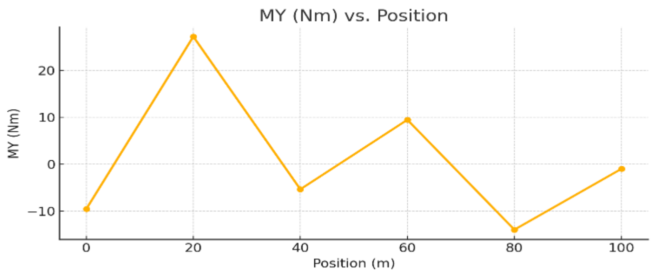
7.7 The structural behavior of the bridge under loading conditions shows typical patterns of shear, bending, and torsion. However, critical positions (0 m, 80 m, and 100 m) demand focused structural checks for safety and serviceability, particularly regarding torsional effects and shear reinforcement.

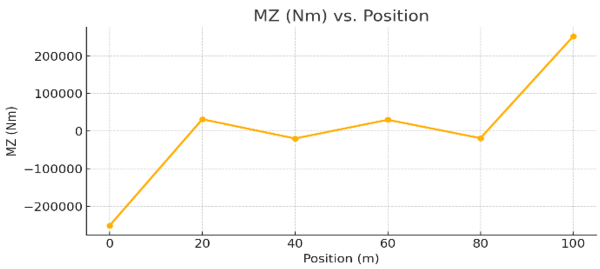










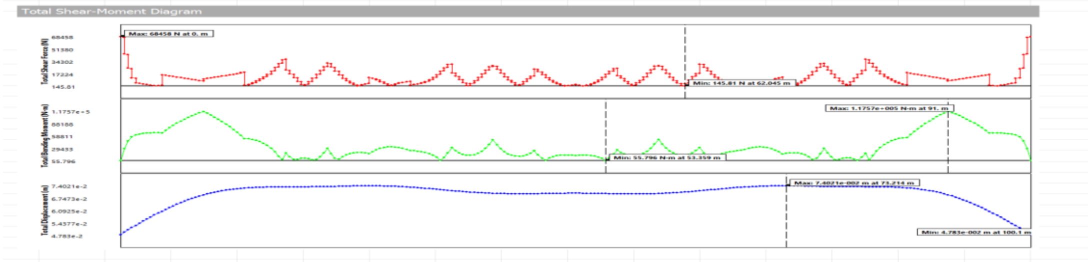


7.8 The above plots clearly illustrate how forces and moments vary across the length of the bridge:

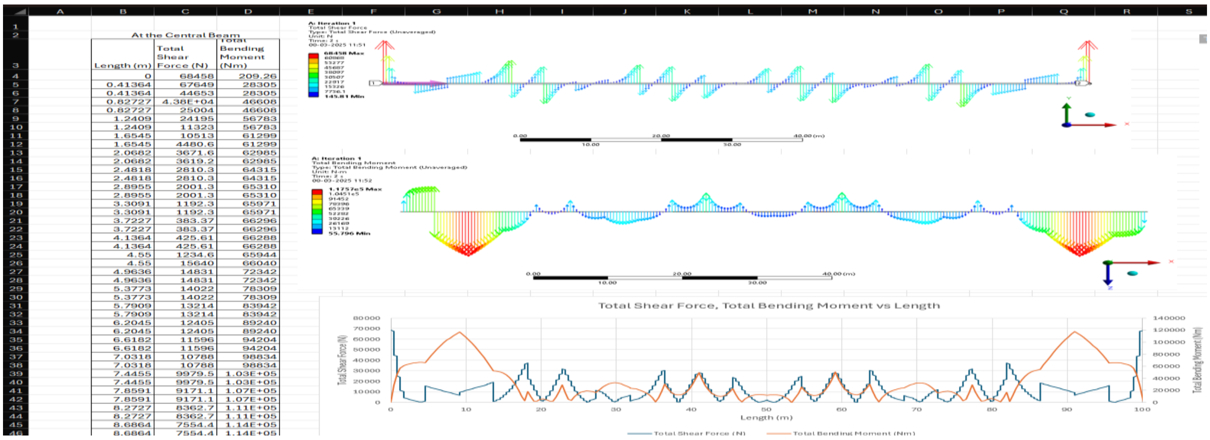
(a) **FX (Axial Force):** Significant tension is observed at 100 m, and maximum compression at 0 m.

ISSN 2250-3153

(b) **FY (Vertical Shear Force):** Peaks near 20 m and 80 m positions, indicating critical sections needing shear reinforcement.
(c) **FZ (Lateral Shear Force):** Lateral forces remain relatively low but fluctuate between positive and negative, indicating minor sway or lateral load effects.
(d) **MX (Bending Moment about X-axis):** Maximum moments appear at the ends (0 m and 100 m), typical for continuous beam structures.
(e) **MY (Bending Moment about Y-axis):** Values remain low, confirming that lateral bending is minimal.
(f) **MZ (Torsional Moment):** Highest torsion at 100 m; special attention is needed for torsional resistance at this location.



Total Displacement, Moment and Shear Force



Length (m)	Total Shear Force (N)	Total Bending Moment (Nm)
0	68458	209.26
0.41364	67649	28305
0.41364	44653	28305
0.82727	4.38E+04	46608
0.82727	25004	46608
1.2409	24195	56783
1.2409	11323	56783
1.6545	10513	61299
1.6545	4480.6	61299
2.0682	3671.6	62985
2.0682	3619.2	62985
2.4818	2810.3	64315
2.4818	2810.3	64315
2.8955	2001.3	65310
2.8955	2001.3	65310
3.3091	1192.3	65971
3.3091	1192.3	65971
3.7227	383.37	66296
3.7227	383.37	66296
4.1364	425.61	66288
4.1364	425.61	66288
4.55	1234.6	65944
4.55	15640	66040
4.9636	14831	72342
4.9636	14831	72342
5.3773	14022	78309
5.3773	14022	78309
5.7909	13214	83942
5.7909	13214	83942
6.2045	12405	89240
6.2045	12405	89240
6.6182	11596	94204
6.6182	11596	94204
7.0318	10788	98834
7.0318	10788	98834
7.4455	9979.5	1.03E+05
7.4455	9979.5	1.03E+05
7.8591	9171.1	1.07E+05
7.8591	9171.1	1.07E+05
8.2727	8362.7	1.11E+05
8.2727	8362.7	1.11E+05
8.6864	7554.4	1.14E+05
8.6864	7554.4	1.14E+05

Stresses along the Length of the Bridge

8. SHM Dashboard Development

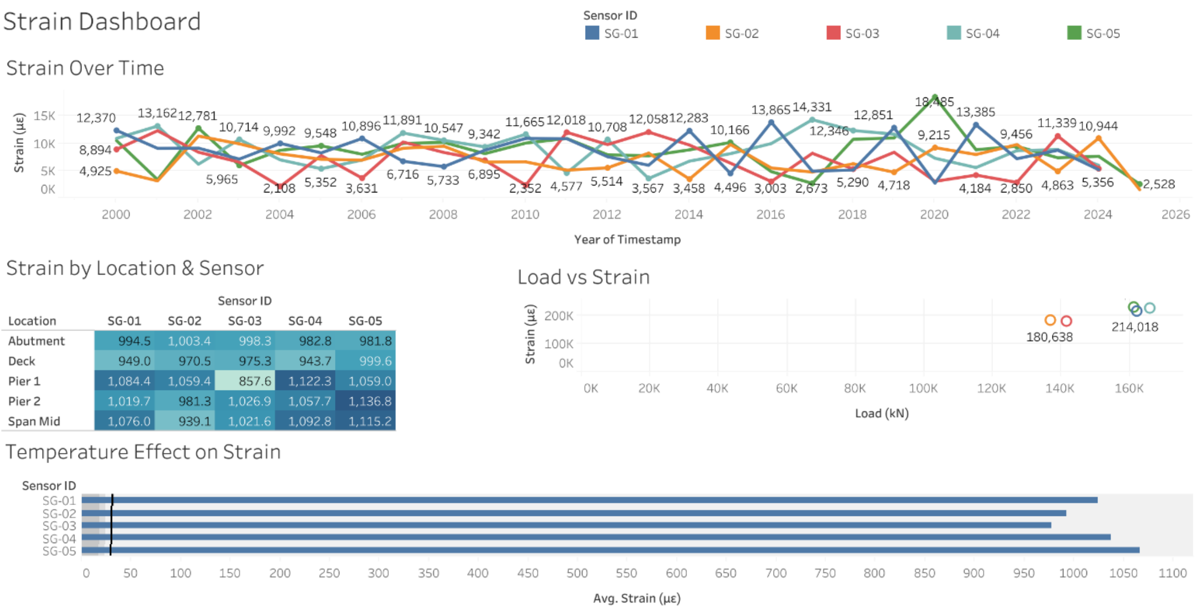
The Dashboard developed below was developed by the author in **Tableau software**, with **random hypothetical loads**, it provides real time data monitoring on the trafficability, loads being ferried, fatigue endured and the possible condition of the structure. It allows the engineer and maintenance teams to monitor in real time, evaluate data through visual representation and plan for predictive maintenance. It allows remote monitoring of structure, regulatory compliance and ensures safety. Hence it is cost effective in the long run.

8.1 Dashboard Visualization

A live dashboard was created using Tableau using random hypothetical to simulate real-time monitoring. The dashboard (Fig. 7) displayed:

(a) **Strain and stress trends over time**
(b) **Fatigue assessment**
(c) **Traffic-induced loading history**
(d) **Sensor health indicators**

8.2 The dashboard was capable of accepting streaming CSV updates (excel file updates), representing how real sensor networks would feed data into a monitoring control system.



Representation of a Strain Guage Dashboard

8.3 Structural Health Monitoring (SHM) Dashboard Overview

The presented Structural Health Monitoring dashboard provides a comprehensive visualization of the **random hypothetical** strain data collected from different locations on a bridge structure using multiple sensors (SG-01 to SG-05). This dashboard aids in real-time condition assessment and informed decision-making for maintenance planning.

8.4 Key Dashboard Components:

(a) **Strain Over Time (Top Plot):**
- (i) This time-series plot illustrates the variation in strain (measured in microstrain, με) recorded by each sensor from the year 2000 to 2025 (random hypothetical data created virtually).
- (ii) Notable spikes, such as **18,485 με in 2020 by SG-05**, indicate possible overloading events or structural distress.
- (iii) The fluctuation patterns help identify aging effects, traffic load variations, and critical years requiring attention.

(b) **Strain by Location & Sensor (Heatmap Table):**
- (i) Displays the distribution of strain values across different bridge components: **Abutment, Deck, Pier 1, Pier 2, and Span Mid**.
- (ii) Highest strain values are observed at **Pier 1 (SG-01: 1084.4 με)** and **Span Mid (SG-05: 1115.2 με)**, indicating these zones experience significant stress and should be prioritized for inspection.

(c) **Load vs Strain Relationship (Scatter Plot) [7]:**
- (i) This plot shows the correlation between applied load (kN) and the resulting strain.
- (ii) Key data points indicate that higher loads (~214,018 kN) produce significantly higher strains, validating the structural response behavior under varying load conditions.

(d) **Temperature Effect on Strain (Bar Chart):**
- (i) Illustrates the average strain measured by each sensor due to temperature variations.
- (ii) Temperature-induced strain is highest for **SG-05 (~1100 με)**, suggesting that temperature effects should be carefully considered during structural performance evaluations, especially in critical areas.

8.5 This SHM dashboard enables engineers and maintenance teams to:
- (a) Monitor real-time structural behavior.
- (b) Identify critical locations with high stress and strain concentrations.
- (c) Correlate environmental effects (temperature) and loading conditions to structural responses.
- (d) Plan proactive maintenance and repairs, thereby enhancing the safety and longevity of the bridge structure.

9. Discussion

The research presented in this technical paper is set out to transform conventional structural health monitoring (SHM) methods by integrating artificial intelligence (AI), **LiDAR-based spatial mapping**, machine learning techniques, and **digital twin** simulations into a comprehensive and automated solution for monitoring bridges and structures. A pragmatic, experiment-driven methodology was followed ranging from **terrestrial and mobile LiDAR** data collection to OpenCV (computer vision) based crack detection and **SolidWorks-Ansys-based digital twin simulations, analysis and further creation of a real time dashboard** using random data (assuming hypothetical sensor data).

9.1 The objectives laid out at the beginning of the research have been successfully achieved. The developed system provides a full-stack AI-based SHM solution with the following features:

(a) **High-resolution 3D data acquisition** using LiDAR
(b) **Automated crack detection and classification** using OpenCV
(c) **Structural simulation using digital twin modelling**
(d) **Virtual sensor data generation for SHM emulation**
(e) **Real-time dashboard interface for visualization**

The integrated pipeline developed herein showcases the feasibility and effectiveness of AI-powered SHM systems in transforming how structural monitoring is approached in civil engineering.

9.2 This technical paper contributes to the field of civil infrastructure monitoring through:

(a) A practical demonstration of **LiDAR and AI integration** for crack segmentation with quantitative dimension extraction.
(b) A novel use of **digital twin simulation** to create SHM-ready bridge models using publicly available tools like SolidWorks and Ansys.
(c) Design of a **visual dashboard** to consolidate real-time and simulated structural data.

These innovations serve as a blueprint for future SHM deployments in both urban and rural contexts, especially in developing nations where budget constraints and skilled labour shortages hinder large-scale inspection programs.

9.3 Benefits of Real-Time Monitoring

(a) Continuous data logging for trend analysis
(b) Early warning for overloading or structural distress
(c) Improved calibration of simulation models
(d) Enhanced maintenance scheduling

9.4 Decision-Making Support The dashboard allows:

(a) Real-time intervention (e.g., traffic diversion)
(b) Comparative performance benchmarking
(c) Generation of maintenance logs and inspection reports

9.5 Benefits and Challenges of Integrated SHM Systems

9.5.1 Benefits

(a) Holistic understanding of bridge behaviour
(b) Real-time fault detection
(c) Reduced manual inspection frequency
(d) Enhanced safety and service life prediction

9.5.2 Challenges

(a) High initial setup costs
(b) Sensor calibration and data drift
(c) Complex data synchronization between digital twin and physical structure
(d) Data privacy and cyber-physical security concerns

9.6 Future Directions

(a) Integration with AI for anomaly prediction
(b) Use of edge computing for on-site processing
(c) Blockchain for tamper-proof SHM logs
(d) AR/VR integration for immersive inspections

10. Conclusion

LiDAR technology has revolutionized the way structural health monitoring is conducted, especially for complex bridge geometries. When combined with AI algorithms, LiDAR provides a non-contact, high-resolution, and scalable approach for crack detection, deformation tracking, and digital twin construction. While challenges such as data size and reflectivity persist, the benefits far outweigh the limitations, establishing LiDAR as a cornerstone of modern SHM.

*This paper presents a complete, field-ready pipeline for surface crack detection using **low-cost technology LiDAR point clouds** as well as terrestrial LiDAR equipment and **AI-powered image processing**. By leveraging 3D-to-2D projection and OpenCV techniques, the system enables fast, automated, and scalable crack detection with geometric precision. It offers a significant advancement over traditional inspection methods in terms of speed, repeatability, and integrability into digital twin systems.*

Future work may include integration with UAV-mounted LiDAR systems, fusion with thermal or acoustic sensors, and extension into subsurface or fatigue crack modeling using simulation.

The use of LiDAR technology proved highly effective for crack detection. Unlike RGB-based photogrammetry, LiDAR is unaffected by lighting conditions and surface textures, thus offering greater precision.
The use of the OpenCV library in Python enabled efficient surface crack localization and classification. This approach leveraged image processing techniques to identify cracks based on grayscale intensity variations and geometric features, eliminating the need for complex machine learning models or large annotated datasets. The method proved effective for rapid analysis and is well-suited for deployment on resource-constrained devices.
The modelling and analysis of a modular steel bridge using SolidWorks and Ansys provided key insights into the bridge's structural response under various loading scenarios. The Ansys simulations revealed that the most vulnerable regions were the joints and mid-span connections where stress concentrations exceeded 200 MPa under dynamic loads.
Additionally, the virtual deployment of sensors in the simulation allowed extraction of strain, displacement, and frequency response data—mimicking real SHM sensor arrays. These outputs were further used to emulate real-time dashboards, demonstrating how digital twin models can serve as a virtual laboratory for failure prediction and sensor calibration.

References

[1] Z. Wang, J. Zhang, and X. Yan, "A digital twin framework for smart bridge management using sensor data and BIM," Automation in Construction, vol. 128, p. 103785, 2021.
[2] G. Heo, H. Lee, and S. Kim, "Real-time crack propagation monitoring using digital twins for composite bridge systems," Composite Structures, vol. 236, p. 111927, 2020.
[3] F. Cerda and C. Chen, "Vibration-based damage detection of bridge structures using time series analysis," Journal of Civil Structural Health Monitoring, vol. 5, no. 3, pp. 317–328, 2015.
[4] ISRO NRSC, "Application of LiDAR and UAV in Infrastructure Monitoring," 2021. [Online]. Available: https://bhuvan.nrsc.gov.in
[5] ANSYS Inc., "ANSYS Twin Builder User Guide," 2022. [Online]. Available: https://www.ansys.com/products/digital-twin
[6] H. Kaartinen, A. Kukko, and J. Hyyppä, "Crack detection on concrete structures using LiDAR intensity data," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 186, pp. 45–56, 2022.
12
[7] L. Cheng, Y. Han, and Y. Zhang, "Deformation monitoring of concrete bridges using terrestrial laser scanning," Sensors, vol. 18, no. 5, p. 1564, 2018.
[8] C. R. Farrar and K. Worden, "An introduction to structural health monitoring," Philosophical Transactions of the Royal Society A, vol. 365, no. 1851, pp. 303–315, 2007.
[9] SHMScloud, "Cloud-based dashboard for structural health monitoring," 2021. [Online]. Available: https://www.shmscloud.com/
[10] Y. Liu, Z. Lin, and W. Wu, "UAV-based LiDAR and photogrammetry integration for surface crack detection," Automation in Construction, vol. 125, p. 103611, 2021.
[11] X. Han, H. Wu, and Y. Ma, "Damage detection in steel structures using DBSCAN clustering on LiDAR data," Structural Control and Health Monitoring, vol. 27, no. 6, p. e2543, 2020.
[12] L. Wu, H. Zhang, and D. Li, "Hybrid point cloud-image approach for retaining wall deformation monitoring," Measurement, vol. 173, p. 108478, 2021.
[13] Indian Roads Congress, "IRC:6-2014 Standard Specifications and Code of Practice for Road Bridges: Section II Loads and Stresses," New Delhi, 2015.
[14] ASTM International, "Standard Guide for SHM of Civil Infrastructure (ASTM E2783-15)," West Conshohocken, PA, 2015.
[15] Shyam Saseethar and Dilip Narkhede, "Revolutionising Visual Bridge Inspection: A Deep Learning Approach for Automated Concrete Bridge Distress Identification & Analysis of Results." [Conference Paper]. Source: https://avestia.com/CSEE2024_Proceedings/files/paper/ICSECT/ICSECT_146.pdf
[16] IRC-SP:52, 1999.
[17] IRC-SP:40, 2019.
[18] Shyam Saseethar and Dilip Narkhede, "Exploring Automated Bridge Damage Identification: Preliminary Insights from a Deep Learning Approach using YOLOv8 Framework and Image Dataset," in Recent Advances in Infrastructure Development (RAID-2024), Calicut, Kerala, 2024.