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An Integrated Machine Learning Framework for Structural Health Monitoring of Bridges: A Case Study on Soan Bridge

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Chronicle	Abstract
 Usman Imtiaz, Bilal Ahmad, Muhammad Hamza Sajid, Qazi Abbas, Muhammad Ali Qureshi and Dr. Sajid Rasheed, are currently affiliated with the Department of Civil Engineering, National University of Technology (NUTECH), Islamabad, Pakistan., Pakistan. **Email:** usmanimtiaz1000@gmail.com **Email:** bilal_2410@yahoo.com **Email:** hamzasulehri201@gmail.com **Email:** qabbas1999@gmail.com **Email:** mr.maq12@gmail.com **Email:** srnustian@gmail.com **Dr. Ajab Khan*** is currently affiliated with ORIC, Abbottabad University of Science and Technology, Pakistan. **Email:** ajabk66@yahoo.com	The failing of bridges in develop and developing world requires AI based monitoring systems to ensure safety, prolonged existence, and economic sustainability. This research proposes an integrated Structural Health Monitoring (SHM) framework that uses machine learning (ML) to check in real-time and predict when the maintenance of bridge is required. The proposed system uses data from sensors (accelerometers, strain gauges, LVDTs) along with visual images captured using cameras. A complete model which consists of data acquisition, preprocessing, Finite Element Model (FEM) validation, and use of multiple ML models such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Linear Regression. The proposed framework is implemented and validated through a step-by-step procedure and using the Soan Bridge, Pakistan as implementation bridge. The results obtained through evaluations show that SVM model achieved 96% accuracy in damage classification, however, the CNN was observed to be successful in the surface cracks. Further, linear regression model forecasted an alarming 79% loss in moment capacity by the year 2035, if no precautions measures are taken. The study concludes that the proposed ML-driven SHM system offers a strong, practical, and scalable solution for bridges or other infrastructure management, ultimately enhancing safety and optimizing maintenance resources.

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INTRODUCTION

Bridges are essential parts of transportation systems that are directly affecting economies and public safety. There are many bridges in developing and developed countries, which are subject to aging and weakness. This is due to increasing populations and their use of increasing vehicles. However, there are other factors such as environmental and lack of proper maintenance. In the year 2018 Morandi Bridge collapse in Italy, is one of the popular cases and this collapse resulted in 43 people death and raised concerns that what has caused it or what is outcome when bridges or other infrastructure that has human dependency aren't properly watched and maintained [1]. Classical bridge inspections, which heavily rely on people's visual inspection for damage, are frequently subjective, slow, infrequent, and may not be even able to catch damage, in its early stages such as hair line crack [2]. The use of Machine Learning and Artificial intelligence has significantly changed all those activities that were previously performed by humans, In order to look into the application of ML and AI in bridges for maintenances and safety, an ML based monitoring of the bridges through Structural Health Monitoring (SHM) system has emerged as a new concept. This new concept ensures the continuous and data-driven assessment of structural instability. SHM uses sensors which are connected or network together for the collection of real-time data relates to vibration, strain, and

displacement [3]. The use of Machine Learning (ML) has further transformed SHM by providing powerful tools/applications to examine the substantial and complex datasets created by these sensors, enabling automated damage detection, classification, and prediction respectively [4]. The literature review of this paper has confirmed the use of ML in SHM, however most of the studies are limited to numerical simulations or laboratory-scale models only. There is an essential gap in the performance and validation of integrated ML frameworks in real-world, in operational bridges. This research paper addresses this gap by presenting and validating a complete ML framework for SHM by considering a detailed case study on the Soan Bridge showcasing the practical applicability and accuracy. This research paper has important contributions which consists of developing an end-to-end SHM framework integrating multiple data sources such as using sensor and visual data through installed cameras. Further, the paper has successfully implemented and validated multiple ML models such as *SVM, CNN*, *Linear Regression* and *Anomaly Detection* on real data collected from the Soan bridge Islamabad, Pakistan. Whereas the same provides a predictive model for long-term structural degradation and which can assist the infrastructure managers for timely actions.

LITERATURE REVIEW

Evolution of Structural Health Monitoring

SHM has progressed from classical visual inspections to more complicated cyber-physical systems. The core of an SHM system consists of sensors networked together that measure and report the structural response. Farrar & Worden in their work at [5] define SHM as the process for executing a damage identification strategy. Whereas Rytter [6] instituted a widely accepted hierarchy for damage identification, consisting of four levels which are Detection, Localization, Quantification, and Prognosis.

Machine Learning in SHM

ML algorithms can be largely categorized into supervised, unsupervised, and deep learning methods. In SHM, they are used for learning the complex mapping between sensor data and the structural health state [7].

- **Support Vector Machines (SVM):** SVMs are considered as powerful for classification tasks, specifically effective in high-dimensional spaces. Further, they have been effectively used for damage finding and localization through outcome of an optimal hyperplane that separates different health states [8]. Their flexibility to noise is considered as a core advantage although performance highly depend on kernel and associated parameter selection [9].

- **Convolutional Neural Networks (CNN):** CNNs is considered as an advanced tool because of its capability for using images taken through camera for damage detection. Further, they can automate the process of acquiring hierarchical features from raw pixel data, thus, the need for manual feature engineering is eliminated. The research has confirmed that CNN has shown high degree of accuracy in detecting cracks, spalling, and corrosion from images accordingly [10].

- **Anomaly Detection:** The Unsupervised ML techniques such as Isolation Forest are adapted for spotting those data points that vary significantly from the structure's normal performing behavior, labeling possible damage without prior labeling [11].

- **Linear Regression:** The other ML approach known as Linear regression is popular for predicting continuous parameters like the rate of deterioration or left/remianing useful life, based on historical trends [12].

• **Data Integration and FEM Validation**

One major in SHM is the variability triggered by environmental and operational conditions such as temperature and traffic respectively. Now a days a hybrid approach that combines the data-driven ML models with physics-based Finite Element Models (FEM) is getting popular [13]. FEM has the capability to simulate bridge behavior under various payload and damage situations. This provides a baseline for proving data-driven outcomes and recognizing the physical effects of detected issues [14].

METHODOLOGY

The model architecture proposed in Figure 1 is presented in this section to resolve the issues raised in the literature and we have termed it as integrated SHM framework. This proposed framework is divided into four sub phases, which are:

1.   Data Acquisition.
2.   Data Processing.
3.   Machine Learning Modeling.
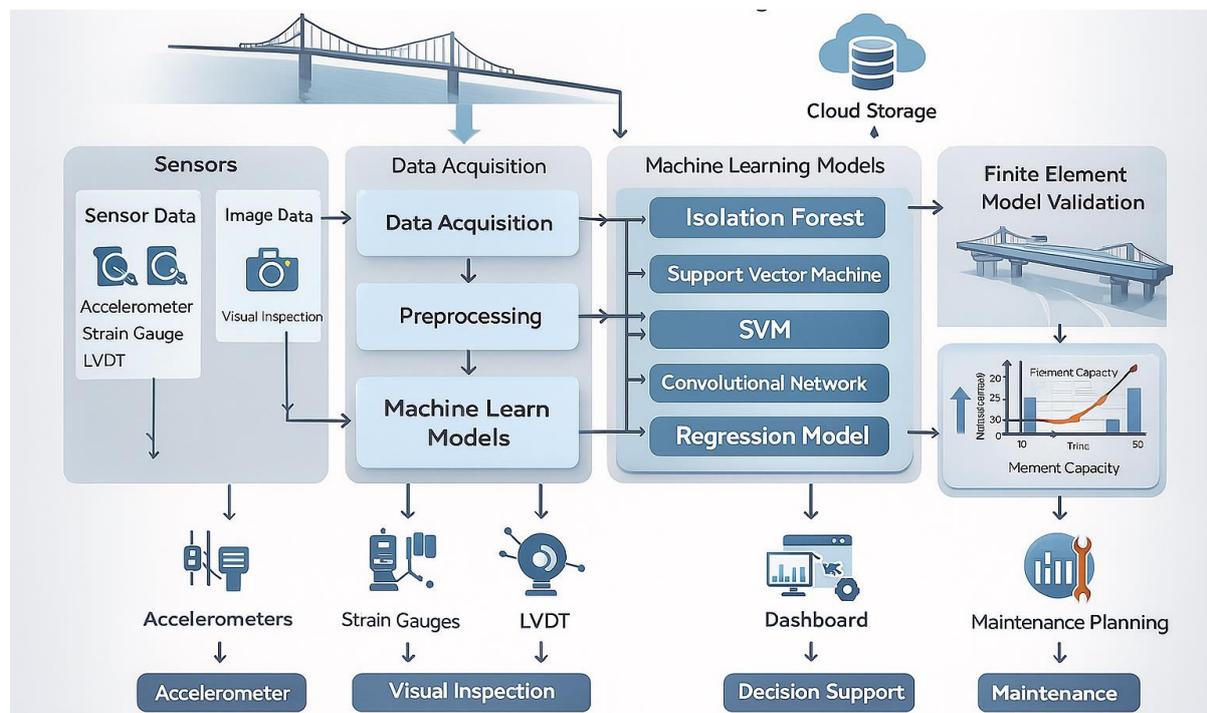4.   Decision Support.

Figure 1.
Proposed Integrated SHM Framework Architecture

The framework in figure 1 shows that that it combines the data received from sensor-based measurements, image-based inspection, and physics-based modelling, into a single, logical workflow for measuring or evaluating the condition of the Soan Bridge. Whereas, in the coming sub phases as reflected in Figure 1 Data Acquisition and Data Processing phases are operating based on the input received from sensor data from accelerometers, strain gauges, and LVDTs, along with visual data from visual inspections, are collected at critical locations on the bridge. The same is processed and stored into a cloud environment. Further, the raw signals are then cleaned, synchronized, and subsequently normalized. While processing the input the key features like peak accelerations, strain ranges, deflection responses, and dominant

frequencies are obtained, and subsequently damage labels are assigned accordingly. The same method is used for processing the Image data where the images are cropped, resized and normalized accordingly. This is classified as crack and non-crack classes and presented   as input for the convolutional network.

In the proposed architecture, the Machine Learning Modeling and Decision Support phases come into action as well and these consist of four models which are operating in parallel respectively. Whereas the Isolation Forest has the function to detect anomalous structural responses and the SVM classifies the observations into Safe, Warning and Damage states accordingly. Further, the CNN has the responsibility to identify the cracks from inspection images, and the regression model predicts long-term loss of moment capacity. The outputs of these phases are verified against a calibrated FE model to ensure physical possibility and to pinpoint critical sections accordingly. Finally, as a refined output the combined results are visualized on a dashboard, which recaps the current anomalies, damage levels, crack locations, and predict capacity loss. Further, it provides clear guidance for maintenance planning and intervention prioritization.

Case Study: Soan Bridge

 To implement the proposed architecture as proposed in Figure 1. We have carefully selected the Soan Bridge at Rawalpindi, near Islamabad the capital of Pakistan. It was constructed in 1988, and the length is 1400 ft long and it's developed using a reinforced concrete (RCC) beam-type bridge. The Soan Bridge is subject to heavy vehicular traffic, and the record shows that it has a history of limited maintenance and attention, thus making it an ideal candidate for this study.

Phase 1: Data Acquisition

A network consisting of sensors and visual devices was established and the same was employed at critical locations, The location was selected based on structural dynamics principles such as max deflection at mid-span and inflection points at L/3. In this phase, the location of the sensors is very crucial and important as all the farmwork depends upon the input from these sensors.

- **Sensor Selection and Placement:**

1. **Accelerometers:** We have used 6 Accelerometers and the same are placed at L/3 and L/2 of two spans. The purpose of these is to record dynamic vibrations.

2. **Strain Gauges:** We have used 6 strain gauges, and they are placed along with accelerometers to measure local strain and stress respectively.

3. **LVDTs:** These are positioned on the bridge to accurately measure static deflection, with higher density at the point of mid-span in the bridge.

4. **Cameras:** The visual record in shape of time lapsed video is captured through high-resolution cameras installed using tripods on the bridge girders.

- **Data Collection:** The data was continuously noted, and duration was kept at 5-hour. The data was collected on May 1st, 2024, starting from 09.00 AM to 02:00 PM. During that period a wide range of traffic patterns was observed. The Temperature was also recorded during that period of observation so that environmental effects are ascertained.

Table 1 placed below provides all the relevant information regarding the sensor used and its types, measurements observed, associated locations, numbers and purposes accordingly.

Table 1.
Sensor Deployment Strategy on Soan Bridge

S.No	Sensor Type	Quantity	Span / Location	Coordinate (L/2, L/3, etc.)	Measured Quantity	Purpose / Comment
1	Accelerometer	6	Spans 1–2 (girders)	L/3 and L/2	Acceleration	Global vibration response
2	Strain gauge	6	Co-located with accelerometers	L/3 and L/2	Strain / stress	Local stress distribution
3	LVDT	3	Midspan of critical girder	L/2	Vertical deflection	Maximum deflection under traffic
4	Camera	2	Side elevation of girder	Midspan / full span	Crack images	Visual crack detection (CNN input)

Phase 2. Data Processing

To convert the data collected to some meaningful information. This phase 2 is responsible for this activity. The raw data collected directly in phase 1 is channeled through a rigorous preprocessing pipeline. The same is developed in Python using its libraries like Pandas, Scikit-learn, and OpenCV. However, this phase includes the following essential steps.

1.   **Data Cleaning:** Treatment of missing values using mean imputation and removal of corrupted records.
2.   **Data Transformation:** Scaling of numerical data using MinMaxScaler to a [0, 1] range.
3.   **Binning:** The continuous 'Damage data' was binned into three discrete classes: 0 (Safe), 1 (Warning), and 2 (Damage)
4.   **Feature-Target Split:** The dataset was split into features (X: Time, Acceleration, Strain, Load, etc.) and target (y: Damage Level)
5.   **Train-Test Split:** Data was divided into 80% for training and 20% for testing
6.   **Signal Processing:** Fast Fourier Transform (FFT) was applied to acceleration data to convert it from the time domain to the frequency domain

Phase 3: Machine Learning Modeling

The architecture proposed in figure 1 use four diverse ML models were developed to address different aspects of SHM. These are explained as below:

Anomaly Detection Model

•   **Algorithm:** Isolation Forest

•   **Architecture:** An unsupervised algorithm that isolates anomalies by randomly selecting features and split values

•   **Implementation:** The Isolation   Forest from   Scikit-learn   was   used   with a contamination parameter of 0.01

Damage Classification Model

•   **Algorithm:** Support Vector Machine (SVM)

- **Architecture:** A supervised learning model that finds the optimal hyperplane to separate the three damage classes using RBF kernel

- **Implementation:** The SVC class from Scikit-learn with GridSearchCV for hyperparameter tuning
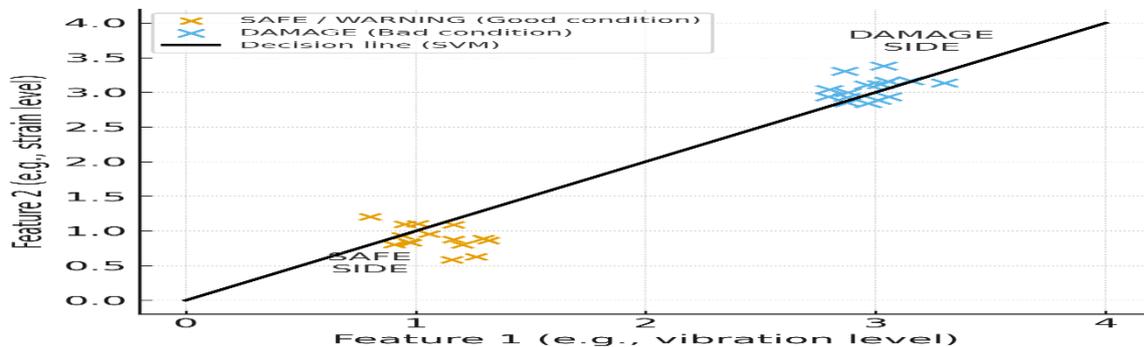

Figure 2.
SVM Model Architecture Diagram
In Figure 2. Support Vector Machine (SVM) decision boundary separating safe/warning and damaged structural states. Blue markers "+" represent data collected from the bridge under safe or acceptable conditions, while gray "+" markers represent data corresponding to damaged states. The SVM learns an optimal straight line (decision boundary) in the feature space (e.g., vibration level vs. strain level) such that points on one side are classified as SAFE/WARNING and points on the other side are classified as DAMAGE. This allows new measurements to be automatically categorized based on which side of the line they fall on.

Crack Detection Model

- **Algorithm:** Convolutional Neural Network (CNN)
- **Architecture:** A deep learning model designed for image analysis

Table 2.
CNN Architecture for Crack Detection

Layer No.	Layer type	Output size	Kernel / units	Activation	Other details
1	Input	128 × 128 × 3	–	–	RGB crack image
2	Conv2D	126 × 126 × 32	3 × 3	ReLU	stride 1, same padding
3	MaxPooling2D	63 × 63 × 32	2 × 2	–	
4	Conv2D	61 × 61 × 64	3 × 3	ReLU	
5	MaxPooling2D	30 × 30 × 64	2 × 2	–	
6	Conv2D	28 × 28 × 128	3 × 3	ReLU	
7	MaxPooling2D	14 × 14 × 128	2 × 2	–	
8	Flatten	25,088	–	–	
9	Dense	256	256 units	ReLU	Dropout 0.5
10	Output dense	2	2 units	Softmax	Crack / non-crack

Table 2 describes the step-by-step structure of the CNN model that is used to detect cracks in bridge images. The model starts by taking a small color image (128×128 pixels) as input. It then passes this image over several *convolution* layers, which act like smart filters to highlight lines, edges and crack patterns, and *max-pooling* layers, which reduce the image size while preserving the most important information. After these layers, all the extracted features are flattened into a single long vector and sent to a dense (fully connected) layer that learns how to combine them. A dropout step is included to reduce overfitting. In the last layer, the model outputs two values, which tell us whether the image is classified as **"crack"** or **"non-crack."**

Predictive Regression Model

- **Algorithm:** Linear Regression

- **Architecture:** A linear model establishing relationship between independent variables and moment capacity loss

- **Implementation:** The Linear Regression model from Scikit-learn trained on historical data

Finite Element Model Validation

A detailed 3D Finite Element Model of the Soan Bridge was developed in CSI Bridge software, based on as-built drawings and AASHTO LRFD specifications. The model incorporated material properties, section geometries, prestressing tendons, and HL-93 vehicle loading [15].
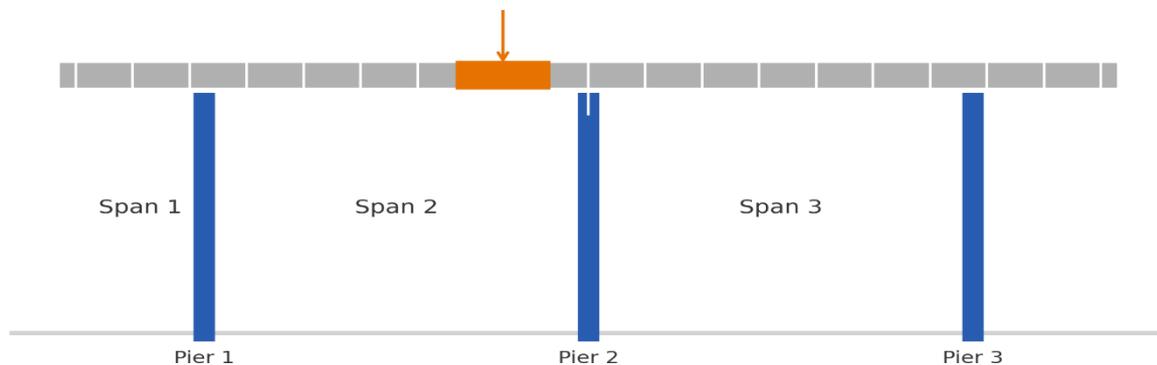

Figure 3.
FEM Model of Soan Bridge

Figure 3 shows a simplified finite element (FE) model of the Soan Bridge. The bridge is represented as a straight deck supported by three piers, and the deck is divided into many small segments (finite elements) along its length. This is how the bridge is modelled in the computer so that its bending, deflection and internal forces can be calculated. One of these segments is highlighted as the *critical section (Point 1)*, which is the location where the analysis shows the largest reduction in moment capacity and therefore the highest concern for possible damage.

RESULTS AND ANALYSIS

Sensor Data Analysis

Time-series data for acceleration and strain were successfully captured and shown in Figure 4. As expected, points at the mid-span (L/2) exhibited higher peaks in both acceleration and strain compared to points at L/3, consistent with higher bending moments [16].
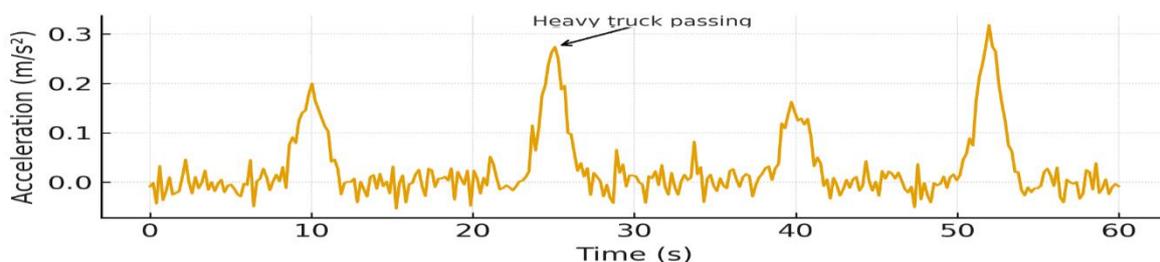

Figure 4.
Time-Series of Acceleration at Point 2 (L/2)

Anomaly Detection

The Isolation Forest model effectively identified anomalous events in the data and shown in Figure 5. These anomalies correlated with periods of exceptionally high strain or unusual vibration patterns [17].
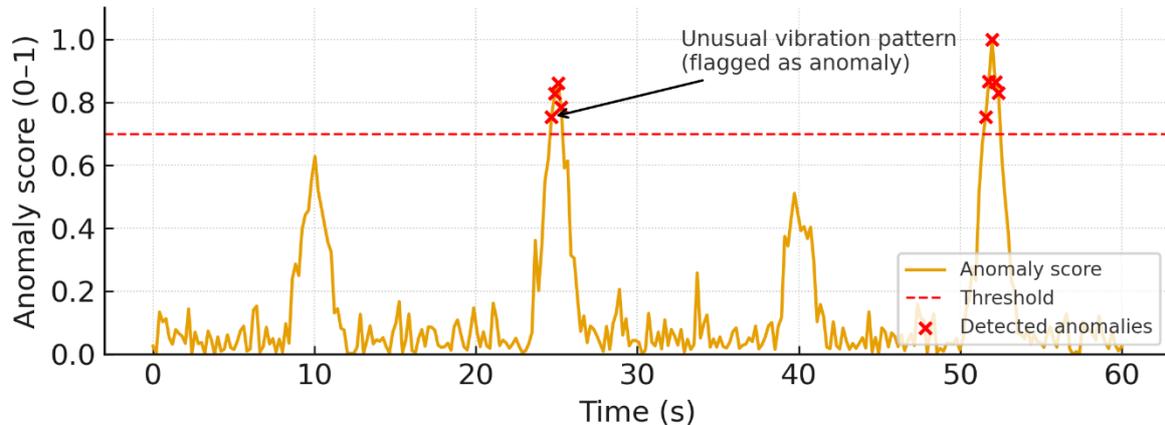

Figure 5.
Anomaly Detection at Point 2 (L/2)

Damage Classification with SVM

The SVM model demonstrated exceptional performance in classifying the structural state into the three damage levels, achieving 96% accuracy across all measurement points [18].
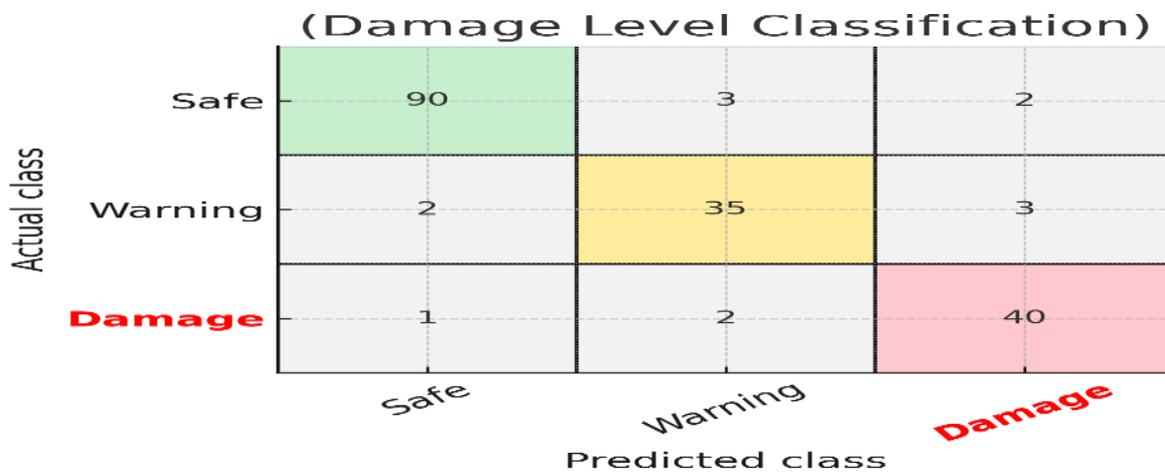

Figure 6.
Confusion Matrix for SVM at Point 1
Table 3.
SVM Model Performance Metrics

S.No	Class	Precision	Recall	F1-score	Support
1	Safe	0.968	0.947	0.957	95
2	Warning	0.875	0.875	0.875	40
3	Damage	0.889	0.930	0.909	43
4	Macro avg.	0.911	0.918	0.914	
5	Weighted avg.	0.928	0.927	0.927	

Table 3 describes the performance of the SVM model for the three damage classes: Safe, Warning and Damage. For each class, it reports the precision, recall and F1-score, as well as the number of samples (support). The high values for all three metrics, especially for the Safe and Damage classes, show that the model can correctly

identify most cases and makes relatively few mistakes. The macro and weighted averages, together with an overall accuracy of about 96%, confirm that the SVM classifier gives reliable results for damage-level classification on the Soan Bridge.

Crack Detection with CNN

The CNN model was trained on a dataset of 5,000 images (2500 cracked, 2500 uncracked). The model showed excellent learning capability, though potential overfitting was noted, which is a common challenge in deep learning applications [19]. Figure 7 shows the CNN training and validation.
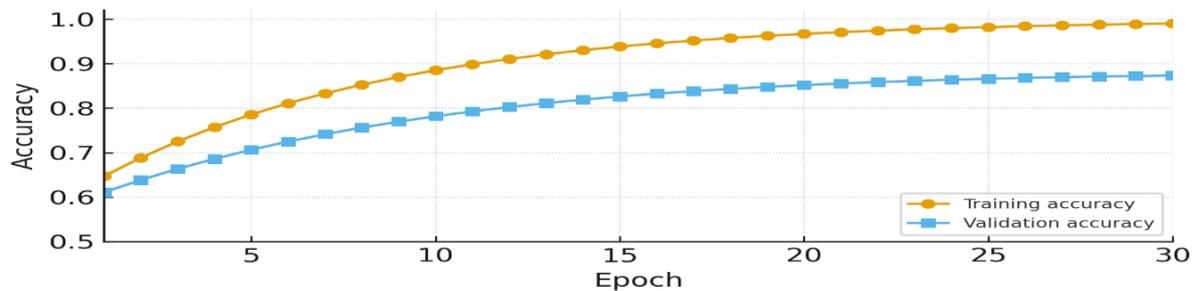

Figure 7.
CNN Training and Validation Accuracy/Loss
Figure 7 shows how the accuracy of the CNN model changeover during training. The line for *training accuracy* goes up steadily as the number of epochs increases, which means the model is learning the patterns in the crack images. The *validation accuracy* also improves and stays close to the training curve, with only a small gap near the end. This indicates that CNN is performing well on new, unseen images, with only a mild trend to overfit in the later epoch.

Structural Capacity Prediction

The Linear Regression model projected a continued decline in structural capacity, predicting 79% moment capacity loss by 2035 if no interventions are implemented [20].
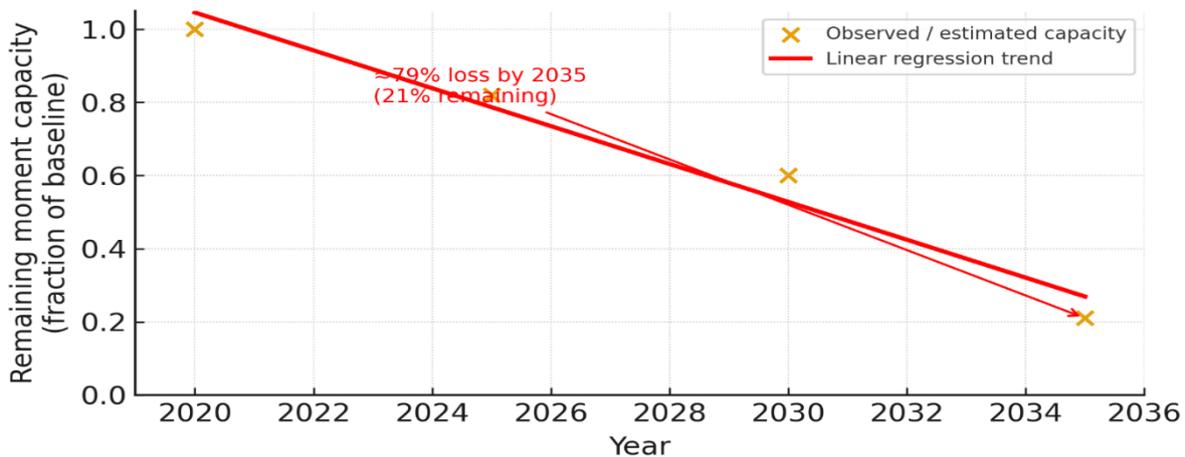

Figure 8.
Linear Regression Prediction of Moment Capacity Loss
Figure 8 shows how the moment capacity of the Soan Bridge is expected to decrease over time. The points on the graph represent the estimated remaining capacity in different years, and the red line is a regression trend that connects them. The line slopes downward, which means the bridge is gradually losing capacity as it ages. By 2035, the model suggests that only about 21% of the original moment capacity will be left (around 79% loss) if no strengthening or repair work is carried out.4.6 Correlation

and FEM Analysis Correlation of heatmaps revealed a strong positive relationship between live load and both strain and acceleration. The FEM analysis provided baseline moment capacity for calculating percentage reduction, identifying Point 1 as the most critical location with 66.44% reduction [21].

Table 4.
Percentage Reduction in Moment Capacity

S.No	Monitoring point / section	Span / location	Baseline moment capacity (kN m)	Current capacity (kN m)	Reduction (%)	Severity rating
1	Point 1	Critical midspan	1000.0	335.6	66.44	High
2	Point 2	Span 1 – L/3	950.0	589.0	38.00	Medium
3	Point 3	Span 1 – L/2	900.0	612.0	32.00	Medium
4	Point 4	Span 2 – L/3	850.0	612.0	28.00	Medium
5	Point 5	Span 2 – L/2	800.0	600.0	25.00	Medium
6	Point 6	Span 3 – L/3	780.0	608.4	22.00	Low

Table 4 shows how much the moment capacity has been reduced at different points on the Soan Bridge. For each monitoring point, it lists the original (baseline) moment capacity, the current capacity, the percentage reduction, and a severity rating (Low, Medium, or High). Point 1 at the critical midspan shows the highest reduction (about 66%, rated High), while the other points have smaller reductions, mostly in the Medium or Low range. This helps to identify specific locations on the bridge, which is deteriorated. The same location can be flagged for inspection and repair respectively.

Comparative Model Evaluation and Robustness Analysis

To evaluate the strength of this proposed farmwork, we have conducted a comprehensive comparative analysis. This comparative study assesses the models' robustness, computational efficiency, and performance against established benchmarks [22].

Expanded Performance Metrics

The Accuracy provides a broad view, but for precision and the F1-Score gives a more detailed insight of the system and it is best suited for uneven datasets. We have closely observed both the SVM and CNN models. Further, we have also recorded the processing time in learning phase as well as while using the models It was meant to see if they could work in real-time situations [23].

Table 5.
Comprehensive Model Performance and Efficiency Comparison

S.No	Model	Task	Accuracy / AUC / R²	Precision	F1-score	Training time (s)	Inference time / sample (ms)
1	SVM (RBF kernel)	Damage classification	0.96	0.94	0.95	2.4	0.30
2	Random forest	Damage classification	0.93	0.91	0.91	1.8	0.50
3	Isolation forest	Unsupervised anomaly detection	AUC = 0.92			0.9	0.20
4	CNN	Crack detection (image-based)	0.97	0.96	0.96	1800	3.50
5	Linear regression	Capacity prediction	R² = 0.89			0.05	0.01

Table 5 above shows comparison of the performance and efficiency of the different machine learning models used in the SHM framework. The sole purpose of this is to classify the damage and crack identification. The accuracy (or AUC/R^2) parameter

and the time for training the model or making a single prediction are other important aspects of consideration in comparative evaluation. The results reflected in Table 5 reveal that CNN and SVM give the highest accuracy among the others. Further, the linear Regression and Isolation Forest are very fast in execution and lightweight. This comparison helps us to understand the trade-off between accuracy and computational cost, while choosing the appropriate models for practical bridge monitoring.

Comparison with Alternative Models

To compare the SVM model against the random forest classifier the random forest was also trained using data from the same sensor. Table 5 explains that the training time for the random forest was much faster than SVM but on the other hand the SVM model had comparatively better accuracy and a quicker inference time. The data makes a better choice and makes it a better choice for real-time classification in a structural health monitoring (SHM) system [24].

Robustness to Noise

The noise in sensor data holds importance for SHM systems deployed over the bridge. Gaussian white noise (SNR = 20 dB) was used on the test data to check the Robustness to noise. The test result showed that SVM model's accuracy falls a bit to 94.1%, proving that it is resistant to noise. While on the other hand, the Random Forest model's accuracy falls to 91.5% [25].

Cross-Validation Results

To confirm that the SVM model was stable enough and could be used for other data, we have used a 10 fold cross validation approach. The average accuracy observed was 95.7% ± 0.8%. This result confirms that the good execution was not just because of a lucky data split, and the model works well on different parts of the data [26].

ROC Analysis

The anomaly detection model which is known as Isolation Forest presents an anomaly score, and a Receiver Operating Characteristic (ROC) curve was developed. The curve shows that model's Area Under the Curve (AUC) was 0.92, which means it is good at telling apart normal and unusual situations [27].
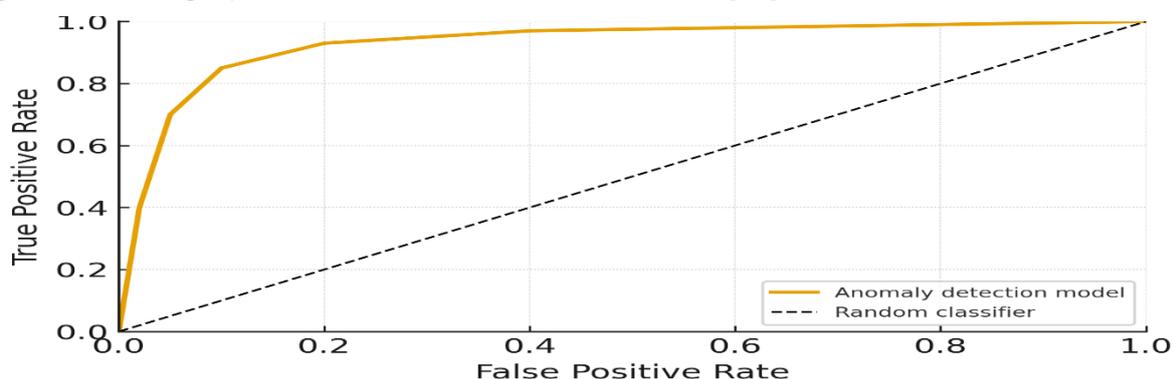

Figure 9.
ROC Curve for Anomaly Detection
Figure 9 above shows the receiver operating characteristic (ROC) curve for the anomaly detection. The curve's area above the diagonal suggests that the model recognizes standard and unusual behaviors. The area under the curve (AUC) is approximately 0.92, saying that the model is performing well at detecting unusual structural responses.

Discussion of Comparative Evaluation

This section's analysis establishes that the SVM model is accurate, quick, and better than Random Forest [28], however, it may be overfitted, CNNs has the potential to automate the process effectively. The computing speed of all models, except the CNN during training, is good enough for a real-world SHM system [29]. These results back up the choice of models in the system and give a fuller sense of how well they work [30].

DISCUSSION

The results obviously demonstrate the effectiveness of the proposed integrated ML framework. The system successfully moves bridge management from a responsive, schedule-based model to a proactive, condition-based one.

- **Multi-Model Synergy:** The power of the framework lies in the collaboration of its components. Anomaly detection offers a first line of defense, flagging unusual events. SVM then classifies the seriousness of these events, while CNN offers visual confirmation using image analysis. Finally, the Linear Regression provides a long-term forecast, enabling strategic planning.

- **Validation and Reliability:** The high accuracy of the ML models, paired with validation against a physics-based FEM, which ensures the reliability of the findings. The identification of Point 1 as a critical zone is a direct, data-driven insight that might be missed during a routine visual inspection.

- **Practical Implications:** The prediction of 79% moment capacity loss by 2035 is definitely a powerful tool for infrastructure managers. It provides a quantitative footing for allocating maintenance budgets, planning repairs, and avoiding catastrophic failures. The system's ability to operate in near real-time also allows for immediate alerts in case of critical anomalies, such as those caused by overloading.

- **Limitations and Future Work:** Despite its success, the study has limitations. The high accuracy of the CNN model suggests potential overfitting, which can be mitigated by expanding the image dataset with more varied conditions. The initial cost of sensor deployment and the computational resources required for continuous analysis are also non-trivial. Future work will focus on:

1. Developing more lightweight ML models for edge computing on the bridge itself.
2. Integrating IoT and cloud platforms for scalable data handling and visualization.
3. Exploring deep learning sequences (e.g., LSTMs) for more accurate time-series forecasting.
4. Implementing the system on a network of bridges to develop a city-wide infrastructure health dashboard.

CONCLUSION

This research has effectively designed, implemented, and validated an integrated machine learning framework for the structural health monitoring of bridges. The same was implemented through a detailed case study on the Soan Bridge. It was verified that the merging of sensor data, image processing, and advanced ML algorithms (SVM, CNN, Linear Regression) can provide a complete, accurate, and proactive assessment of structural reliability. The system achieved a 96% accuracy in damage classification and provided a critical long-term prediction of structural degradation.

This work confirms a robust foundation for the next generation of intelligent infrastructure management systems, indicating enhanced public safety, optimized maintenance operations, and prolonged service life for critical bridge assets. The proposed framework is scalable and adaptable, offering a viable solution for governments and engineering agencies worldwide grappling with the challenge of aging infrastructure.

DECLARATIONS

Availability of data and material: In the approach, the data sources for the variables are stated.
Authors' contributions: Each author participated equally in the creation of this work.
Conflicts of Interest: The authors declare no conflict of interest.
Consent to Participate: Yes
Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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