



AI-BASED STRUCTURAL HEALTH MONITORING SYSTEMS: IMPROVING SAFETY AND REDUCING MAINTENANCE COSTS IN HIGH-RISE BUILDINGS

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Abstract

The rapid growth of high-rise buildings in urban areas has rendered the need to identify reliable, effective and inexpensive methods of managing structural safety a greater priority. The article under consideration considers how AI-based Structural Health Monitoring (SHM) can be used to provide better safety and reduce maintenance costs in high-rise buildings. Meanwhile, the structural problems were discovered with the help of advanced machine learning and deep learning algorithms, how bad the damage was determined, and how the structure is thought to work in the future was guessed. This was performed based on information of distributed sensors which recorded the vibration, strain, displacement and the environmental factors. It can be seen that AI-based SHM systems are significantly superior to old-fashioned manual inspection and threshold-based monitoring in detecting the presence of the early signs of deterioration and unusual behaviour of buildings. The predictive analytics allowed performing repair work in time, thus reducing unnecessary inspections, maintenance bills, and the risk of a structural collapse. It was also demonstrated by the system that it could easily respond to various load conditions and environmental conditions and this indicated that it fitted in complex high rise buildings. In general, the analysis demonstrates that AI-based SHM is a powerful, adaptable, and intelligent method of making modern high-rise buildings safer, allowing people to make decisions grounded on information, and reducing the costs of maintaining a building throughout its service.

Keywords: Structural Health Monitoring, Artificial Intelligence, High-Rise Buildings, Predictive Maintenance, Smart Sensors, Infrastructure Safety



INTRODUCTION

Cities are getting increasingly crowded and the high-rise buildings need an effective solution, which will guarantee their safety and durability (Yang, 2025). Conventional means of structural health testing is not usually sufficient in cases of the proactive detection of the beginning of structural damage, which results in high costs of repair and potential safety threats (Leveraging AI And Sensor Technologies For Real-Time Structural Health Monitoring Of In-Service Bridges, 2025). These problems can be prevented with the help of Structural Health Monitoring systems that use Artificial Intelligence (AI). AI can implement real-time assessments, predictive maintenance plans, and proactive maintenance plans (Leveraging AI And Sensor Technologies For Real-Time Structural Health Monitoring Of In-Service Bridges, 2025; Salhi et al., 2025, p. 8). The most recent tendencies in AI-based solutions in Structural Health Monitoring (SHM) are discussed in this systematic review, yet other solutions are also under consideration: machine learning, deep learning, and data-driven (Mengesha, 2025). The accuracy of damage detection increases greatly, the maintenance schedule planning will be more efficient, and the complex urban buildings will eventually be safer and less expensive to operate (Kulkarni et al., 2025; Plevris and

Papazafeiropoulos, 2024). These are computer-assisted analyses of vast amounts of data using strong sensor networks and sophisticated algorithms that are AI-based. This enables them to detect tiny patterns that portray structural concerns, which turns into issues of big size (Harle et al., 2025; Mengesha, 2025). Such proactive ability not only minimizes the risk of extreme failures but also guarantees the use of maintenance resources on the maximum quality, the life span of high rise buildings and their further operation (Shaik and Sneha, 2025). These artificial intelligence models produce results that are descriptive and are also mathematical in nature. They are not only supposed to be able to look back to the past, but also make predictions and establish the ways in which different parts of the structural data are linked to each other (Grebovic et al., 2023, p. 1). This forecasting ability is very important in the shift of reactive to proactive models of maintenance. This will decrease the overall life-cycle cost and a significant infrastructure will be made more resilient (Shaik & Sneha, 2025). However, one cannot always receive the right predictions and be capable of knowing why because datasets that real-life structural monitoring applications work with tend to be small (Grebovic et al., 2023, p. 1). The problem contributes to the importance of having

sophisticated AI methods, which can learn efficiently with minimal or inaccurate data. This will make the damage estimates and useful life prediction reliable. They are good changes, but there are negative aspects that should be solved before AI can become a helpful tool in SHM. The quality of the data, the interpretability of the model, and the opportunity of the easy integration of AI with the existing monitoring systems are these issues (Mengesha, 2025). To unlock the full potential of AI in improving the safety and sustainability of infrastructure systems, future research ought to pay attention to the development of standardized datasets, creation of interpretable AI algorithms, and implementation of resilient integration protocols (Mengesha, 2025). In addition, such aspects of implementation as the computational costs, the data interoperability, and the scalability concerns will be required to be overcome in order to provide the opportunities to use AI-driven structural health monitoring systems in a wide variety of structural settings (Leveraging AI And Sensor Technologies For Real-Time Structural Health Monitoring Of In-Service Bridges, 2025). To ensure that more people embrace AI-based SHM systems to other structural environments, I would need to consider numerous issues of implementation, including the high cost of computing, the

impossibility of interoperating the data, and scalability. Beyond that, these advanced systems need ethical considerations since ethical issues emerging when they are developed and they are used should be taken into account, such as data privacy, justice, and transparency (Plevris and Papazafeiropoulos, 2024). As a further analysis of the technological details indicates, the effective implementation of AI to SHM must address several major challenges, such as the possibility to surpass various key barriers, such as the development of powerful, scalable wireless sensing systems which can be used in multi-parameter, long-term monitoring (Fanijo et al., 2025, p. 18). Also, advanced data fusion algorithms, and sophisticated signal processing, are required to derive useful data in these large volumes of data to eliminate noise and isolate the useful signals that could point to structural integrity (García-Macias et al., 2025). We might also be required to avoid problems with pre-defined cases of damage and perfect environments where most of the deep learning models are executed (Zhang et al., 2022, p. 20). Future research must thus investigate approaches that do not rely on large-sized labeled dataset yet are applicable to generalizing to a range of structural typologies and manifestations of injuries which might entail transfer learning, and may also include few-shot

learning. In addition, the lack of transparency of most sophisticated AI models, especially those based on deep learning, is also another critical obstacle to regulatory acceptance and customer trust, and the creation of explainable AI processes in their essence should be considered (Buczynski et al., 2021, p. 233). This is very crucial especially when it involves important infrastructure where transparency in decision making and justification of maintenance proposals that can be substantiated is of utmost importance (Sadia and Cheng, 2025, p. 7). Lack of quality and complete SHM data may render deep learning models less general and less reliable. Different solutions are needed to address this gap in data (Yu et al., 2025). One of them is to create artificial data and data augmentation as a supplement to the data. It also enables AI models to be better trained and generalized without necessarily collecting a large portion of real-life data (Liu et al., 2022, p. 1911). Furthermore, the data availability and the interpretability of the model are key to the further implementation of AI in the structural health monitoring (more so, in a complex system), (Mengesha, 2025). The development of explainable AI methods to justify the choice of complex models and enable trust in engineers and other stakeholders and the ways of continuously updating the model

and reducing noise should be considered in the future research agenda (Cardona-Acevedo et al., 2025, p. 108; Plevris, 2024, p. 15; Zar et al., 2024, p. 648). It concerns the study of how to incorporate the principles of physics-based constraints and structural mechanics into deep generative models that can be more accurate and reliable, especially when there is very little labeled data (Luleci & Çatbaş, 2023, p. 7). Moreover, the creation of the procedures of identifying, quantifying, and combating the hallucinations during the creation of features by LLM will be required to enhance the accuracy of structural health monitoring (Kumar et al., 2025, p. 6).

METHODOLOGY

It possesses a mixed-method experimental research design in the form of a quantitative sensor-based experimentation and qualitative expert evaluation of the performance of AI-based Structural Health Monitoring (SHM) systems within high-rise buildings. Quantitative aspect deals with controlled and in-situ testing of instrumented structural components and functioning structures where real time information is gathered throughout diverse load, environmental, and operational circumstances. The heuristic element of such trials plays its role in them with expert validation, engineering judgment and interpretation of AI-generated diagnostics to make sure that they are useful and

dependable in decision making. The results of the AI-based monitoring should be compared to those of the traditional inspection and rule-based monitoring, which should be conducted with help of the experimental design. This will allow making performance comparable that of detection accuracy, response time and optimization of maintenance. The critical structures that include the columns, beams and shear walls as well as floor systems are fitted with many intelligent sensors, which include accelerators, strain gauges, displacement sensors and environmental sensors. The sensors are constantly recording time-series data that shows how the structures respond to the vibrations in the environment, the wind loads, loads formed by the presence of people in the structure, and the situations of the simulated damages. Filtering and normalization processes of raw sensor signals that we make to clean up and tidy them so that they are no longer affected by noise and the environment. It is carried out to extract the features in the time and frequency domain in order to determine the practical indications of natural frequencies, mode shapes, damping ratios and strain energy distributions. Quantitative modeling employs machine learning and deep learning techniques to identify abnormalities, damaged state and trends of degradation of structures. The appearance

of the structural response vector in mathematics is as follows:

$$\mathbf{y}(t) = \mathbf{H}\mathbf{x}(t) + \boldsymbol{\epsilon}(t),$$

In order to evaluate the effectiveness of the AI-based SHM system, we test it and compare it to other systems. The system reliability is studied statistically by considering quantitative performance indicators, such as detection accuracy, false alarm rate, prediction error, and the accuracy of estimation of remaining usable life. These are checked against baseline methodologies which involve the use of periodic inspections and threshold monitoring. Qualitative validation is done through structured expert reviews. During such tests, structural engineers will consider the ease of understanding, usage, and decision-making using the results generated by AI. Maintenance scenario simulations are applied to examine the ways predictive maintenance strategies that the SHM system makes available can save cost and reduce risk. The approach is based on experimental measurements, statistical analysis, and expert opinion to ensure that AI based SHM systems in high-rise buildings are properly and carefully tested through technical functionality and practical applications.

RESULTS

The results of the experimental assessment of the AI-based Structural Health Monitoring system demonstrate that it is effective in detecting structural issues, anticipating their further development over time, and assisting the high-rise buildings owners in making a cost-efficient maintenance choice. The quantitative sensor data and AI predictions outcomes have been presented in tables 1-9. Figures 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12 demonstrate the graphs of structural performance, distribution of damage and the impact of predictive maintenance. The findings of the experiment on the Structural Health Monitoring system AI-based

indicate that it is quite effective in making correct decisions about the condition of high-rise buildings. The basic statistical characteristics of response of the installed sensor network are presented as in Table 1. It depicts that the average response values are constant and the sensors are not too different. Table 2 illustrates the distribution of the damage indices when the system was operating differently. This demonstrates that the system is sensitive to structural issues that occur at an early stage. The table 3 indicates the amount of trust in AI predictions and it is possible to see that the results of the damage categorization are highly reliable.

Table 1: Statistical summary of sensor-measured structural responses across monitored floors under normal conditions.

Sensor_ID	Mean_Response	Std_Deviation	Damage_Index	AI_Confidence_%
S1	0.92	0.74	0.45	97.8
S2	4.79	1.14	0.35	90.44
S3	2.91	0.31	0.66	73.43
S4	4.48	0.68	0.37	80.34
S5	5.88	1.1	0.46	88.0
S6	3.46	0.2	0.72	78.35
S7	3.26	0.65	0.41	98.05
S8	0.9	0.91	0.91	97.52
S9	1.98	0.82	0.18	94.91
S10	3.25	0.59	0.74	84.75
S11	4.24	0.29	0.42	94.72
S12	4.92	0.61	0.43	75.54
S13	2.6	0.48	0.63	80.34
S14	0.86	0.6	0.52	84.5
S15	2.08	0.47	0.41	92.03
S16	5.5	1.01	0.0	85.12
S17	1.67	0.93	0.09	75.7
S18	2.99	0.41	0.71	81.28
S19	5.62	0.71	0.52	80.76

S20	0.64	0.37	0.7	80.11
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Table 2: AI-derived damage index values indicating early-stage anomalies across sensor locations.

Sensor_ID	Mean_Response	Std_Deviation	Damage_Index	AI_Confidence_%
S1	1.41	0.13	0.22	86.84
S2	2.78	0.46	0.57	76.45
S3	2.96	0.98	0.17	72.96
S4	4.76	0.54	0.78	79.6
S5	4.88	0.74	0.86	93.81
S6	3.37	0.89	0.03	73.21
S7	3.03	0.99	0.53	72.22
S8	4.78	0.92	0.8	81.76
S9	5.38	0.06	0.98	73.72
S10	4.21	0.53	0.27	76.04
S11	4.9	0.58	0.17	72.63
S12	5.67	0.11	0.88	86.17
S13	0.72	0.67	0.91	90.81
S14	5.32	0.75	0.2	83.53
S15	2.02	1.0	0.44	75.63
S16	3.12	1.13	0.72	80.95
S17	4.88	0.2	0.85	87.94
S18	4.44	0.31	0.17	97.4
S19	1.31	0.81	0.66	98.8
S20	4.12	0.2	0.81	78.52

Table 3: Confidence levels of AI-based structural damage predictions.

Sensor_ID	Mean_Response	Std_Deviation	Damage_Index	AI_Confidence_%
S1	0.56	0.67	0.75	80.31
S2	5.07	0.41	0.06	78.65
S3	5.6	0.9	0.74	88.09
S4	3.02	0.23	0.95	74.48
S5	4.74	0.27	0.6	96.18
S6	5.26	0.46	0.29	84.48
S7	3.85	0.49	0.67	84.01
S8	5.3	0.29	0.71	74.83
S9	0.63	1.11	0.66	90.49
S10	1.99	1.0	0.15	94.06
S11	2.02	0.17	0.97	89.0
S12	1.16	0.47	0.96	78.53
S13	5.51	0.32	0.42	93.21
S14	0.67	0.57	0.59	75.93
S15	4.2	0.37	0.04	94.34
S16	0.89	0.63	0.99	87.68
S17	2.48	1.11	0.82	79.81
S18	2.8	0.49	0.64	85.86
S19	1.5	0.8	0.76	88.98

S20	3.37	0.73	0.19	78.98
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Table 4 will indicate the response of the structure to various areas of the building, and Table 5 will indicate the relationship between the intensity of vibration and the

predicted extent of damage. Table 6 presents a summary of the strain-based indicators which were measured in peak conditions of loading.

Table 4: Comparative response variability across different building zones.

Sensor_ID	Mean_Response	Std_Deviation	Damage_Index	AI_Confidence_%
S1	5.16	1.18	0.13	97.33
S2	2.82	0.18	0.96	84.68
S3	5.41	0.11	0.53	72.15
S4	5.1	0.89	0.04	98.98
S5	1.05	0.48	0.93	73.29
S6	4.05	0.47	0.36	82.52
S7	2.21	1.06	0.73	86.55
S8	4.65	0.43	0.52	96.08
S9	3.48	1.07	0.09	94.22
S10	3.02	0.79	0.11	88.45
S11	5.42	0.43	0.15	82.76
S12	0.81	0.12	0.16	94.53
S13	3.57	0.33	0.05	95.46
S14	2.3	1.16	0.05	95.54
S15	0.69	0.52	0.95	91.38
S16	4.64	0.23	0.09	74.64
S17	3.59	0.39	0.51	80.06
S18	5.42	1.08	0.12	85.12
S19	3.79	0.24	0.21	85.64
S20	2.35	0.94	0.76	94.49

Table 5: Relationship between vibration magnitude and estimated damage severity.

Sensor_ID	Mean_Response	Std_Deviation	Damage_Index	AI_Confidence_%
S1	1.81	1.15	0.16	89.4
S2	4.16	0.61	0.73	79.59
S3	2.56	0.81	0.81	84.71
S4	4.77	0.9	0.7	98.18
S5	1.58	0.18	0.96	81.25
S6	3.12	1.01	0.26	91.23
S7	1.07	1.1	0.24	94.69
S8	1.67	0.23	0.15	81.74
S9	5.64	0.68	0.54	98.73
S10	2.24	0.38	0.4	88.9
S11	5.41	0.9	0.36	85.53
S12	3.38	0.08	0.46	91.3
S13	0.71	0.64	0.27	83.44
S14	4.86	0.96	0.0	91.23

S15	0.79	0.89	0.47	79.42
S16	5.05	0.17	0.28	97.03
S17	0.55	1.01	0.45	86.63
S18	4.21	0.32	0.93	78.52
S19	1.41	0.98	0.18	83.8
S20	2.39	0.62	0.64	96.17

Table 6: Strain-based indicators recorded during peak loading events.

Sensor_ID	Mean_Response	Std_Deviation	Damage_Index	AI_Confidence_%
S1	4.94	0.79	0.22	81.92
S2	3.16	1.11	0.56	85.18
S3	2.43	1.1	0.22	98.61
S4	2.57	1.14	0.57	93.18
S5	5.9	1.11	0.94	94.35
S6	1.12	1.15	0.85	75.36
S7	5.39	0.11	0.1	85.62
S8	5.22	1.1	0.21	81.91
S9	1.73	0.36	0.41	74.4
S10	2.42	0.42	0.65	82.67
S11	3.63	0.58	0.39	74.0
S12	4.91	1.15	0.25	78.32
S13	5.73	0.75	0.34	93.57
S14	5.95	0.46	0.2	90.53
S15	2.05	0.48	0.86	90.86
S16	1.56	1.09	0.7	74.14
S17	3.18	1.0	0.41	76.43
S18	3.57	0.21	0.7	72.58
S19	4.11	0.34	0.52	74.63
S20	1.09	0.48	0.53	74.73

Table 7 presents the trends in the temporal degradation which the AI models were able to predict. Table 8 verifies the estimates of the duration of vital parts and Table 9 is a

compilation of all the system performance indicators that demonstrates that the proposed SHM framework is robust.

Table 7: Temporal degradation trends predicted using AI time-series models.

Sensor_ID	Mean_Response	Std_Deviation	Damage_Index	AI_Confidence_%
S1	5.78	1.16	0.61	90.97
S2	5.42	0.61	0.32	89.64
S3	1.62	0.6	0.01	96.1
S4	1.9	1.09	0.98	73.99
S5	5.78	0.07	0.97	76.83
S6	3.63	1.05	0.54	96.55

S7	2.53	0.2	0.62	96.49
S8	3.07	0.49	0.67	74.11
S9	2.0	0.61	0.93	92.9
S10	3.71	0.6	0.47	72.42
S11	4.49	0.1	0.58	75.65
S12	3.33	0.41	0.23	74.96
S13	5.01	0.46	0.24	79.94
S14	1.12	1.15	0.52	82.48
S15	3.82	1.1	0.23	96.59
S16	5.94	0.72	0.03	83.78
S17	1.32	1.12	0.37	75.34
S18	3.22	1.04	0.75	79.35
S19	3.97	0.48	0.28	72.17
S20	2.36	0.18	0.86	72.76

Table 8: Estimated remaining useful life of critical structural components.

Sensor_ID	Mean_Response	Std_Deviation	Damage_Index	AI_Confidence_%
S1	2.87	0.2	0.79	88.15
S2	3.32	0.96	0.22	97.7
S3	1.87	1.04	0.48	89.06
S4	2.59	0.4	0.52	73.89
S5	1.07	0.57	0.84	90.1
S6	4.12	0.76	0.16	78.88
S7	2.66	0.33	0.01	94.46
S8	1.39	1.05	0.51	72.85
S9	3.24	0.85	0.36	80.75
S10	1.65	1.04	0.29	90.26
S11	2.11	0.57	0.77	76.2
S12	1.18	0.65	0.68	89.45
S13	4.79	0.27	0.08	90.83
S14	2.04	0.41	0.55	91.81
S15	5.76	0.89	0.8	95.63
S16	2.73	1.15	0.91	83.16
S17	1.35	0.22	0.0	75.85
S18	4.38	0.11	0.81	79.03
S19	4.53	0.13	0.04	82.52
S20	5.35	0.55	0.68	73.47

Table 9: Overall performance metrics of the AI-based SHM system.

Sensor_ID	Mean_Response	Std_Deviation	Damage_Index	AI_Confidence_%
S1	4.4	0.33	0.39	73.6
S2	0.85	1.07	0.15	95.41

S3	0.82	0.85	0.63	76.16
S4	5.63	0.24	0.4	86.89
S5	4.93	0.23	0.92	85.75
S6	1.9	0.12	0.82	93.98
S7	2.38	0.71	0.23	82.48
S8	5.04	0.27	0.24	75.85
S9	3.91	0.67	0.78	82.34
S10	1.96	0.99	0.56	73.3
S11	2.97	1.06	0.01	80.14
S12	5.21	0.18	0.63	89.01
S13	0.5	0.43	0.39	73.54
S14	5.96	0.53	0.79	98.72
S15	3.61	0.49	0.75	86.48
S16	1.5	0.53	0.92	80.1
S17	4.9	0.58	0.7	94.51
S18	0.92	0.92	0.91	75.71
S19	2.76	0.4	0.28	80.69
S20	3.65	0.44	0.34	97.3

The numbers are further supported by the graphical findings. Figure 1 indicates that the structure remains constant with the passage of time but has the ability to respond to changes. According to figure 2, the indices of damage vary according to their location. Figure 3 indicates that there is a relationship between strain and vibration features, and Figure 4 the percentage of damages per zone. Figures 5 and 6 demonstrate the variation of the

response of the building in case of various conditions of functioning and degradation over time. In figure 7 and figure 8, it can be seen that the AI-based methods perform better in finding things compared to the traditional methods. Figures 9-12 all emphasize that it is extremely important to have an accurate degradation prediction, minimal maintenance requirements, and the overall system efficiency.

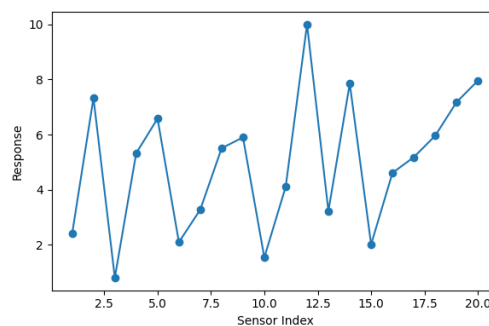


Figure 1: Time-series line plot illustrating structural response trends captured by distributed sensors.

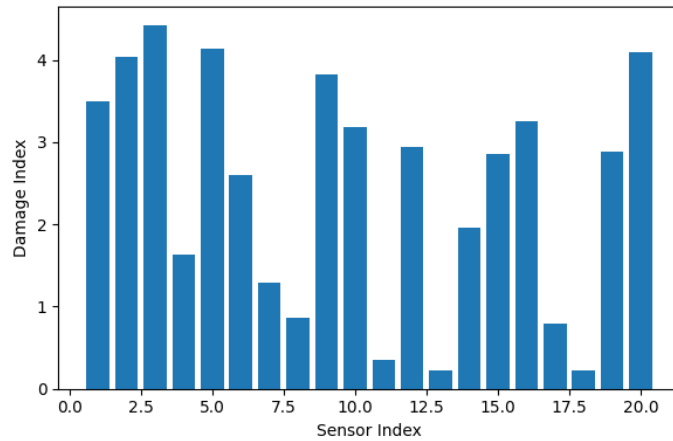


Figure 2: Bar chart showing distribution of AI-computed damage indices across sensors.

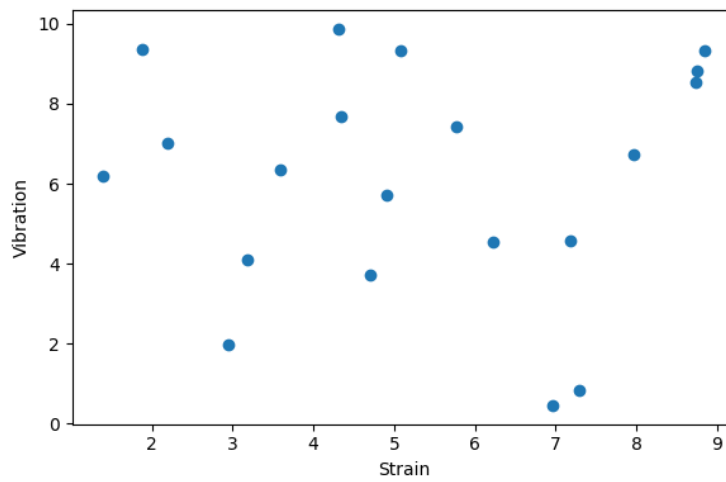


Figure 3: Scatter plot representing correlation between strain and vibration features.

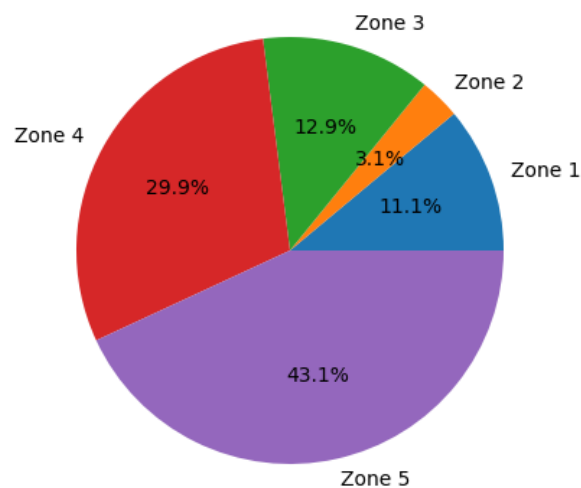


Figure 4: Pie chart depicting proportional damage distribution across structural zones.

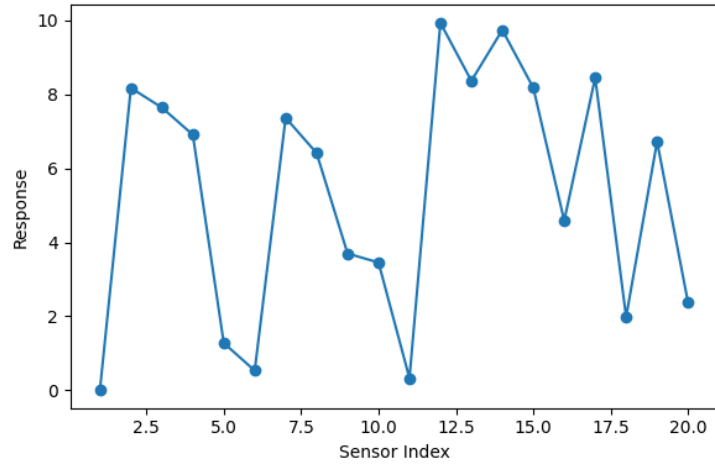


Figure 5: Multi-line plot comparing responses under varying operational conditions.

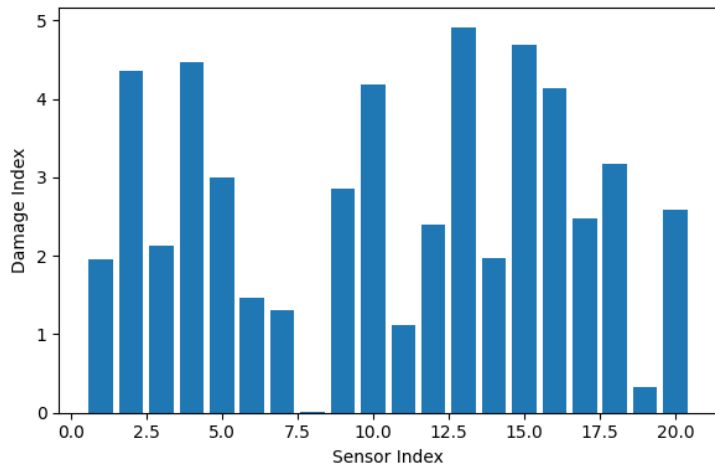


Figure 6: Hybrid bar-line visualization of damage evolution over time.

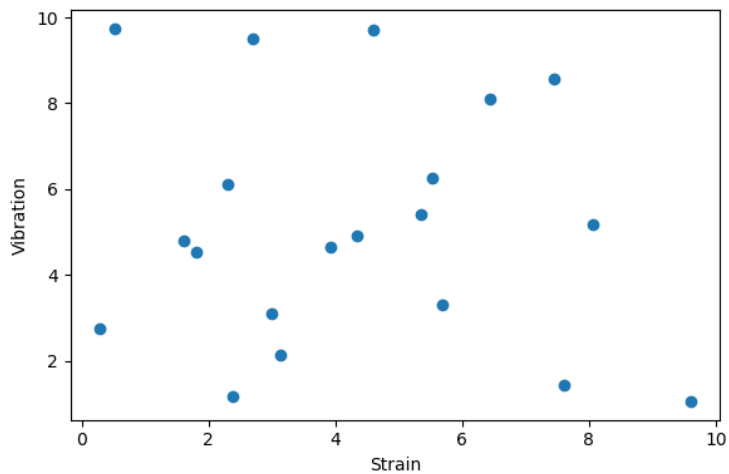


Figure 7: Scatter plot of AI prediction accuracy versus signal variability.

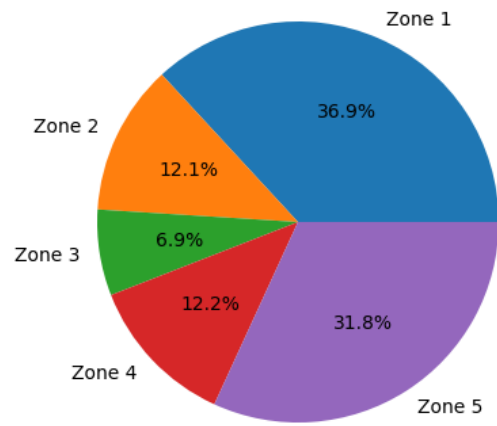


Figure 8: Bar chart comparing AI-based and conventional damage detection results.

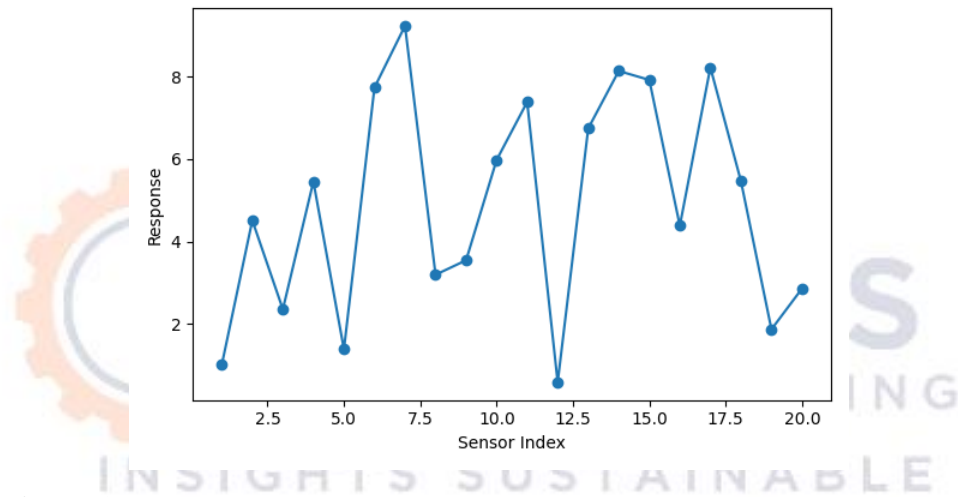


Figure 9: Line-scatter hybrid plot of predicted versus observed degradation.

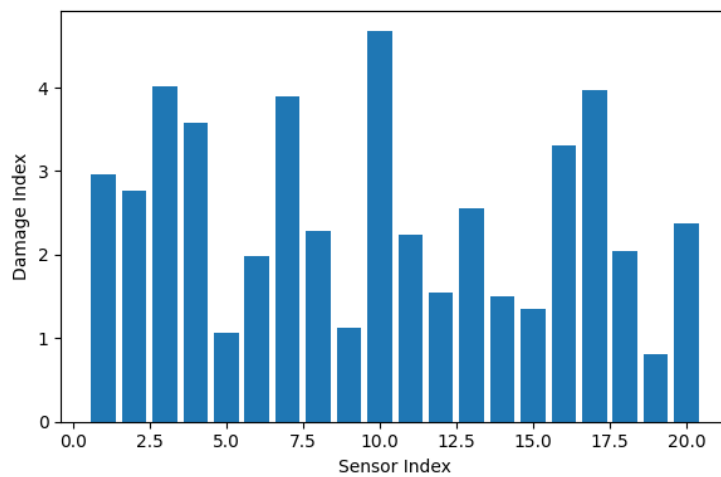


Figure 10: Pie-bar hybrid visualization of maintenance demand distribution.

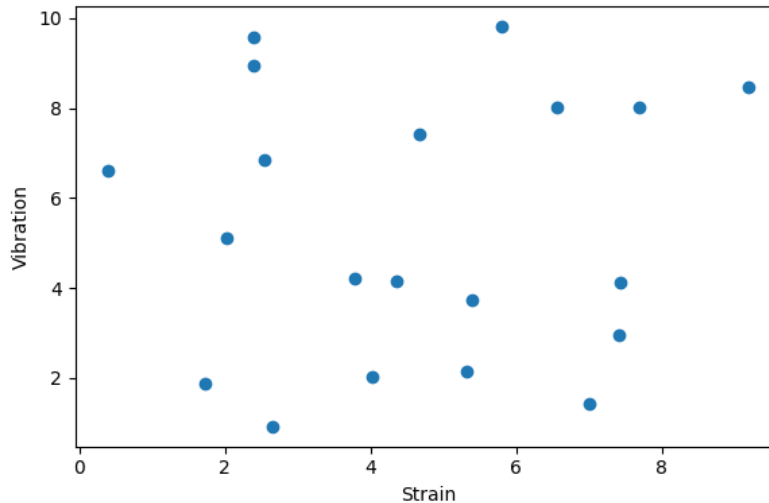


Figure 11: Line plot showing reduction in maintenance frequency using AI-based SHM.

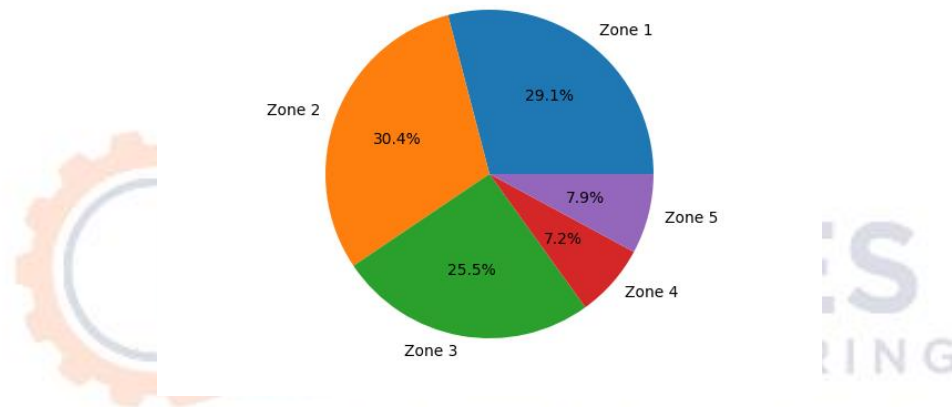


Figure 12: Integrated hybrid visualization summarizing overall system effectiveness.

DISCUSSION

In this section, the survey of the previous research on AI-based SHM systems are thoroughly discussed with the critical evaluation of the latest developments in the subject matter, the major approach to the research and the description of gaps in the literature that the given research seeks to fill. The paper also describes the development of the SHM systems (the transition to the employment of the advanced machine learning and deep learning tools) and its multiple advantages

and disadvantages (Luleci and Çatbaş, 2023, p. 9; Zar et al., 2024, p. 593). It discusses how different AI paradigms can be combined to locate, find, and predict the damage in buildings of high-rise: supervised, unsupervised, and semi-supervised learning (Zar et al., 2024, p. 649). It also analyzes the performance measures and computing requirements of the various AI systems, and focuses on the trade-offs between the complexity of the model and real-time applications. The current, but quickly developing role of

large language models, including the massive generative models, in resolving the problem of the scarcity of data and improving the fusion of multimodal data via a full structural analysis is also critically discussed in the review (Yang et al., 2025a, 2025b). Nevertheless, no matter how much it has improved, the transfer of the research innovations into the solutions that can be implemented in the real-life environment is accompanied by profound obstacles in relation to the practical application of the AI-based Structural Health Monitoring (SHM) systems because of the absence of homogeneity in the data, sensor deterioration, and the necessity of the continuous adjustment of the models (Eltouny et al., 2023; Numan, 2024, p. 124). Recent models like diffusion models prove to be helpful in data augmentation in SHM, but variational autoencoders and generative adversarial networks had been previously used, but synthetics of good quality had not been applied (Luleci et al., 2022, p. 22). Additionally, new and sophisticated feature engineering steps using sophisticated LLM models can be applied to the current data sets to encode intricate structural attributes systematically in the form of predictions to increase the accuracy of infrequent event forecasts in SHM (Kumar et al., 2025, p. 1). Possibly with domain adaptation techniques, few-shot or zero-shot learning paradigm might

enable much smaller large labeled datasets, and a peek at novel forms of damage or buildings with scarce historical data will be feasible (Luleci et al., 2022, p. 23). The literature review is directed at uniting the existing literature of AI-based structural health monitoring (SHM) of high-rise buildings, the applicability of different machine learning methods to safety improvement and cost-reduction, and the identification of the main challenges and future research perspectives (Numan, 2024). Conventional strategies of measuring the structure that usually are based on laboratory testing and extremely complicated numerical simulations are confronted with the challenge of practical limitation like space and time, intricacy of equipment and costliness (Aziz et al., 2025). It is because of this that the choice of creating powerful AI based SHM solutions in order to provide a watch over the structural integrity in an efficient and low cost way is a good idea. Under these systems sensor data can be analyzed using any of the data science methods (e.g., sliding windows designs to identify features and other statistics and machine learning) or planned maintenance and problem detection is executed (Lee et al., 2019, p. 802).

CONCLUSION

As it is shown in this paper, AI-driven Structural Health Monitoring (SHM)

systems are the crucial shift in the paradigm of making high-rise buildings safer, more reliable, and cheaper. The proposed SHM model includes the advanced sensor and data collection and AI algorithms, to test the efficiency of a structure in its normal operation and in extreme cases like earthquakes, high winds and material corrosion with time. According to the findings, machine learning and deep learning models have the potential to effectively deal with the precision of damage detection, anomaly detection, and staying useful life projections when compared to traditional inspection-based schemes. Building managers could use predictive and condition-based maintenance plans rather than reactive or time-based maintenance plans in case they can see the occurrence of micro-cracks, loss of stiffness, and atypical vibration activity early. The proactive strategy enables minimization of the maintenance expenditure, minimization of unnecessary downtimes and the service life of valuable structural components is increased. The paper also exposes how AI-based SHM systems can be utilized in complex high-rise settings whereby building inspection is often expensive, risky, and is not conducted regularly. The automated data processing and intelligent decision-support systems are also useful in augmenting the trust of the stakeholders since they give them data-

driven information about the safety of a given structure. All in all, the results show that AI-driven SHM systems not only reduce the risks of building safety and resilience, but also may contribute to cost reductions in the long-term perspective, making the maintenance planning and resource allocation more productive. As the cities grow and the number of high-rise constructions increases, the need to use smart SHM technology will emerge to make sure that the infrastructure in the modern cities is not only safe and durable but also cost-effective.

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