nature portfolio

# Peer Review File

## Mechanics-informed autoencoder enables automated detection and localization of unforeseen structural damage

REVIEWER COMMENTS

Reviewer #1 (Remarks to the Author):

The paper presents a new methodology for early detection of damages in structures. It is based on an enhanced version of autoencoder, which is mechanically informed by means of a distributed mesh of sensors applied on the structure. The procedure is developed in order to be inexpensive, automated, reliable, robust and applicable to any type of structures.
The proposed approach appears to be one of the first which combines automated detection and localization of early damage. These two features are of paramount importance for effective SHM of structures.
General and detailed comments are listed below.
The paper is well written, the strategy is clearly presented and explained. The procedure is validated numerically and experimentally.
In the numerical example, a gusset plate is implemented in Abaqus and several damage scenarios are tested. Results are compared with other anomaly detection approaches based on machine learning.
Authors developed also an experimental campaign, realizing a gusset plate and considering two different damage scenarios: a crack and a loosened constraint.
Performance of the present methodology, considering different features, outperforms other methods based on ML.
Results have been provided with good context and consideration of available works.
Provided references appear appropriate to the topic.
Figures are clear and well prepared.
My suggestion is to better underline the limits of the proposed approach. On one hand, it shows promising potentialities, however it has also some limitations that should be better addressed by the authors since they claim the procedure is 'ready to use'. This is not completely correct since looking at figure 4, the number of requested sensors (in this case strain gauges) is extremely high for such a small plate. On one side, strain gauges are inexpensive sensors, but on the other a very fine mesh of sensors is needed. Additionally, all these sensors are wired (in the picture this aspect is not shown) since every single sensor needs to be electrically supplied. For larger structures, such a fine mesh of sensors is not viable. I suggest authors to carry out simulations and/or experimental tests considering a variable number of sensors and providing damage detection results varying this parameter. More details are provided in the list of the detailed comments.
Detailed comments are listed below:
- In Lines 62-72, the authors point out the scarcity of literature regarding early damage detection in structural health monitoring (SHM) approaches. However, early detection constitutes the primary objective of all SHM methodologies, as detecting damage in its advanced stages yields no tangible benefits. I recommend the revision of this section to convey this point more effectively.
- At Lines 115-116, the authors claim that their approach "enables the system to adapt to diverse structures and detect known and unknown anomalies without relying on additional model knowledge." Nevertheless, in my opinion, this assertion contradicts the claim of employing a "mechanics-informed" approach. The discrepancy likely stems from the terminology employed. The term "mechanics-informed," synonymous with "physics-informed," implies the incorporation of physical principles into the methodology, whereas the proposed method is entirely data-driven. The authors should clarify this point comprehensively.
- The paper novelty should be better emphasized. There are several methods grounded in autoencoder reconstruction error for damage detection (refer to, for example, DOI: 10.1111/mice.12943). Also, the authors refer to prior works employing the data compression strategies used in this study. To my understanding, the novelty of the proposed approach is in the second part of Equation (6). The authors should clarify this part and discuss the underlying physical rationale of the observed improvement. Notably, the improved efficacy seems to lie in the ability of the method to assign different weights to the measurements based on sensor proximity, a feature extracted directly from the measurements themselves rather than being user-inputted into the model. This key aspect should be emphasized.
- The authors assert that their method is "deploy-and-forget," highlighting the reduced need for human intervention. However, the practicality of attaching dozens of strain sensors to a single small plate (perhaps each plate of the bridge) is questionable. Beyond the initial expense of acquiring and installing these sensors, ongoing maintenance is necessary. Additionally, if the

monitoring approach operates continuously, as implied by the claim of real-time early detection, it raises concerns about power supply and data management.
- Taking into account variations caused by environmental and loading fluctuations in the baseline, as discussed in Lines 116-119, generally decreases false alarms. However, if the underlying causes of these variations are not measured and explicitly modeled, this approach essentially involves adjusting the anomaly threshold, potentially impeding early damage detection. It is unclear whether environmental and operational conditions are merely included in the baseline dataset or modeled in a specific way. For instance, temperature is never explicitly mentioned in the discussion of the experimental results.
- Is recording noise introduced by the authors in the simulated dataset? Considering the presence of noise commonly encountered in field applications is crucial to validate the robustness of the method.
- In the section "Data Compression and Dataset Construction," it is necessary to include the sampling frequencies of the strain data and the time discretization of applied loads in the FEA. Moreover, employed metaparameters (i.e., number of neurons, network architectures…) should be provided regarding the implementation of both the proposed autoencoder and the alternative methods used for comparison.
- Regarding the authors' comment at Lines 584-585, where they mention setting λ to 0.5 for simulations and 0.2 for experiments, it is essential to clarify the rationale behind these values. Such determination appears highly dependent on specific cases. Is there a means to evaluate these values before damage occurrence?

Reviewer #1 (Remarks on code availability):

I did not review the code

Reviewer #2 (Remarks to the Author):

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

Reviewer #3 (Remarks to the Author):

In this manuscript, authors propose a new approach for automated detection and localization of damage in structures, based on strain measurements and an autoencoder enhanced with new terms in the loss function, which is meant to take into account correlation of strains between all pairs of sensors. Authors claim that their method is more efficient than existing methods and allows up to 35% earlier detection than the standard autoencoder. In the reviewer's opinion, this work has some serious flaws, which need to be addressed.

1. Efficiency of the proposed approach is high because a large number of sensors is employed to monitor the structure. This can be seen as a limitation, which makes the approach not feasible for real-life large-scale structures.
2. Confusing and misleading notations: throughout the manuscript, authors talk about "crack propagation", but they are not simulating a propagating crack, they simply increase the crack length. In computational mechanics, these two are completely different problems. If the authors really mean for the crack to propagate, then it needs to be modeled properly.
3. Interestingly, in Figures 2e, proposed method seems to quickly reach its maximum performance and do not improve as the length of crack increases. Such tendency is counter-intuitive, as it is expected that larger cracks are easier to detect. Also, it is not clear what point with 0 crack length

represents. Shouldn't the accuracy of the method for a healthy structure be close to 1, if the autoencoder - AE is trained on such cases?
4. What exactly is shown in Figure 3a? Distribution of strains? Actual or reconstructed? It is interesting that there is absolutely no change of strains in the healthy structure. Even though under the action of applied loading, higher strains must occur near the loaded boundaries.
5. In Methods: the range of amplitudes of the applied loadings is not specified. Time variation of applied loads is not specified. Does "periodic" mean periodic with respect to time or x and y? It is also not clear, why this loading represents traffic.
6. It is not specified, in what directions strains are measured. For example, if all strains are in y-direction, as indicated in figure 1, then it would be impossible to detect vertical cracks (alpha = 90 degrees).
7. Width of cracks (w) is not specified.
8. What is the rationale behind equation (3)? What norm is defined by notation ||*||? In the paragraph after equation (6), Delta_i is defined as "norm difference", but it is the difference of norms.
9. Equation (2) already uses strains, then why autoencoder only with equation (2) is not mechanics-informed, but adding equation (3) makes it mechanics-informed?

Reviewer #4 (Remarks to the Author):

This paper deals with the early damage detection and localization of structural damage. The authors propose an Autoencoder-based strategy improved by a further layer of information provided to the algorithm, i.e. mechanics information. The authors conduct their investigation by focusing on evolving crack propagation in gusset plates as a use-case scenario. The model is first conceptualized in FEM environment, its performance is compared to other baseline models from the literature and then is validated considering the experimental testing of gusset plates specimens. The approach proposed shows enhanced performance in comparison to the compared models both in terms of detection and localization capability.

In my opinion, the paper is interesting and well-written undoubtedly, the methodology employed is appreciable and the results show good potential for early damage detection and localization. Despite its good potential, I believe there is still space for improvement. I present my main concerns about the work in the following.

MAJOR COMMENTS:

1. I believe that the main issue with the work is the lack of precise contextualization. From a structural engineering point of view, the contextualization is quite weak. There is not even a valuable state of the art analyzing the adoption of different Deep Learning (DL) strategies in structural engineering. Despite being present in the structural engineering literature in many different fields of application, structural engineering appears only as an expedient to investigate the methodology proposed and the mechanics-informed approach. This state-of-the-art would help to identify the context in which the authors propose their work and the novelties.

2. In line with the previous point, there is no reference or contextualization of the work presented with other studies in the literature investigating quite similar topics. The proposed modelling approach seems to be quite in line with the Physical-Informed Neural Network (PINN) approach, in which the "physical" and "mechanics" insight of the real system is injected into the DL model by conforming a custom Loss function for the training procedure. Moreover, the "mechanics-informed" models are also studied with approaches employing different data structures to represent the physical systems, such as the Graph Neural Networks (GNN). Some examples of works investigating such topics are reported in the following:
a. Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational physics, 378, 686-707.
b. Raissi, M., & Karniadakis, G. E. (2018). Hidden physics models: Machine learning of nonlinear

partial differential equations. Journal of Computational Physics, 357, 125-141.
c. Song, L. H., Wang, C., Fan, J. S., & Lu, H. M. (2023). Elastic structural analysis based on graph neural network without labeled data. Computer-Aided Civil and Infrastructure Engineering, 38(10), 1307-1323.
d. Parisi, F., Ruggieri, S., Lovreglio, R., Fanti, M. P., & Uva, G. (2024, January). On the use of mechanics-informed models to structural engineering systems: Application of graph neural networks for structural analysis. In Structures (Vol. 59, p. 105712). Elsevier.
3. In the abstract and the introduction is reported many time the reference to the "not expensive and real-time" SHM approach. Although being stated, I feel that this work cannot fully represent a generalized SHM approach but more a study investigating a detailed topic, i.e. a model to detect crack propagation in a gusset place. The authors are considering 27 sensors on a single sub-component of a structure, which is also very specific. What happens when we talk about a full-scale structural system? Is this approach applicable? I perceive that there could be issues in the generalization of this approach so that we can't properly talk about applications on different structural systems. I believe that this aspect should be addressed.
4. Talking about the generalization of the approach, what about structural systems in which different components have variable importance in the general behaviour? Is this correlation-based mechanics-information strategy still effective? It seems that the approach proposed can "inject" into the DL model only "geometric-based" knowledge of the system, i.e. the position of the sensors.
5. I understand that asking for other computations is quite time and effort-demanding, but it could be useful to apply the method to another type of structural system, even without the "experimental validation phase". The authors have already validated experimentally, while further application could help to clarify the generalization issue.
6. Authors could consider improving the discussion by comparing the investigation results with results from the literature highlighted in point 2. Also, the generalization aspect could be further addressed in the discussion.

**REVIEWER COMMENTS**

We want to express our gratitude to the reviewers for their insightful evaluation of our manuscript and for providing us with many helpful comments and suggestions for improving it. We carefully addressed the referees' comments and have made the necessary modifications. Specifically, in the revised manuscript, we significantly reduced the number of sensors used in conducting damage detection and localization tasks and demonstrated robust performance. Additional laboratory experiments on a large-scale beam-column structure with multiple connected components and simulations were performed to showcase the generality and scalability of the proposed method. We believe the suggested improvements have significantly strengthened the overall quality of the work.

We also revised the manuscript to improve the exposition and grammar, fix typos, and rephrase sentences to enhance clarity. To improve exposition, we named our approach Mechanics-Informed Damage Assessment of Structures, abbreviated as MIDAS, and changed the abbreviation of the Mechanics-Informed Autoencoder to MIAE from Mechanics-AE.

We want to highlight our key contribution: the seamless integration of inexpensive sensors, data pre-processing in the form of compression, and a customized autoencoder called Mechanics-Informed Autoencoder.

In the following response, we address the reviewers' comments point-by-point, and the corresponding changes in the updated manuscript are referenced using figures, line numbers, and page numbers.

**Reviewer #1:**

The paper presents a new methodology for early detection of damages in structures. It is based on an enhanced version of autoencoder, which is mechanically informed by means of a distributed mesh of sensors applied on the structure. The procedure is developed in order to be inexpensive, automated, reliable, robust and applicable to any type of structures.

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Performance of the present methodology, considering different features, outperforms other methods based on ML.

Results have been provided with good context and consideration of available works.

Provided references appear appropriate to the topic.

Figures are clear and well prepared.

My suggestion is to better underline the limits of the proposed approach. On one hand, it shows promising potentialities, however it has also some limitations that should be better addressed by the authors since they claim the procedure is 'ready to use'. This is not completely correct since looking at figure 4, the number of requested sensors (in this case strain gauges) is extremely high for such a small plate. On one side, strain gauges are inexpensive sensors, but on the other a very fine mesh of sensors is needed. Additionally, all these sensors are wired (in the picture this aspect is not shown) since every single sensor needs to be electrically supplied. For larger structures, such a fine mesh of sensors is not viable. I suggest authors to carry out simulations and/or experimental tests considering a variable number of sensors and providing damage detection results varying this parameter. More details are provided in the list of the detailed comments.

**Reply:** We thank the reviewer for the positive assessment of our work and the helpful suggestions for improvements. In response, we have addressed the following comments in detail.

- In Lines 62-72, the authors point out the scarcity of literature regarding early damage detection in structural health monitoring (SHM) approaches. However, early detection constitutes the primary objective of all SHM methodologies, as detecting damage in its advanced stages yields no tangible benefits. I recommend the revision of this section to convey this point more effectively.

**Reply:** We revised the section to reflect both the early detection and localization objective across SHM methodologies more accurately (see lines 28-47 in the Introduction section on page 1). First, while early detection is a fundamental goal of all SHM approaches, our discussion was intended to highlight the particular challenges and the limited literature explicitly addressing the effectiveness of emerging data-driven methods under variable conditions. Thus, we emphasize the importance of integrating domain knowledge to enhance the robustness and accuracy of automated damage assessment systems.

Furthermore, we underscore that effective damage localization is equally crucial. Our work strongly emphasizes early damage localization, noting that existing data-driven methods often lack effective means. This dual focus on early detection and localization improves the overall efficacy of SHM systems.

- At Lines 115-116, the authors claim that their approach "enables the system to adapt to diverse structures and detect known and unknown anomalies without relying on additional model knowledge." Nevertheless, in my opinion, this assertion contradicts the claim of employing a "mechanics-informed" approach. The discrepancy likely stems from the terminology employed. The term "mechanics-informed," synonymous with "physics-informed," implies the incorporation of physical principles into the methodology, whereas the proposed method is entirely data-driven. The authors should clarify this point comprehensively.

**Reply:** We appreciate the reviewer's observation and recognize the potential for confusion caused by our terminology. In our manuscript, "additional model knowledge" refers to empirical information such as common crack patterns and typical crack locations. Some studies use this prior information to enhance model learning or damage assessment. To clarify, our approach does not incorporate traditional physical principles directly into the model but leverages basic mechanics knowledge inherent in any structure to enhance its predictive capability. Specifically, we are using the relative strain relation between two adjacent points in a linear undamaged flat continuous structure without geometric variation, from continuum mechanics. Thus, we refer to our approach as “mechanics-informed”, instead of entirely data-driven method.

To ensure clarity, we have revised the sentence to: “Due to the sheer diversity of structures and associated damage they may endure, SHM methods have to contend with unknown or novel damage without being able to rely on prior knowledge or annotated data” (see lines 39-43 in the Introduction section on page 1).

- The paper novelty should be better emphasized. There are several methods grounded in autoencoder reconstruction error for damage detection (refer to, for example, DOI: 10.1111/mice.12943). Also, the authors refer to prior works employing the data compression strategies used in this study. To my understanding, the novelty of the proposed approach is in the second part of Equation (6). The authors should clarify this part and discuss the underlying physical rationale of the observed improvement. Notably, the improved efficacy seems to lie in the ability of the method to assign different weights to the measurements based on sensor proximity, a feature extracted directly from the measurements themselves rather than being user-inputted into the model. This key aspect should be emphasized.

**Reply:** We recognize that autoencoder-based methods are well-established for damage detection. In comparison, our paper makes the following contributions. 1) From a method perspective, our contribution is the seamless integration of inexpensive sensors, data pre-processing in the form of compression, and a customized autoencoder called Mechanics-Informed Autoencoder—edited in lines 117-120 in the Introduction section on page 1. Existing methods either do not use multiple sensors or do not compress the data, i.e., use raw data, before learning the autoencoder. 2) From a technical perspective, we integrated mechanics-informed knowledge into deep autoencoders (see below for a more elaborate discussion). 3) From an application perspective, our paper seeks simultaneous detection and localization of structural damage, while prior autoencoder-based approaches are employed for damage detection only. Our method significantly enhanced the early detection and localization performance compared to existing approaches.

We appreciate the reviewer's insight in pointing out the key novelty in Equation (6). Our approach leverages the “mechanics-featured pattern”—inherent in intact structures but absent in damaged ones. This pattern is discerned by analyzing variations in data across different sensors, allowing the model to learn and recognize deviations from the baseline more effectively when damage occurs. In the updated manuscript, we have clarified how these mechanics-featured patterns, which change in damaged structures, lead to poorer data reconstruction and, thus, higher detection and localization performance. This demonstrates the underlying mechanical rationale for the observed improvements (added in lines 755-766 in the Method section on page 12).

Furthermore, we highlight that our method assigns weights based on corresponding sensor measurements rather than relying on manual input or predefined assumptions about sensor importance. This approach properly reflects the actual mechanical features of the structure, such as stress concentrations at boundaries, whereas methods that assign weights based on geometry do not capture the mechanical relations. This capability to utilize sensor data to automatically capture and leverage structural mechanics is a crucial aspect of our novel approach. We emphasize these advantages in the manuscript (see lines 769-780 in the Method section on page 12).

Regarding data compression, we acknowledge that it is not novel by itself. However, its application distinctly sets our work apart from existing autoencoder-based methods that process raw time-series signals directly. Incorporating data compression enhances robustness to noise and temperature variations, optimizes data processing, network training, and prediction efficiency, and facilitates near-real-time anomaly detection. This is extremely important for advanced wireless sensors that require efficient data storage and transmission. We believe that our proposed framework can be seamlessly integrated with wireless sensor technology as a framework for fully automated SHM solutions, greatly contributing to advancing the field (see lines 591-607 in the Discussion section on page 10).

- The authors assert that their method is "deploy-and-forget," highlighting the reduced need for human intervention. However, the practicality of attaching dozens of strain sensors to a single small plate (perhaps each plate of the bridge) is questionable. Beyond the initial expense of acquiring and installing these sensors, ongoing maintenance is necessary. Additionally, if the monitoring approach operates continuously, as implied by the claim of real-time early detection, it raises concerns about power supply and data management.

**Reply:** We acknowledge the concerns regarding the high number of sensors in the original manuscript submission. In response, we have significantly reduced the number of sensors required for effective training, damage detection, and localization, as demonstrated in the additional results presented in the updated Figure 4 and Figure 5(b-c) and the corresponding text on pages 5-7 of our updated manuscript. We also conducted additional experiments on a beam-column structure using a significantly reduced number of sensors (see pages 9-10 and Figure 6).

Moreover, our research builds upon previous work where self-powered wireless sensors were successfully deployed in the field. These sensors do not require an external power supply and are designed for easy installation in dense networks at a very low cost. The devices are built to last several decades with minimal maintenance. They record and compress data on-device and communicate wirelessly, greatly reducing the challenges typically associated with continuous monitoring systems. This technology underpins the practicality of our approach in real-world applications, contributing to an efficient and automated SHM solution. References to our previous research are provided to substantiate these claims of practicality. This related information and references are included in lines 591-607 in the Discussion section on page 10. Furthermore, it is important to note that the computational methods developed in this paper can be applied to any sensing technology, from simple strain gages to advanced wireless devices with edge computing capabilities.

Alavi, Amir H., et al. "An intelligent structural damage detection approach based on self-powered wireless sensor data." *Automation in Construction* 62 (2016): 24-44.

Alavi, Amir H., et al. "Damage detection using self-powered wireless sensor data: An evolutionary approach." *Measurement* 82 (2016): 254-283.

Hasni, Hassene, et al. "A new approach for damage detection in asphalt concrete pavements using battery-free wireless sensors with non-constant injection rates." *Measurement* 110 (2017): 217-229.

Hasni, H., et al. "Continuous health monitoring of asphalt concrete pavements using surface-mounted battery-free wireless sensors." *Bearing Capacity of Roads, Railways and Airfields*. CRC Press, 2017. 637-643.

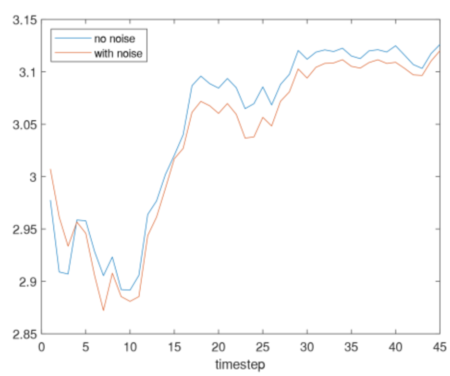
- Taking into account variations caused by environmental and loading fluctuations in the baseline, as discussed in Lines 116-119, generally decreases false alarms. However, if the underlying causes of these variations are not measured and explicitly modeled, this approach essentially involves adjusting the anomaly threshold, potentially impeding early damage detection. It is unclear whether environmental and operational conditions are merely included in the baseline dataset or modeled in a specific way. For instance, temperature is never explicitly mentioned in the discussion of the experimental results.

**Reply:** We thank the reviewer for highlighting the importance of considering environmental factors such as temperature. In the updated manuscript, we have addressed this by including temperature variations in our additional numerical experiments. During training, data from the undamaged structure are generated under varying temperatures at 5, 10, 15, 20, 25, and 30 degrees Celsius, with intervals of 5 degrees. The model was then evaluated for undamaged and damaged cases at 10 and 13 degrees Celsius temperatures. In Figure 4d of the updated manuscript, the results from MIAE are more robust than those of standard autoencoders, which failed to detect damage at 10 and 13 degrees. The performance is comparable to those from the original simulations, demonstrating our method's robustness in accommodating temperature variations (see lines 367-380 in the Results section on page 7).

- Is recording noise introduced by the authors in the simulated dataset? Considering the presence of noise commonly encountered in field applications is crucial to validate the robustness of the method.

**Reply:** We thank the reviewer for suggesting that we add noise to our simulated dataset. In response, we have introduced a Gaussian noise level of 0.5% to all our raw strain data and utilized this new dataset for training our neural network. The results indicate that adding noise has not significantly affected training accuracy, damage detection, or damage localization (see lines 348-366 in the Results section on page 7).

This robustness can be attributed largely to the data compression algorithm we employ. Unlike methods that directly use raw time-series sensor data for network training, our approach significantly mitigates the impact of noise. The algorithm aggregates cumulative values from designated time windows of strain measurements, which helps smooth out the noise effects. As demonstrated in the figure below, the compressed data features exhibit very similar values and patterns despite the added noise, confirming the effectiveness of our approach in handling real-world noise conditions.




An example of a compressed sensor data feature with noise applied to the raw sensor data.

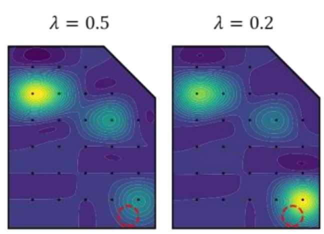
- In the section "Data Compression and Dataset Construction," it is necessary to include the sampling frequencies of the strain data and the time discretization of applied loads in the FEA. Moreover, employed metaparameters (i.e., number of neurons, network architectures…) should be provided regarding the implementation of both the proposed autoencoder and the alternative methods used for comparison.

**Reply:** We appreciate the reviewer's suggestion to provide more detailed information regarding data processing. In response to this feedback, we have thoroughly revised the methods section of the manuscript. We now include the sampling frequencies of the strain data and the time discretization details in the FEA (see lines 635-636 in the Method section on page 11). Additionally, we have detailed the meta parameters, such as the number of neurons in each layer and the specific network architectures used for the proposed mechanics-informed autoencoder and the standard autoencoder included for comparison (see lines 736-750 in the Method section on page 12).

- Regarding the authors' comment at Lines 584-585, where they mention setting λ to 0.5 for simulations and 0.2 for experiments, it is essential to clarify the rationale behind these values. Such determination appears highly dependent on specific cases. Is there a means to evaluate these values before damage occurrence?

**Reply:** We thank the reviewer's insightful comment. The previous intention of fine-tuning $\lambda$ was to demonstrate that the performance of a standard autoencoder is not as robust as that of MIAE. As shown in the figure below, using an autoencoder, a smaller $\lambda$ value of 0.2 can accurately localize variations in boundary conditions, while a larger $\lambda$ value of 0.5 will fail. In contrast, MIAE achieves good localization at $\lambda$=0.5 without any tuning. However, we acknowledge that identifying the ideal $\lambda$ value for each scenario is challenging due to the complex interplay of loading conditions, environmental factors, and structural variations in different cases.

To address this, we have adjusted the manuscript to apply a $\lambda$ value of 0.5 to maintain consistency in localization across all numerical and experimental cases. Since the type and nature of damage can vary widely and unpredictably, we aim to detect and localize all potential damages without bias toward any specific feature type. This choice ensures an equal contribution from the $\mu$ and $\sigma$ data. This is updated in the manuscript at line 867 in the Method section on page 14.




Localization contour differences using different $\lambda$ values using an autoencoder

**Reviewer #2 (Remarks to the Author):**

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

**Reply**: We appreciate the reviewer for the time and effort dedicated to reviewing our manuscript.

**Reviewer #3 (Remarks to the Author):**

In this manuscript, authors propose a new approach for automated detection and localization of damage in structures, based on strain measurements and an autoencoder enhanced with new terms in the loss function, which is meant to take into account correlation of strains between all pairs of sensors. Authors claim that their method is more efficient than existing methods and allows up to 35% earlier detection than the standard autoencoder. In the reviewer's opinion, this work has some serious flaws, which need to be addressed.

1. Efficiency of the proposed approach is high because a large number of sensors is employed to monitor the structure. This can be seen as a limitation, which makes the approach not feasible for real-life large-scale structures.

**Reply**: We appreciate the reviewer's comments and concerns about the number of sensors used in our initial study, which might seem impractical for widespread application in large-scale structures. To address this concern, we conducted additional experiments with significantly fewer sensors to demonstrate the feasibility and efficiency of our approach, even when scaled down. These results, showing effective damage detection and localization with a reduced sensor array, are presented in updated Figure 4 and Figure 5(b-c) of the updated manuscript. We also carried out an additional experiment of a large-scale beam-column structure with just 4 sensors (see the Result section on pages 9-10 and Figure 6). These results demonstrate the practicality, versatility and effectiveness for real-life, large-scale structural monitoring.

2. Confusing and misleading notations: throughout the manuscript, authors talk about "crack propagation", but they are not simulating a propagating crack, they simply increase the crack length. In computational mechanics, these two are completely different problems. If the authors really mean for the crack to propagate, then it needs to be modeled properly.

**Reply**: We thank the reviewer's point regarding the terminology of "crack propagation." We acknowledge that our manuscript may have inaccurately used this term and caused confusion. In our evaluation, we are not simulating the dynamic process of crack propagation but are instead assessing the damage (detection and localization) at various instantaneous stages of crack propagation. To avoid confusion, we revised the terminology as "different crack lengths" in Fig. 2e of the updated manuscript to more accurately reflect that we are examining different crack stages, rather than modeling the crack propagation process.

3. Interestingly, in Figures 2e, proposed method seems to quickly reach its maximum performance and do not improve as the length of crack increases. Such tendency is counter-intuitive, as it is expected that larger cracks are easier to detect. Also, it is not clear what point with 0 crack length represents. Shouldn't the accuracy of the method for a healthy structure be close to 1, if the autoencoder - AE is trained on such cases?

**Reply**: The crack with length zero is intended to represent the undamaged scenario. We recognized that calculating detection metrics such as recall, precision, and F1-score is not possible because there is no anomalous data (positive samples). Thus, we decided to remove the zero crack length data from those metrics and instead show only the accuracy metric for the undamaged performance in Fig. 2e of the updated manuscript.

To determine the accuracy or differentiate damages, the reconstruction errors obtained from the neural network are classified as positive (damaged) or negative (undamaged) using a manual set threshold. As for why the accuracy for a healthy structure doesn't approach 1, this threshold was set to a high value, resulting in many false classifications (false positives). And consequently, the overall accuracy is low and does not reach 1.

In response, we tuned the threshold to obtain a lower false positive rate of 0.02. This threshold achieves a higher testing accuracy of undamaged samples above 90%. This testing accuracy metric is now shown in the first graph of Fig. 2f. Additionally, the accuracy and other metrics approach 1 as the crack length increases, as shown in the remaining graphs of Fig. 2f.

4. What exactly is shown in Figure 3a? Distribution of strains? Actual or reconstructed? It is interesting that there is absolutely no change of strains in the healthy structure. Even though under the action of applied loading, higher strains must occur near the loaded boundaries.

**Reply**: Figure 3a illustrates the localization contours for different methods across varying crack sizes. The contour values are calculated based on the difference between the neural network's input and output, with higher values indicating larger variations and suggesting a potential crack nearby. The methodology for computing these values is thoroughly detailed in the 'Damage Localization Metric' section through Equations (7-9).

The contour values for a healthy structure are usually less than one, while they can reach thousands or even higher for a damaged structure. However, in the manuscript, we opted not to display the exact values as our primary goal was to localize damage, and our approach effectively reduced variations at the boundaries.

Regarding the reviewer's observation about strain distribution, it is true that peak strains often occur near boundaries, even in healthy structures, due to loading conditions. However, these peaks do not necessarily indicate damage. Instead of using raw strain values for neural network training, our approach compresses the strain data into mean $\mu$ and standard deviation $\sigma$. These features capture the essential variations in the data while avoiding the direct impact of stress concentrations at the boundaries. Consequently, the reconstruction is performed only for these features, not for the raw strain values, accounting for changes in structural conditions through variations in $\mu$ and $\sigma$.

5. In Methods: the range of amplitudes of the applied loadings is not specified. Time variation of applied loads is not specified. Does "periodic" mean periodic with respect to time or x and y? It is also not clear, why this loading represents traffic.

**Reply**: We appreciate the reviewer's comment. Below, we thoroughly explain how we generate random loadings.

We assume that random loads follow the Fourier series. The loads, discretized in the x or y components, consist of combinations of randomly generated sine and cosine functions:

$$load_m(\text{x/y direction}) = \begin{cases} A_0 + \sum_{n=1}^{20} [A_n \cos\omega(t - t_0) + B_n \sin\omega(t - t_0)] & \text{for } t \geq t_0, \\ A_0 & \text{for } t < t_0, \end{cases}$$

where coefficients $A_0, \omega, A_n, B_n, t_0$ are randomly chosen based on the following distributions. $A_0$, $A_n$ and $B_n$ follow a normal distribution $N(0, 1)$. $\omega$ follows a normal distribution $N(4\pi, \frac{3}{2}\pi)$. $t_0$ follows a uniform random distribution between 0 and 1 i.e., U[0,1]. The subscript $m$ is 5, indicating that 5 loadings are applied to the same location of the structure in the same direction ($x$ or $y$). This further increases the complexity of random loading. Thus, the total force in one direction is:

$$F_{x/y} = \text{amplitude} * \sum_{m=1}^{5} load_m(\text{x/y direction})$$

The amplitude is calculated as pressure multiplying the loading length 0.2m and plate thickness 0.012m, $\text{amplitude} = 1{,}000{,}000 \times 0.2 \times 0.012 = 2{,}400N = 2.4kN$. As each load component $load_m$ is randomly generated, the maximum load magnitude in total is expected to be around 2,000$kN$.

Regarding the time variation, the timestep is set to 0.025s for the simulation (added in lines 635-636 in the Method section on page 11) and 0.1s for the experiment to ensure that the machine applies accurate loading in the real experiment (see lines 684-686 in the Method section on page 11).

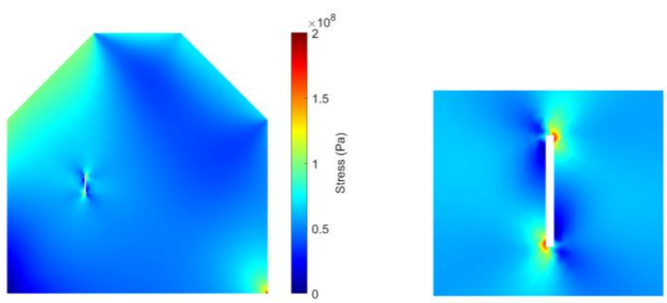
The term "periodic" refers to time due to the construction of the Fourier series. However, as explained above, we applied this time-varying periodic loading separately in the $x$ and $y$ directions.

Regarding why this loading represents traffic, we believe that using the Fourier series with randomized parameters, the model mimics the complex interplay between predictable traffic patterns (e.g., daily rush hours) and inherent randomness (e.g., vehicle mix and cargo fluctuations). This could effectively simulate the varying amplitude, frequency, and direction of traffic loads on a structure. This explanation is also included in the updated Supplementary note 5.

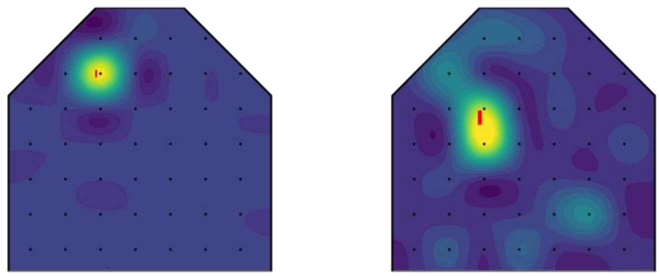
6. It is not specified, in what directions strains are measured. For example, if all strains are in y-direction, as indicated in figure 1, then it would be impossible to detect vertical cracks (alpha = 90 degrees).

**Reply**: The strains are measured exclusively in the y direction (even in simulations, only vertical strains are extracted). However, it is still feasible to detect vertical cracks due to the stress concentration that occurs at the crack tip. For experimental studies, this information is provided in lines 654-657 in the Method section on page 11. For numerical simulation, this is in lines 645-646 in the Method section on page 11.

The following figures present results from a finite element analysis (FEA) of a gusset plate with a vertical crack. The loading is applied from the top left and top right edges of the plate, while the bottom edge is fixed. On the right side of the figure, we observe the stress concentration near the crack tip, indicating that nearby strain gauges will record changes in strain values. Moreover, the proposed framework successfully localizes the vertical crack, as demonstrated in the lower row of the figure below.




FEM stress distribution for a vertical crack and the stress concentration details



Two vertical crack scenarios localized by the proposed framework

7. Width of cracks (w) is not specified.

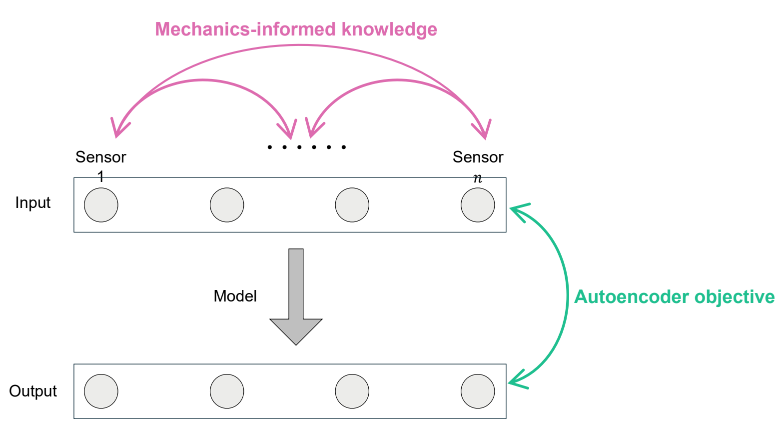
**Reply**: We thank the reviewer for pointing out this omission. In the simulation, the crack width varies from 1mm to 7mm across different cases, with an interval of 1mm. Specifically, the crack width shown in Figure 2 is 4mm. We have updated the manuscript in lines 192-193 in the Result section on page 3 and lines 639-640 in the Method section on page 11 to include this information.

8. What is the rationale behind equation (3)? What norm is defined by notation ||*||? In the paragraph after equation (6), Delta_i is defined as "norm difference", but it is the difference of norms.

**Reply**: Before explaining the rationale behind Equation (3), we would like to explain the standard autoencoder's rationale. For a healthy structure, the autoencoder model is trained using undamaged data to learn a baseline model or "data pattern" representing the undamaged condition. Any "shift in patterns" within the damaged dataset is identified as an anomaly during damage detection and damage localization.

Our mechanics objective function, represented by Equation (3), aims to identify and optimize a "mechanics featured pattern" commonly present in intact structures but not valid for damaged structures. This pattern is discerned by analyzing variations in data across different sensors, allowing the model to learn and recognize deviations from the baseline more effectively when damage occurs.

The following figure shows how our mechanics-informed knowledge differs from the standard autoencoder objective. Based on mechanics-informed knowledge incorporated in Equation (3), this additional pattern strengthens the sensor relationship. It enables the autoencoder to learn more distinctive patterns from undamaged data, making it more sensitive to any 'shift in patterns' caused by anomalies.



Mechanics-informed knowledge takes into account relationships between the sensors. The updated manuscript incorporates this figure into Fig. 7c.

To illustrate this qualitatively, consider the concept of stress concentration. Strain sensors generally detect changes in a local area. A sensor located near a damaged area (e.g., Sensor #1) has a higher probability of showing abnormal behavior, whereas a sensor far from the damage (e.g., Sensor #2) is likelier to exhibit normal data patterns, yielding low reconstruction error during testing. By explicitly modeling these relationships with mechanics-informed loss functions, the network becomes better at distinguishing between normal and anomalous behavior, improving its sensitivity to subtle shifts caused by damage. This information is included in lines 755-766 in the Method section on pages 12.

Our notation $|| * ||$ denotes $L_2$ norm. We have clarified this in the manuscript using the notation $|| * ||_2^2$ to avoid confusion.

We thank the reviewer for pointing out our misuse of terms. “Difference of norms” is indeed more accurate than “norm difference,” and we have updated the manuscript accordingly (see line 798 in the Method section on page 12).

9. Equation (2) already uses strains, then why autoencoder only with equation (2) is not mechanics-informed, but adding equation (3) makes it mechanics-informed?

**Reply**: We appreciate the reviewer's question. The term “mechanics-informed” does not solely relate to the type of data used but refers to the explicit incorporation of mechanical correlations into the neural network training process. A standard autoencoder typically relies exclusively on data and is considered purely data-driven. In this approach, any correlations within the data remain hidden and are learned implicitly.

In contrast, our mechanics-informed approach explicitly leverages the mechanical correlations present within structures as interpretable features. Equation (3) introduces a mechanics-informed loss that serves as an objective function, enforcing known mechanical relationships between different strain sensors during training. This explicit incorporation of domain knowledge helps the autoencoder learn meaningful features more accurately, making the model “mechanics-informed.”

Equation (2) alone doesn't provide sufficient mechanical information to differentiate it from a standard data-driven approach. Adding Equation (3) aligns the learning process with mechanical principles, ensuring that the network not only reconstructs strain data but also understands the fundamental mechanical relationships within the structure.

**Reviewer #4 (Remarks to the Author):**

This paper deals with the early damage detection and localization of structural damage. The authors propose an Autoencoder-based strategy improved by a further layer of information provided to the algorithm, i.e. mechanics information. The authors conduct their investigation by focusing on evolving crack propagation in gusset plates as a use-case scenario. The model is first conceptualized in FEM environment, its performance is compared to other baseline models from the literature and then is validated considering the experimental testing of gusset plates specimens. The approach proposed shows enhanced performance in comparison to the compared models both in terms of detection and localization capability.

In my opinion, the paper is interesting and well-written undoubtedly, the methodology employed is appreciable and the results show good potential for early damage detection and localization. Despite its good potential, I believe there is still space for improvement. I present my main concerns about the work in the following.

MAJOR COMMENTS:

1. I believe that the main issue with the work is the lack of precise contextualization. From a structural engineering point of view, the contextualization is quite weak. There is not even a valuable state of the art analyzing the adoption of different Deep Learning (DL) strategies in structural engineering. Despite being present in the structural engineering literature in many different fields of application, structural engineering appears only as an expedient to investigate the methodology proposed and the mechanics-informed approach. This state-of-the-art would help to identify the context in which the authors propose their work and the novelties.

**Reply**: We appreciate the reviewer's observation regarding the need for more thorough contextualization within our literature review. In response, we have included additional references in our manuscript to illustrate the application of deep learning strategies within the broader field of structural engineering, such as dynamics prediction using Physics-Informed Neural Network (PINN) and Graph Neural Networks (GNN). More importantly, we have emphasized how our research specifically advances the application of machine learning in Structural Health Monitoring (SHM), an area within structural engineering. To clearly define our contribution in this field, we have highlighted a key reference that represents the state-of-the-art in applying deep learning for SHM applications:

Giglioni, Valentina, et al. "Autoencoders for unsupervised real-time bridge health assessment." Computer-Aided Civil and Infrastructure Engineering 38.8 (2023): 959-974.

This reference uses a standard autoencoder for damage assessment, which can serve as a baseline for our work. In comparison to the above reference, our study starts from a data-driven perspective and uniquely incorporates simplified mechanics knowledge as “mechanics-informed” information, enhancing the model's ability to detect and localize structural issues. This approach allows us to clearly demonstrate the novel aspects of our approach and its significance within the SHM field. This literature review information is included in line 93 in the Introduction section on page 2.

2. In line with the previous point, there is no reference or contextualization of the work presented with other studies in the literature investigating quite similar topics. The proposed modelling approach seems to be quite in line with the Physical-Informed Neural Network (PINN) approach, in which the “physical” and “mechanics” insight of the real system is injected into the DL model by conforming a custom Loss function for the training procedure. Moreover, the “mechanics-informed” models are also studied with approaches employing different data structures to represent the physical systems, such as the Graph Neural Networks (GNN). Some examples of works investigating such topics are reported in the following:

(a). Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational physics, 378, 686-707.

(b). Raissi, M., & Karniadakis, G. E. (2018). Hidden physics models: Machine learning of nonlinear partial differential equations. Journal of Computational Physics, 357, 125-141.

(c). Song, L. H., Wang, C., Fan, J. S., & Lu, H. M. (2023). Elastic structural analysis based on graph neural network without labeled data. Computer-Aided Civil and Infrastructure Engineering, 38(10), 1307-1323.

(d). Parisi, F., Ruggieri, S., Lovreglio, R., Fanti, M. P., & Uva, G. (2024, January). On the use of mechanics-informed models to structural engineering systems: Application of graph neural networks for structural analysis. In Structures (Vol. 59, p. 105712). Elsevier.

**Reply**: We thank the reviewer for highlighting these pertinent studies. Building on the previous point, we have included more references on applying deep learning strategies in structural engineering.

We believe our approach differs from the PINN and GNN approaches. Thus, we deliberately use the term 'mechanics-informed' to distinguish our method from 'physics-informed' models, noting that true physics-informed machine learning for SHM with strong physical knowledge is still an evolving field. Our approach, in contrast, begins with a data-driven perspective and aims to integrate domain knowledge into the machine learning model to analyze data patterns more effectively.

PINNs are indeed widely used for forward and inverse modeling of dynamic systems. They integrate physical laws into the machine learning process and incorporate data from multiple sources, including boundary conditions (BCs) and input forces. However, applying PINNs in structural health monitoring (SHM) can be challenging due to the complexity of real-world structures, which often feature unknown constraints and insufficiently detailed information about loading conditions. Additionally, PINNs typically require extensive spatial measurements, which may not be practical in real-world settings due to the impracticality of installing a very dense array of sensors. These limitations make it difficult to fully leverage PINN models in practical SHM contexts. In contrast, our approach seeks to localize structural damages without leveraging physics information (PDE equation, BCs, initial conditions, etc.).

Regarding the references to GNN provided, such as (c) and (d), while these models offer significant advances in structural analysis, they are generally applied to truss structures with well-defined or implicitly given boundary conditions. Truss structures typically require the estimation of unknown responses for a limited number of elements compared to more complex plate structures. These studies focus primarily on static analysis and do not account for the spatially and temporally varying conditions typical of real-world scenarios.

Additionally, we found that graph convolutional networks (GCNs) are popularly used for damage detection. However, these methods are mostly supervised, which makes it difficult to generalize to new and unseen structures, as labeled damage data may be hard to obtain during the training stage. We have included the above discussions in lines 60-72 in the Introduction section on page 1 of the updated manuscript.

We appreciate the opportunity to clarify how our work relates to and differs from these existing methods, and we believe that our mechanics-informed approach provides a viable alternative given the practical constraints and complexities of real-world SHM.

Finally, we summarize this information in the table below, which is also included in the Supplementary Information section. As can be seen, our autoencoder-based approach is the most efficient, as it only requires one type of data (the response).

Table: ML method comparison for structural engineering

| Methods | Require known PDEs | Require BCs & forces data | Supervised (labels) | Require response data |
|---|---|---|---|---|
| PINN [1-2] | √ | √ | √ | √ |

| | | | | |
|---|---|---|---|---|
| GNN [3-5] | | ~ | √ | √ |
| GCN [6] | | | √ | √ |
| **MIDAS** | | | | √ |
| ~: varies depending on the specific application | | | | |

[1] Raissi, Maziar, and George Em Karniadakis. "Hidden physics models: Machine learning of nonlinear partial differential equations." Journal of Computational Physics 357 (2018): 125-141.

[2] Raissi, Maziar, Paris Perdikaris, and George E. Karniadakis. "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations." Journal of Computational physics 378 (2019): 686-707.

[3] Parisi, Fabio, et al. "On the use of mechanics-informed models to structural engineering systems: Application of graph neural networks for structural analysis." Structures. Vol. 59. Elsevier, 2024.

[4] Song, Ling-Han, et al. "Elastic structural analysis based on graph neural network without labeled data." Computer-Aided Civil and Infrastructure Engineering 38.10 (2023): 1307-1323.

[5] Chou, Yuan-Tung, et al. "StructGNN: An efficient graph neural network framework for static structural analysis." Computers & Structures 299 (2024): 107385.

[6] Zhan, Pengming, et al. "A Novel Structural Damage Detection Method via Multisensor Spatial–Temporal Graph-Based Features and Deep Graph Convolutional Network." IEEE Transactions on Instrumentation and Measurement 72 (2023): 1-14.

3. In the abstract and the introduction is reported many time the reference to the “not expensive and real-time” SHM approach. Although being stated, I feel that this work cannot fully represent a generalized SHM approach but more a study investigating a detailed topic, i.e. a model to detect crack propagation in a gusset place. The authors are considering 27 sensors on a single sub-component of a structure, which is also very specific. What happens when we talk about a full-scale structural system? Is this approach applicable? I perceive that there could be issues in the generalization of this approach so that we can’t properly talk about applications on different structural systems. I believe that this aspect should be addressed.

**Reply**: We acknowledge the concern regarding the number of sensors used in our initial study, which may seem impractical for large-scale applications. In real-world structural health monitoring, sensor placement is often strategically limited to critical areas prone to stress, such as connections at joints where boundary condition variations (e.g., bolts loose) and cracks due to stress concentration are most likely to occur.

In response, we have revised our manuscript to include a detailed analysis of the effects of varying the number of sensors. We demonstrate that our methodology still performs exceptionally well even with a significantly reduced sensor count from 28 to as low as 4. The results of these experiments are presented in Figure 4 and Figures 5(b-c), with the corresponding text on page 6 of our updated manuscript. We also carried out additional experiments on a beam-column structure using 4 sensors (see pages 9-10 and Figure 6). We believe those results highlight our approach's effectiveness in damage detection and localization, even with limited sensors.

Furthermore, to address concerns about generalization to full-scale structural systems, we have conducted an additional experiment on a large-scale beam-column structure. In the updated manuscript, experimental results show that our approach adapts well to larger structures and outperforms existing methods like standard autoencoders in terms of damage detection and localization, with as few as 4 sensors. This supports the scalability and practicality of our method for broader SHM applications.

4. Talking about the generalization of the approach, what about structural systems in which different components have variable importance in the general behaviour? Is this correlation-based mechanics-information strategy still effective? It seems that the approach proposed can "inject" into the DL model only "geometric-based" knowledge of the system, i.e. the position of the sensors.

**Reply**: We appreciate the reviewer's comment regarding the generalization of our methodology across diverse structural systems with components of varying importance. While the placement of sensors—what might be perceived as "geometric-based" knowledge—is indeed crucial for damage localization, our methodology fundamentally relies on the correlation between sensor responses when under the same loadings to the structural system. Therefore, our methodology is not strictly confined to geometric data; instead, it effectively captures the interplay among sensors positioned on any part of the structure or across different structural components.

To further demonstrate the generalization and effectiveness of our approach, we have included additional experimental work of a beam-column structure in the updated manuscript (see pages 9-10). This new experiment explores the impact of placing sensors not only on the beam but also on the column. Our findings indicate that with additional sensors on the column, the proposed method can achieve early damage detection and localization as the damage grows severe, while the autoencoder method could not detect or localize small damages. We believe this additional experiment substantiates the generalization capabilities of our methodology, showcasing its applicability beyond simple geometrical configurations.

5. I understand that asking for other computations is quite time and effort-demanding, but it could be useful to apply the method to another type of structural system, even without the "experimental validation phase". The authors have already validated experimentally, while further application could help to clarify the generalization issue.

**Reply**: In response to the previous point and the reviewer's suggestion, we have conducted a large-scale experimental test on a beam-column structure (see pages 9-10 and Figure 6). This test was designed to further clarify and demonstrate the generalization capabilities of our methodology across different types of structural systems with different geometry and multi-components.

6. Authors could consider improving the discussion by comparing the investigation results with results from the literature highlighted in point 2. Also, the generalization aspect could be further addressed in the discussion.

**Reply**: We appreciate the reviewer's suggestion to enhance our discussion by comparing our findings with other works in structural engineering. However, it is important to note that building machine learning models like PINNs, GNNs, and graph convolutional networks (GCNs) typically requires labeled data for supervised learning, as well as extensive details on loading information and boundary conditions. Such information is often unavailable in the SHM configuration we consider and may be challenging to acquire in real-world scenarios.

Consequently, within the context of unsupervised learning, our comparison is made with state-of-the-art methodologies that do not require labeled data. For example, we refer to the work by Giglioni, Valentina, et al. on 'Autoencoders for unsupervised real-time bridge health assessment' from Computer-Aided Civil and Infrastructure Engineering 38.8 (2023): 959-974, which is closely aligned with our approach.

Furthermore, in our additional experiments addressing the generalization issue, we compare our results against those obtained from a standard autoencoder. These comparisons show that our methodology achieves superior damage detection and localization performance, further validating its generalization capabilities across different structural systems.

REVIEWERS' COMMENTS

Reviewer #1 (Remarks to the Author):

The paper has been extensively revised according to the reviewers' comments.
The authors have carefully considered each comment and made revisions to address all the criticisms.
In particular, they have worked on analyzing more deeply the issues related to the number of sensors and their configuration, as well as the effect of noise and environmental factors on the results. The authors conducted an additional investigation on a full-scale beam-column structure employing a reduced number of sensors.
This reviewer appreciates the efforts made by the authors and thinks that the paper has greatly improved. The answers they provided are considered satisfactory by this reviewer. There are still some aspects to be further explored, such as the 'deploy and forget' definition of their approach. However, in a methodology development stage, this is probably not a big issue, as it is important to first prove the methodology working and further improvements may better define this aspect with future on field applications.
As a minor revision, please consider that there is a typo in the paper: the sentence in lines 55-59 is exactly the same as the one in lines 99-102 (introduction).

Reviewer #2 (Remarks to the Author):

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

Reviewer #3 (Remarks to the Author):

All reviewer's points have been thoroughly addressed, and the manuscript can be recommended for publication in the revised form.

Reviewer #4 (Remarks to the Author):

This is probably the best paper I have revised, and it has been an honour for me to review it.
I suggest the publication in this form.

**REVIEWER COMMENTS**

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As a minor revision, please consider that there is a typo in the paper: the sentence in lines 55-59 is exactly the same as the one in lines 99-102 (introduction).

**Reply**: We appreciate the reviewer's affirmation of the revisions we have made, including those related to the reduced number of sensors, the impact of noise and environmental factors, and the additional experimental work on a full-scale beam-column structure. We are glad that these efforts have greatly improved the quality of the work.

Regarding the 'deploy and forget' definition, we acknowledge that such technology may still be in the development stage. As this research article primarily focuses on methodology development, we agree that further improvements, along with the integration of advanced smart sensors, may better refine this aspect in future on-field applications.

Finally, we have addressed the typo by deleting the repeated sentences accordingly.

Reviewer #2 (Remarks to the Author):

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

**Reply**: We appreciate the reviewer for the time and effort dedicated to reviewing our manuscript and helping to improve our work.

Reviewer #3 (Remarks to the Author):

All reviewer's points have been thoroughly addressed, and the manuscript can be recommended for publication in the revised form.

**Reply**: We thank the reviewer for the positive feedback and recommendation. We are pleased that the revisions have satisfactorily addressed all the reviewer's points.

Reviewer #4 (Remarks to the Author):

This is probably the best paper I have revised, and it has been an honour for me to review it. I suggest the publication in this form.

**Reply**: We are honored and sincerely appreciate the highly positive feedback from the reviewer. We thank the reviewer for the thorough review of our work and the recommendation for publication.