International Journal of Early Childhood Special Education (INT-JECSE)
DOI:10.48047/intjecse/v14i5.1192 ISSN: 1308-5581 Vol 14, Issue 05 2022

Revolutionizing Structural Damage Identification and Health Monitoring in Civil Infrastructure with Deep Learning

Mr. Achal Agrawal[1], Dr. Nidhi Asthana[2]
[1]SVKM's Institute of Technology-Dhule Maharashtra India
[2]STME, NMIMS Indore, M.P. India
**Communicating Author, E-mail:* achal.a@svkm.ac.in

Abstract. The use of deep learning techniques to the fields of damage diagnosis and structural health monitoring (SHM) in civil infrastructure has garnered significant attention recently. There is an increasing demand for more efficient repair and management of aging infrastructure, and timely and accurate diagnosis of structural deterioration is essential to preserving public safety and optimizing maintenance resources. A succinct synopsis of the use of deep learning techniques for SHM and damage detection in civil infrastructure is provided in this work. The first section of the introduction covers the many aspects of deep learning and how important it is becoming to track structural health. We investigate how structural damage detection can be made more accurate and efficient by utilizing deep learning techniques like neural networks and data analytics. While highlighting the advantages of deep learning implementation in SHM, it is unafraid to mention the challenges associated with this innovation. Technical challenges, data needs, and ethical limitations are only a few of the challenges that academics and practitioners must overcome in order to fully fulfill the promise of deep learning in structural health monitoring.This article looks ahead, offering insights into potential future paths and opportunities in addition to presenting the current state of affairs. It demonstrates how deep learning has the ability to totally alter how we monitor and maintain essential infrastructure, not just make it simpler.
Keywords: Structural Health Monitoring (SHM), Infrastructure Maintenance, Neural Networks, Deep Learning, Damage Detection, Data Requirements

1. Introduction

Large bridges, dams, and skyscrapers are some of the civil engineering structures most vulnerable to deterioration that renders them unusable. This unbreakable cycle requires urgent maintenance [1-3]. On-site investigations still call for the erection of structures or the closing of bridges in order to carry out the required checks. Many scholars have proposed various forms of systemic health monitoring (SHM) protocols. SHM is a relatively new technology that has emerged in the last few decades. Structure-based health monitoring is one of the main applications of new sensor growth (SHM). Damage that is discovered as soon as feasible can be fixed more swiftly and for less money.In recent decades, engineers and scholars who are still in active practice have placed a high priority on safety and the necessity of lowering inspection costs. Many forums have stressed the significance of economic systemic health surveillance (ESM) in order to guarantee long-term structural stability and safety [5-7]. Different types of modern SHM technologies (use-echo impact, ultrasound surface waves, soil penetrating radar, and electric resistance) [8–10] can expedite frequent inspections and lower the direct and indirect costs associated with needless ageing failures in addition to conventional inspections and non-destructive tests. Any approach or framework related to SHM starts with sensors and sensor data, or observable reactions.

Deep learning approaches have attracted a lot of interest recently in the areas of damage detection and structural health monitoring (SHM) for civil infrastructure. The diagnosis of structural deterioration in a timely and precise manner is essential to maintain public safety and maximize maintenance efforts as our aging infrastructure requires more and more repair and management.

Table 1: The Need for Structural Health Monitoring

Challenges	**Importance**
Aging infrastructure	There are several old-fashioned buildings, tunnels, bridges, and dams scattered across our cities. But as they get older, these structures are more prone to damage and decay.

DOI:10.48047/intjecse/v14i5.1192 ISSN: 1308-5581 Vol 14, Issue 05 2022

Safety concerns	The residents' safety must always come first. Unnoticed structural degradation may result in disastrous breakdowns that put people's lives and property in jeopardy.
Maintenance optimization	In addition to saving money, proactive maintenance based on real-time data can increase the life of infrastructure.

Table 2: Deep Learning Techniques in SHM

Technique	**Application in SHM**
Convolutional Neural Networks (CNNs)	Examine sensor data (from accelerometers or strain gauges, for example) to find abnormalities or departures from normal behavior.
Recurrent Neural Networks (RNNs)	Utilizing past sensor readings, handle sequential data (time-series analysis) to offer insights into structural health.
Autoencoders	Reassemble typical behavioral patterns and mark any variations as possibly harmful.

Table 3: Advantages of Deep Learning in SHM

Advantage	**Impact**
Data-driven insights	From massive amounts of sensor data, deep learning algorithms are able to extract complex patterns that conventional methods can miss.
Real-time monitoring	Early detection of anomalies or damage is made possible by continuous analysis.
Scalability	Deep learning models do not require extensive reconfiguration after they are taught and applied to different types of structures.

Table 4: Challenges and Future Directions

Challenge/Future Direction	**Considerations**
Data quality	Sufficient sensor data is essential for precise forecasting.
Interpretability	improving deep learning models' transparency to facilitate improved decision-making.
Edge computing	putting models directly on edge devices or sensors to enable decision-making in real time.
Transfer learning	enabling effective training by tailoring pre-trained models to particular types of infrastructure.

The application of deep learning to SHM has the potential to improve our built environment's overall safety, dependability, and efficiency. We can proactively address structural faults and create a more robust and secure civil infrastructure by utilizing data-driven methodologies.

2. Data Analysis and Structural Health Monitoring

Advancements in sensor technology and networking (contact, cellular, etc.) have boosted data acquisition speed and capacity. Numerous innovations have also been included into other software and hardware support. One important area of focus, for example, was the creation of new technologies for repairing infrastructure and the application of viable remedies, such as unmanned aerial systems (UAS). A drone team, at the very least, inspects a ground-based bridge for human defects [8–10]. Large sensor arrays have historically been difficult to place on public networks because of the requirements for power and data transmission, as well as the capabilities and challenges associated with the deployment of captive systems. Generally speaking, SHM approaches designed for validated multi-physical models cannot be applied to active models. The obtained data requires the least amount

DOI:10.48047/intjecse/v14i5.1192 ISSN: 1308-5581 Vol 14, Issue 05 2022

of noise for simulations, although this is not practical for systems and functional scenarios. Consequently, data-driven models exhibit adaptability. Machine learning (ML) is a subtype of artificial intelligence (AI). Developing useful algorithms that might potentially create predictions by utilizing pre-existing approximated or simulated algorithms is the aim of machine learning approaches [11–15].


Figure 1: Unmanned aerial aircraft (Source: pwc.com)

The intention behind creating the ML-based SHM models is to let them learn on their own. ML-based SHM models come in three flavors: enhanced learning, unsupervised learning, and supervised learning. When using supervised learning, an ML model can be trained using a set of training data. If the algorithm's results are independent or categorical variables, the model is categorized as either regression (e.g., neural networks, decision-making process, linear, non-linear regression) or classification (e.g., vector support, neighbor k-near, Bayesian, decision-making, deep learning) [16–20].There is no training dataset in unsupervised learning. The intention behind creating the ML-based SHM models is to let them learn on their own. ML-based SHM models come in three flavors: enhanced learning, unsupervised learning, and supervised learning. When using supervised learning, an ML model can be trained using a set of training data. If the algorithm's results are independent or categorical variables, the model is categorized as either regression (e.g., neural networks, decision-making process, linear, non-linear regression) or classification (e.g., vector support, neighbor k-near, Bayesian, decision-making, deep learning) [16–20]. There is no training dataset in unsupervised learning.

3. Methods for Monitoring Structural Health

The five stages of structural health monitoring (SHHM)—detection, location, classification, assessment, and prediction—form the foundation of vibration-based HRM. The two primary classifications of structural degeneration are linear and non-linear. A linear-elastic structure will exist where modal properties and variations can be observed in a linear equation due to geometric or materialistic changes. Non-linear damage, on the other hand, results from the original non-linearity of a linear-elastic pattern or structure after damage. Both types of damage can usually be successfully detected using a damage detection technique [21–23]. The SHM technique involves a number of different steps, as was previously indicated. First and foremost, a variety of sensors continuously monitor the system, and results are derived from conventional dynamic response measurements sampled from the same sensors. The extraction of the features is the next step when these measurements produce the characteristics that could cause harm. To assess the current state of affairs and the structural health, these responsive features are exposed to additional statistical investigation. For the purpose of real-time damage detection in the structural system of buildings and aircraft, SHM is widely used [24–25].

DOI:10.48047/intjecse/v14i5.1192 ISSN: 1308-5581 Vol 14, Issue 05 2022

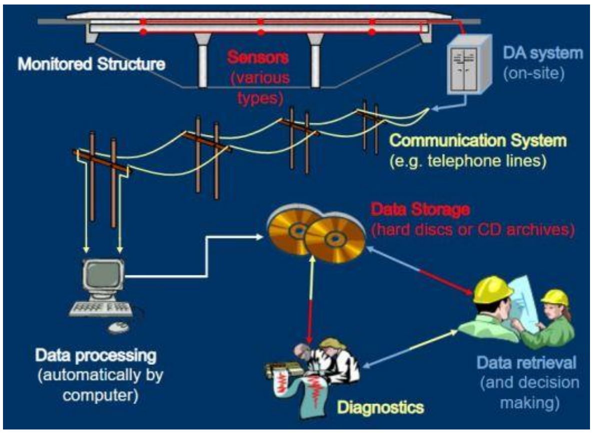

Figure 2: Components of Structural Health Monitoring System (Source: theconstructor.org)

Condition Monitoring [CM], similar to SHM but used in the computation of damage to SHM, is a technique for detecting damage in rotating mechanical systems and the shared equipment used in power plant production. An offline, localized method for evaluating damage is called non-destructive evaluation, or NDE. In addition, the NDE monitors a variety of prefabricated structures, including railroads and pressure containers. In order to investigate the characteristics of a specific damage, NDE must be used and conducted inside the framework that identifies potential damage sites, incorporating only the preliminary information on a damaged site. Statistical Process Control (SPC) is seen as a process-driven technology, in contrast to the structure system, where a wide variety of sensors are applied to detect process irregularities that can supply information regarding structural deterioration.

Improving Structural Health Monitoring in Deep Convolutional Neural Nets via Transfer Learning. Water flow deteriorates concrete surfaces, exposing rebar and causing spalling. Finding this damage is essential to protecting the infrastructure. In order to achieve this goal, a highly accurate deep convolution neural network with transfer learning network damage detection approach is introduced. Pictures captured with a high-definition camera that has an image enlargement gear attached are also processed [26–27]. To identify harm, the implementation of hydro-connection learning transfers in a deep neural convolution network The five different types of labels in the dataset are rebar, intact exposure, intact drain, intact spall, and crack. The Inception-v3 network serves as the primary network and enhances the usefulness of the images [28–29]. Transfer learning is particularly well suited for small datasets at once.

4. Utilizing Deep Learning for Anomaly Detection in Structural Health Monitoring Data

A large amount of data is produced by the growing use of state-of-the-art SHM systems for civil infrastructure. Consequently, mining and interpreting SHM data has recently attracted the attention of civil engineering [30–31]. Unfortunately, a lot of abnormalities are produced by the dynamic nature of civil infrastructure systems, tainting the data. It considerably reduces the data analysis's efficacy. The primary obstacle to autonomous real-time notifications is the incapacity to differentiate between structural damage and the normalcy associated with false results. Most existing data cleaning methods focus on eliminating noise, but it takes a lot of experience and effort to identify erroneous information. SHM provides a manual inspection process and a machine vision method that were both modeled after real-world procedures.SHM provides a machine vision and anomaly system for profound understanding through Deep Neural Visualization Networks, Construction, and Anomaly Recognition Training [32–34]. This tactic imitates the moral reasoning and biological processes of humans. During visualization, time series signals are converted into picture vectors and partially tracked in grayscale images. In the second level, a training data set consisting of randomly selected vectors is manually mixed with a deep neural network or deep-neural network cluster that has been trained utilizing techniques known as automatically stacked encoders and greedy layer specific training. Deep neural networks that can recognize likely abnormalities can be developed using vast volumes of unfettered structural health monitoring data [35–37].Acceleration data are used in conjunction with a really long-term structural health monitoring system to track the efficacy of the recommended solution and illustrate the training process. The results show that data multi-pattern irregularities can be automatically and effectively identified by taking a comprehensive approach to

DOI:10.48047/intjecse/v14i5.1192 ISSN: 1308-5581 Vol 14, Issue 05 2022

anomaly detection in SHM systems and computer vision. A machine-recognizable image is initially created from the time-series data in SHM in order to train a Deep Neural Network (DNN) that mimics a human expert. The DNN is created and trained using the greedy layer training method.

The long-distance SHM's acceleration data can be utilized to confirm the design and training of the DNN are accurate and viable. The complete cleaning and maintenance of the SHM system is aided by the distribution of data abnormalities and sensor counting findings [38–40]. Comparing computer vision and a deep learning technique, the manual inspection system is far behind. The method is new and crucial for automatic real-time monitoring and alerting of SHM systems, as well as offline data processing. This topic is limited to acceleration data, but it can also be used to other types of sensors. Future research should focus more on the unattended assessment of anomalous photographs to prevent manual interference. The data acquired in SHM systems for competitor abnormalities can also be classified using the multi-label method [41–43].

5. Findings and Conclusions

This paper provides an overview of research and development in the field of structural monitoring of civil infrastructure. After a thorough examination of the ideas, methods, innovations, and sensor implementations, the following conclusion was made: Sensors were widely used because of their special benefits. When monitoring civil constructions including bridges, dams, pipelines, wind turbines, railway projects, and life-cycle structures, a variety of data must be measured, including pressures, levels, accelerations, and more. It is imperative to adhere to the implementation standards for sensor safety because of the corrosion and cracking of concrete. For concrete constructions, impact recognition and assessment, early age strength control, and structural health monitoring, an advanced multifunctional intelligent unit is needed on a large scale. Damage index matrices are produced by the early age tracking, which can be used to extract data on damage time and place. Critical damages can be identified faster with structural health monitoring than with conventional monitoring techniques, according to evaluations of the system. It is also feasible to pinpoint the precise location of the damage and the amount of cracks.

References

1. Chathurdara Sri NadithPathirage et al., “Structural Damage Identification Based on Autoencoder Neural Networks and Deep Learning,” Engineering Structures 172, no. April (2018): 13–28, https://doi.org/10.1016/j.engstruct.2018.05.109.
2. Alberto Diez et al., “A Clustering Approach for Structural Health Monitoring on Bridges,” Journal of Civil Structural Health Monitoring 6, 3, 429–45, (2016).
3. Hossein BabajanianBisheh et al., “Damage Detection of a Cable-Stayed Bridge Using Feature Extraction and Selection Methods,” Structure and Infrastructure Engineering 15, 9, 1165–77,(2019).
4. YuequanBao et al., “Computer Vision and Deep Learning–Based Data Anomaly Detection Method for Structural Health Monitoring,” Structural Health Monitoring 18, 2, 401–21,(2019) .
5. EbrahimNazarian et al., “Machine-Learning-Based Approach for Post Event Assessment of Damage in a Turn-of-the-Century Building Structure,” Journal of Civil Structural Health Monitoring 8, 2, 237– 51,(2018) .
6. Giacomo Vincenzo Demarie and Donato Sabia, “A Machine Learning Approach for the Automatic Long-Term Structural Health Monitoring,” Structural Health Monitoring 18, 3, 819–37, (2019) .
7. RadiaBelkeziz and ZahiJarir, “A Survey on Internet of Things Coordination,” Proceedings - 2016 3rd International Conference on Systems of Collaboration, SysCo 2016, 3, 619–35,(2017).
8. AranudDeraemaeker et al., “New Trends in Vibration Based Structural Health Monitoring,” International Centre for Mechanical Sciences, 520, 1–643,(2010).
9. RafaellePiazzaroliFinotti, Alexandre AbrahãoCury, and Flávio de Souza Barbosa, “An SHM Approach Using Machine Learning and Statistical Indicators Extracted from Raw Dynamic Measurements,” Latin American Journal of Solids and Structures 16, 2, 1–17,(2019).
10. Ahmed Ibrahim et al., “A Machine Learning Approach for Structural Health Monitoring Using Noisy Data Sets,” IEEE Transactions on Automation Science and Engineering 17, 2, 900–908,(2020) .

11. William Nick et al., "A Study of Machine Learning Techniques for Detecting and Classifying Structural Damage," International Journal of Machine Learning and Computing 5, 4, 313–18, (2015).
12. P. Gardner, R. J. Barthorpe, and C. Lord, "The Development of a Damage Model for the Use in Machine Learning Driven SHM and Comparison with Conventional SHM Methods," Proceedings of ISMA 2016 - International Conference on Noise and Vibration Engineering and USD2016 - International Conference on Uncertainty in Structural Dynamics, 3, 3333–46, (2016).
13. A. E. Aktan, A. J. Helmicki, and V. J. Hunt, "Issues in Health Monitoring for Intelligent Infrastructure," Smart Materials and Structures 7, 5, 674–92, (1998).
14. Dongho Kang and Young Jin Cha, "Autonomous UAVs for Structural Health Monitoring Using Deep Learning and an Ultrasonic Beacon System with Geo-Tagging," Computer-Aided Civil and Infrastructure Engineering 33, 10, 885–902, (2018).
15. A. C. Neves et al., "Structural Health Monitoring of Bridges: A Model-Free ANN-Based Approach to Damage Detection," Journal of Civil Structural Health Monitoring 7, 5, 689–702, (2017).
16. Daniel Frank Hesser and Bernd Markert, "Excitation Strategies for Vibration Based Damage Detection Using Piezoelectric Transducers and Machine Learning," Pamm 16, 1, 141–42, (2016).
17. Vicente Lopes et al., "Impedance-Based Structural Health Monitoring with Artificial Neural Networks," Journal of Intelligent Material Systems and Structures 11, 3, 206–14, (2000).
18. Mohammad Hossein Rafiei and HojjatAdeli, "A Novel Machine Learning-Based Algorithm to Detect Damage in High-Rise Building Structures," Structural Design of Tall and Special Buildings 26, 18, 1–11, (2017).
19. Mohammad Hossein Rafiei and HojjatAdeli, "A Novel Unsupervised Deep Learning Model for Global and Local Health Condition Assessment of Structures," Engineering Structures,56,598–607, (2018).
20. Yunzhu Chen and XingweiXue, "Advances in the Structural Health Monitoring of Bridges Using Piezoelectric Transducers," Sensors (Switzerland) 18,12,1–24, (2018).
21. Diego A. Tibaduiza Burgos et al., Damage Identification in Structural Health Monitoring: A Brief Review from Its Implementation to the Use of Data-Driven Applications, Sensors (Switzerland), 20,10, (2020).
22. Andrea E Del Grosso, "Structural Health Monitoring: Research and Applications," Key Engineering Materials, 558, 13, (2013).
23. K Smarsly and D Hartmann, "Artificial Intelligence in Structural Health Monitoring," The Third International Conference on Structural Engineering, Mechanics and Computation. Cape Town, South Africa,1, 705–10, (2007).
24. M. Azarbayejani et al., "A Probabilistic Approach for Optimal Sensor Allocation in Structural Health Monitoring," Smart Materials and Structures, 17, 5, (2008).
25. Sandeep Sony, SheaLaventure, and Ayan Sadhu, "A Literature Review of Next-Generation Smart Sensing Technology in Structural Health Monitoring," Structural Control and Health Monitoring 26, 3, 1–22, (2019).
26. OnurAvci et al., "Structural Damage Detection in Real Time: Implementation of 1D Convolutional Neural Networks for SHM Applications," Conference Proceedings of the Society for Experimental Mechanics Series, 10, 49–54, (2017).
27. Chuncheng Feng et al., "Structural Damage Detection Using Deep Convolutional Neural Network and Transfer Learning," KSCE Journal of Civil Engineering 23, 10, 4493–4502, (2019).
28. RaminGhiasi, PeymanTorkzadeh, and Mohammad Noori, "A Machine-Learning Approach for Structural Damage Detection Using Least Square Support Vector Machine Based on a New Combinational Kernel Function," Structural Health Monitoring 15, 3, 302–16, (2016).
29. Diego Tibaduiza et al., "A Damage Classification Approach for Structural Health Monitoring Using Machine Learning," Complexity, 18, 5, (2018).
30. Alvaro Araujo et al., "Wireless Measurement System for Structural Health Monitoring with High Time-Synchronization Accuracy," IEEE Transactions on Instrumentation and Measurement 61, 3, 801–10, (2012) .

DOI:10.48047/intjecse/v14i5.1192 ISSN: 1308-5581 Vol 14, Issue 05 2022

31. X. W. Ye, C. Z. Dong, and T. Liu, "A Review of Machine Vision-Based Structural Health Monitoring: Methodologies and Applications," Journal of Sensors, 16, 8, (2016).
32. Ting Hua Yi, Hong Nan Li, and Xu Dong Zhang, "A Modified Monkey Algorithm for Optimal Sensor Placement in Structural Health Monitoring," Smart Materials and Structures, 21,10, (2012).
33. Xia Zhao et al., "Designing Strategy for Multi- Agent System Based Large Structural Health Monitoring," Expert Systems with Applications 34, 2 1154–68, (2008).
34. Everaldo S. De Freitas et al., "Equivalent Circuit of Piezoelectric Diaphragms for Impedance-Based Structural Health Monitoring Applications," IEEE Sensors Journal 17, 17, 5537–46, (2017).
35. MajdiFlah et al., "Machine Learning Algorithms in Civil Structural Health Monitoring: A Systematic Review," Archives of Computational Methods in Engineering, 4, 9, (2020),.
36. X. W. Ye, C. Z. Dong, and T. Liu, "A Review of Machine Vision-Based Structural Health Monitoring: Methodologies and Applications," Journal of Sensors, 16, 8, (2016).
37. Ting Hua Yi, Hong Nan Li, and Xu Dong Zhang, "A Modified Monkey Algorithm for Optimal Sensor Placement in Structural Health Monitoring," Smart Materials and Structures , 21,10, (2012).
38. Xia Zhao et al., "Designing Strategy for Multi- Agent System Based Large Structural Health Monitoring," Expert Systems with Applications 34, 2 1154–68, (2008).
39. Everaldo S. De Freitas et al., "Equivalent Circuit of Piezoelectric Diaphragms for Impedance-Based Structural Health Monitoring Applications," IEEE Sensors Journal 17, 17, 5537–46, (2017).
40. MajdiFlah et al., "Machine Learning Algorithms in Civil Structural Health Monitoring: A Systematic Review," Archives of Computational Methods in Engineering, 4, 9, (2020),
41. Jaime Vitola et al., "Structural Damage Detection and Classification Based on Machine Learning Algorithms," 8th European Workshop on Structural Health Monitoring, EWSHM 2016,4,2853–62, (2016).
42. Michel J. Murillo et al., "A Low-Cost Approach to Monitoring the Structural Health of Pedestrian Bridges," Espacios,40, 27 , (2019).
43. Bibin Kurian and RanjithLiyanapathirana, Proceedings of the International Conference on E-Learning, ICEL, Proceedings of the International Conference on E-Learning, ICEL, 2018, 10, (2018).