Data-driven Crack Detection in the Realm of Structural Health Monitoring: An Overview*

Hassan Dabaja, Hassan Noura, and Mustapha Ouladsine[1]

Abstract— **The advancements of sensor technologies, improvements in computational power, and massive amounts of data from the increasing number of sensors deployed on structures have augmented the need for data-driven techniques in structural health monitoring (SHM), particularly for fatigue crack detection. Data-driven methods and tools are increasingly used in analyzing structures to ensure the absence of any fatigue crack in various engineering fields including civil, mechanical, aerospace, and maritime engineering. This overview aims to present the most recent research that utilizes data-driven methods for fatigue crack detection in engineering structures that fall within the realms of signal processing (SP) and machine learning (ML). It focuses on studies utilizing Deep Learning (DL) for crack detection, highlighting the importance of Transfer Learning (TL).**

I. INTRODUCTION

Ensuring life safety and reducing inspection costs is a top priority for engineers and researchers. Cost-effective Structural Health Monitoring (SHM) is significant for long-term structural integrity utilizing various methods for monitoring and inspection. The implementation of SHM systems in structures and mechanical systems to detect structural issues in the early stages is substantial by contributing to increasing structural durability, reducing life cycle costs, and enhancing safety. Continuous real-time monitoring aids in identifying potential problems before they escalate.

SHM systems typically consist of various components, including sensors, data acquisition devices, data transmission systems, databases for data management, data analysis, modeling tools, condition assessment, visualization interfaces, and software [1]. Sensor and communication technologies have advanced, enabling efficient infrastructure maintenance. SHM has witnessed a remarkable evolution, propelled by a synergy of advanced techniques and sensor technologies. Employing an array of sensors, including accelerometers, strain sensors, ultrasonic sensors, and more, SHM systems aim to detect and assess structural issues such as fatigue cracks. SHM techniques can be classified into two main categories: local and global [2]. Local techniques are limited to the area under the sensor's surveillance, while global techniques can detect damage anywhere in the structure through a network of sensors.

Advancements in sensor and SHM technology have led to a significant move toward data-driven methods to handle large amounts of sensor data, replacing traditional physics-based models [3]. The systematic collection of data from diverse sensors is coupled with signal-processing techniques to isolate critical information. Machine learning (ML) algorithms play a crucial role in tasks such as damage detection. Notably, Deep learning (DL) is increasingly applied in SHM due to advances in big data, cloud-based computation, computer hardware, software, and data science. DL-based SHM is characterized by its ability to predict patterns hidden in data, leveraging advancements in transfer learning (TL) for efficiency and time-saving. TL facilitates the efficient training of neural networks. The integration of Big Data techniques contributes to the storage, analysis, and management of extensive datasets in SHM applications. These advancements underscore the pivotal role of data-driven techniques in enhancing the accuracy and overall efficiency of SHM systems.

A typical approach in Data-driven Crack Detection for SHM, as shown in figure 1, initiates with gathering sensor data relevant to the system under surveillance, followed by thorough preprocessing steps aimed at refining data quality. Data normalization, denoising and filtering are among the techniques employed to enhance data for further analysis. Then, signal processing (SP) techniques that include time-domain, frequency-domain and time-frequency features are used to extract relevant features serving as a foundation for crack detection. To address the complexity of the feature space, dimensionality reduction techniques are applied, preserving essential information while streamlining computational efforts. This methodology is founded on building ML models that can predict damage indicators or health states. In this context, DL stands out as a powerful tool especially when handling vast datasets showing great results with vision-based crack detection. These machine-learning models enable the establishment of decision-making frameworks for automated crack detection. These frameworks facilitate proactive maintenance strategies.

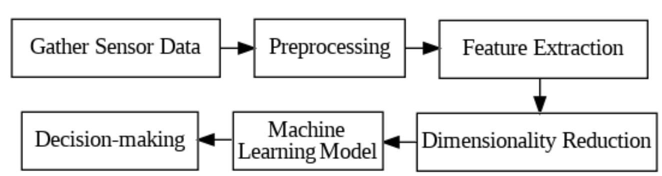

Fig. 1. A typical Data-driven Crack Detection approach.

*This research was funded by BPI France under grant agreement PSPC No. 9, as part of the TNTM (Transformation Numérique du Transport Maritime) project.

[1]Hassan Dabaja, Hassan Noura, and Mustapha Ouladsine are with Aix Marseille Univ, CNRS, LIS, Marseille, France (e-mails: {hassan.dabaja, ayah.youssef, hassan.noura, mustapha.ouladsine}@lis-lab.fr).

II. Industrial Applications of Crack Detection

Crack detection plays a pivotal role in civil engineering to ensure the structural integrity of critical infrastructure. Different materials such as concrete, steel, and asphalt are used in civil infrastructure. Cracks can develop in these materials over time due to factors such as aging, seismic activity, and traffic loads. For instance, concrete structures may encounter significant stress, cracking, and deformation over time due to exposure to extreme structural loads and weather conditions, leading to crack formation. These cracks can extend resulting in potential structural failure. Researchers worked on crack detection in concrete structures such as bridges, buildings, and dams. Ramli *et al.* [4] investigate crack detection in concrete structures using triaxial accelerometers, focusing on plain self-compacting concrete and steel-fiber-reinforced beams. Their results demonstrate that triaxial accelerometers are effective in locating both micro- and macro-cracks, offering valuable data for real-time monitoring and early warning of structural failures. Figure 2 shows a steel-fibre-reinforced concrete beam failing after a crack formation. Mojidra *et al.* [5] presented a computer vision-based method with global motion compensation for enhanced fatigue crack detection in civil infrastructure, particularly steel bridges.

Fig. 2. Failure in a steel-fibre-reinforced concrete beam [4].

Fig. 3. A Crack in the fuselage of an aircraft [6].

Fig. 4. A Crack in the hull of a ship [7].

Crack detection is also important in mechanical engineering. For example, cracks can form in components such as fan blades or gear teeth, changing the behavior of the mechanical system. The presence of cracks can lead to a change in the vibration data collected from the mechanical system. Researchers can detect these cracks by utilizing signal-processing techniques. Ma *et al.* [8] present a Vibro-Acoustic Signals Hybrid Fusion Model for enhanced blade crack detection in centrifugal fans. Rangel *et al.* [9] utilized ML to detect cracks in wind turbine blades via vibration signals with impressive accuracy. Chen *et al.* [10] proposed an advanced SVD-based method for gear tooth crack detection, addressing non-fault vibrations.

Another example is the aerospace industry. Crack detection is crucial in preventing catastrophic failures. Aircraft components such as wings, fuselage, and engine parts are subjected to stress, making them vulnerable to cracks that must be detected. Figure 3 shows a crack in the fuselage of an aircraft. A study presents a technique leveraging depth-wise separable convolution and feature pyramids to achieve fast and precise crack detection in aircraft structures enabling real-time application in diverse aircraft components [6].

In maritime engineering SHM is essential in maintaining the integrity of ship hull structures, ensuring the safety of seaborne transport crucial for global trade. In particular, crack detection within hull structures prevents catastrophic maritime accidents caused by structural failures, safeguarding human lives, economic assets, and marine environments. Figure 4 shows a crack in the hull of a ship.

III. Signal Processing

Signal processing (SP) plays a crucial role in the extraction of features as well as the analysis of SHM data. They are included as a part of data-driven crack detection because they are essential for extracting, refining, and quantifying crack-related features from raw sensor data. SP encompasses diverse functions such as data filtering, dimensionality reduction, and temporal and spectral analysis.

Vital steps in data-driven methodology include data integration and incorporating feature engineering for effective pattern recognition. Data collected from sensors during data acquisition and integration undergoes feature extraction. Feature extraction isolates critical features through SP techniques, facilitating the development of robust algorithms. The features may encompass frequency-domain, time-frequency domain, statistical, and mechanical features [11]. These features give profound insights into the significant health characteristics of the structure, preparing data into subsequent stages involving ML algorithms.

To ensure the suitability, accuracy, and effectiveness of ML models data cleaning and organizing are needed. Data cleaning deals with challenges like addressing noise, handling outliers, and filling in missing values. SP techniques play a pivotal role in data cleaning by eliminating noise, filtering signals, and normalizing the data. Various filtering techniques, such as band-pass, high-pass, and low-pass filters, can be utilized on sensor data to mitigate noise and extract valuable information, representing a pivotal step in the data-driven methodology.

In dimensionality reduction, subspace analysis, like Principal Components Analysis (PCA), is widely employed. PCA efficiently reduces data dimensionality by identifying essential components, aiding in the detection of structural damage [12]. PCA has many variants, including Moving Principal Component Analysis (MPCA) and Probabilistic Principal Component Analysis (PPCA). MPCA is well-suited for continuous monitoring, offering enhanced accuracy and computational efficiency [13]. PPCA tackles the shortcomings of PCA, particularly in managing missing data [14]. This approach introduces probabilistic variations by employing Gaussian latent variable models, proving effective in situations where there may be gaps in the data.

Some SP methods employ analysis in the time domain to extract significant characteristics from sensor data. Time series analysis, including approaches like autoregressive (AR) modeling, are useful to derive features in the time domain. Many researchers utilize these models to find reliable damage-sensitive features for SHM applications. The difference between the model's output and actual data or residuals can indicate damage.

The study conducted by Zhang, Li, and Qu proposes a data-driven approach utilizing AR models and amplitude-aware permutation entropy (AAPE) for diagnosing nonlinear damage in civil engineering structures such as cracks, demonstrating its efficacy through numerical simulations and experimental data analysis [15]. Their research addresses the limitations of current SHM techniques by focusing on the detection and localization of minor nonlinear damage, showcasing the superiority of AAPE-based classifiers in capturing changes in both signal complexity and amplitude for enhanced damage diagnosis.

Kauss *et al.* demonstrate the efficacy of their semi-supervised approach for SHM in accurately localizing and quantifying both linear and non-linear structural damage, including instances such as cracks or loosening of bolts, through the integration of AR models with a metaheuristic algorithm and experimental validation on a three-story laboratory frame and the Z24 bridge [16]. Employing AR, ARMA, ARX, and ARMAX models, the method optimizes model orders using the Progressive Deterioration Criterion. This approach robustly addresses environmental variations and operational uncertainties, demonstrating its versatility and effectiveness in diverse structural scenarios.

Joshuva and Sugumaran proposed an algorithmic methodology by using vibration signal classification for the detection and localization of cracks on a wind turbine blade. The feature selection technique employed was the J48 decision tree algorithm, which effectively identified statistically significant histogram and ARMA features for crack detection. These features later contributed to improving the efficiency of the classification process [17].

Fourier Transform and Wavelet Transform, popular frequency domain representations, excel at capturing temporal and frequency features, providing a holistic understanding of structural behavior and identifying spectral features indicating cracks [12].

The Fourier Transform analyzes sensor data to examine frequency components, revealing spectral patterns that indicate structural issues. Vashisht and Peng introduce a novel crack detection method for rotor-bearing systems, employing transient response analysis, Short-time Fourier Transform (STFT), and active control strategies. Their study underscores the efficacy of time-frequency analysis in identifying cracks amid nonlinearities like ball bearings, while also exploring robust control methods and switching control strategies to bolster crack detection in rotor systems [18]. Liu *et al.* introduced a dual guide network for crack detection, combining global frequency domain information with convolutional neural networks (CNNs) to outperform existing methods [19]. Their method utilizes fast Fourier transform (FFT) for low-level feature extraction, followed by CNNs to learn local features, culminating in fused detection outcomes.

Wavelet Transform is used to extract transient features from sensor data, enabling time-frequency analysis and assisting in identifying cracks from signals like acoustic emissions. The utilization of wavelet transform is a prevalent tool used in literature for vibration-based crack detection. For example, Zhu *et al.* introduced a novel wavelet-based damage index for accurately locating and estimating the depths of cracks in functionally graded material beams [20]. Applying Timoshenko beam theory and continuous wavelet transform to analyze mode shapes, the authors incorporated an intensity factor for precise crack depth estimation. Moreover, Nguyen *et al.* developed a defect identification approach in structures subjected to moving loads by combining two independent algorithms in wavelet analysis through DL [21]. This approach directly applies wavelet analysis to original deflection signals, improving accuracy, and simplifying the assessment of crack status, especially in structures with multiple cracks. Furthermore, in research by Taher *et al.*, a fatigue crack monitoring approach is introduced integrating a Wireless Large-Area Strain Sensor and a specialized algorithm [22]. The algorithm, comprising automated traffic event detection, Generalized Morse Continuous Wavelet Transform for peak identification, and a Modified Crack Growth Index calculation, is validated through numerical simulations and field deployment. Spectral correlation methods are employed for crack detection. Liu *et al.* pioneered a baseline-free fatigue crack detection method using spectral correlation to extract nonlinear modulation components from ultrasonic responses, achieving successful early-stage detection amid ambient noise and vibrations [23]. A method based on cyclic spectral analysis and spectral correlation was introduced by Prawin *et al.* for detecting, localizing, and characterizing fatigue-breathing cracks in engineering structures [24]. The technique exhibits robustness against measurement noise and excels in the early detection of minor fatigue cracks, offering valuable insights for implementation in challenging environments.

IV. Machine Learning

A. Classical Machine Learning

ML algorithms are crucial in many SHM applications. Integrating ML models into vital infrastructure allows continuous real-time monitoring and early fault detection. They are used with vibrations and vision information and include embedded ML, K-nearest neighbor, random forest, and support vector regression [25], [26], [27]. Unsupervised learning methods focus on structural damage detection by training statistical models solely on data from intact structures, making them perceived as more practical than their supervised counterparts for implementing early-warning damage detection systems in civil structures [12]. Supervised learning is typically more accurate than unsupervised learning in both localizing and quantifying damage.

Supervised learning algorithms effectively tackle both classification and regression the domain of crack detection. Regression models excel in estimating attributes such as the size, depth, or location of cracks, while classification models adeptly determine the presence or absence of cracks. For example, Support Vector Machines (SVM) can be used to distinguish between non-cracked and cracked regions in images [28]. Limitations have led to the adoption of ensemble learning methods for enhanced classification performance. Random Forests excels in addressing both regression and classification aspects of crack detection tasks, demonstrating resilience and robust performance in navigating high-dimensional feature spaces. In the domain where spatial information is crucial, K-Nearest Neighbors is simple and effective in pattern recognition and classification [29].

Unsupervised learning methods, including clustering and association analysis, find applications in SHM across multiple domains, including damage detection, system identification, retrofitting assessment, load effect analysis, and load pattern recognition [11].

ML models should be adaptable over time and adjusted to changing circumstances by being retrained with fresh data as cracks emerge or structures deteriorate. Despite theadvancements in automation, the human element remains integral in SHM decision-making. Human experts play a crucial role in validating findings, providing domain expertise, and making important decisions based on the output of ML models.

B. Deep Learning

Deep learning (DL) models, classified into supervised, unsupervised, semi-supervised, and self-learning models, excel in different tasks such as crack classification, crack object detection, and crack segmentation. Supervised learning models are widely used for crack classification, while unsupervised learning models are used in crack segmentation [30]. Both semi-supervised and self-learning models leverage limited labeled data to mitigate data quantity and quality issues.

Convolutional neural Networks (CNNs) are powerful in detecting surface or structural cracks in images due to their autonomous feature learning capabilities, especially when enhanced by contour analysis, edge detection, and color thresholding techniques. Models such as VGG, ResNet, and DenseNet are recommended for crack classification [30]. For handling sequential data from sensors, Recurrent Neural Networks (RNNs) prove ideal, showcasing their proficiency in discerning temporal dependencies. For tasks requiring the amalgamation of spatial and temporal information, Recurrent Convolutional Neural Networks (RCNNs) and Long Short-Term Memory Networks (LSTMs) can excel by offering a holistic approach to intricate crack detection challenges. Crack object detection involves architectures such as Faster R-CNN, RetinaNet, Yolo, and SSD. Faster R-CNN stands out for its superior accuracy in locating and categorizing cracks. Crack segmentation uses models like Mask R-CNN, U-Net, and pix2pix [30].

DL, particularly through Fully Convolutional Networks (FCNs), marks a revolutionary breakthrough in image segmentation. FCNs enable pixel-level predictions, showcasing superior accuracy compared to conventional approaches. The applications of FCNs span diverse industrial scenarios, from surface defect segmentation to crack inspection. Concurrently, other models like U-Net, SegNet, Mask R-CNN, and PSPNet, each employing an encoder-decoder architecture, contribute substantially to image segmentation in varied industrial applications [31].

Deep CNNs excel at accurate image classification and pixel-level labeling, playing a crucial role in SHM for assessing deflection, corrosion, concrete damage, fatigue, and other structural issues. Kim *et al.* [32] present an approach using DL for the objective detection and measurement of cracks in small-scale facilities, overcoming challenges linked to traditional, subjective inspection methods. Their framework integrates CNN and image processing (IP) techniques, demonstrating high accuracy in crack classification and segmentation, with promising implications for advancing civil engineering crack inspection methodologies. Furthermore, Sun *et al.* [33] introduced a data-driven strategy for flaw detection in structures, integrating CNN and the boundary element method (BEM). Their approach demonstrated through both single and multiple flaw detection tasks, effectively addressed non-uniqueness challenges. The combination of BEM for dataset generation, block LU decomposition for computational efficiency, and the application of data augmentation techniques showcased the robustness against noise.

Researchers utilized the U-Net model as a method for semantic segmentation based on its effectiveness in crack detection within the automated image analysis process. A paper introduces the U-Net architecture, showcasing its superior performance in semantic segmentation, particularly in automating concrete crack detection, compared to earlier FCN-based methods [34]. Liu *et al.* [35] present a two-step CNN-based method, incorporating modified YOLOv3 for crack detection and a modified U-Net for segmentation, showcasing enhanced accuracy and efficiency over current state-of-the-art approaches. This approach amalgamates crack detection with segmentation and rectifies the shortcomings of methodologies centered primarily on segmentation. Khan *et al.*'s dense U-net model surpasses traditional methods in railway sleeper crack detection, offering detailed insights into crack locations and severity [36]. Their comprehensive crack quantification algorithm, assessing length, width, area, and ratio, contributes significantly to understanding crack severity and ensures effective rail safety and maintenance.

Researchers explored various approaches to address challenges related to image quality, including issues like blurriness and insufficient pixel resolution. Bae et al [37] developed SrcNet, a two-phase DL model aiming to automate crack detection in civil infrastructure inspections, overcoming challenges in low-resolution UAV and climbing robot images through a Residual in Residual structure for super-resolution and a VGG-16-based network for crack detection. Training involves high and low-resolution image pairs from datasets like DIV2K. Experimental validation on in situ bridges demonstrates SrcNet's significant improvement in crack detectability, with increased recall but a trade-off of higher false positives.

Researchers are leveraging the power of vision and DL to advance crack detection methodologies in concrete structures, pushing the boundaries of automated inspection and maintenance. Ren *et al.* [38] revolutionized tunnel infrastructure inspection with their advanced CrackSegNet model, a deep FCN that outperforms conventional methods in concrete crack detection. Featuring modular design and an optimized loss function, the model shows high potential for automation, offering a robust solution for long-term tunnel crack inspection and monitoring.

Rajadurai *et al.*'s [39] study on automated crack detection in concrete structures uses deep CNNs, specifically a fine-tuned AlexNet model, achieving an impressive classification accuracy. This research not only addresses the crucial aspect of timely crack detection and repair but also underscores the efficacy of DL, particularly AlexNet, in offering efficient solutions to challenges in aging concrete infrastructure, thus enhancing structural reliability.

Shim *et al.* [40] introduced an advanced deep neural network with adversarial learning and stereo-vision-based triangulation, enhancing crack detection and enabling precise 3D reconstruction. Additionally, their semi-supervised learning strategy, optimizing training data ratios, effectively addresses challenges in recognition performance under new environmental conditions, providing a holistic solution to improve the efficiency and applicability of crack detection in concrete structures.

Zhang *et al.* [41] introduced a method for non-contact inspection of concrete bridge cracks, using binocular stereo vision and a FCN for semantic segmentation. Their approach not only achieved impressive pixel-level crack detection precision but also demonstrated enhanced shooting flexibility and three-dimensional reconstruction, overcoming constraints of traditional frontal image acquisition and offering a comprehensive dimensional depiction of concrete cracks.

C. Transfer Learning

Transfer learning (TL) is essential in SHM for rapid training of neural networks in image classification tasks. TL involves utilizing a pre-trained neural network on a larger dataset and fine-tuning it for a new, analogous classification task with a smaller dataset. This method significantly reduces training time by transferring preexisting weights from the base model. The depth of neural networks poses a challenge, demanding substantial time and data for training. TL addresses this by incorporating prior knowledge, enabling efficient fine-tuning with lower computational costs and less extensive data requirements.

Various TL strategies are implemented based on the degree of similarity between target and source domains. In the context of CNNs, a common practice involves freezing convolutional layers while fine-tuning fully connected layers, optimizing the model for the specific SHM task [3]. Many pre-trained Deep Neural Networks are frequently utilized in SHM and crack detection, including AlexNet, VGG16, Inception, ResNet, GoogleNet, and ZFNet. CrackNet is a CNN designed explicitly for crack detection on 3D asphalt surfaces [42]. The model is characterized by robustness, performance speed, as well as precision, and recall rates.

Dung *et al.* [43] present an approach to early fatigue crack detection in gusset plate joints of aging steel bridges using deep CNN. Their study explores 3 methods: building a shallow ConvNet from scratch, transfer learning using VGG16 architecture features, and fine-tuning the top layers of VGG16. The authors highlight the efficacy of transfer learning, leveraging the pre-trained VGG16 model to enhance crack detection. The image dataset incorporates photographs from fatigue tests and bridge inspections, with data augmentation for improved training. Results indicate the highest accuracy for fine-tuning methods.

V. Conclusion

Crack detection is essential in several domains to maintain structural integrity. Developments in sensor technology have propelled a shift toward data-driven methodologies. This overview highlights recent studies employing data-driven approaches using signal processing (SP) and machine learning (ML) techniques for fatigue crack detection. SP is used in feature extraction and data analysis, while ML methods, including deep learning (DL), are highly used for crack detection. Transfer learning is valuable to accelerate and optimize the training of DL models, enhancing their effectiveness in crack detection. Although data-driven techniques excel in crack detection, challenges remain in real-world applicability, noise robustness, and generalizability across materials. Future research may focus on edge computing solutions for real-time deployment and hybrid models that combine physics-based and data-driven approaches. Standardized benchmarks and synthetic data generation could improve scalability and performance validation.

References

[1] Y. Bao, Z. Chen, S. Wei, Y. Xu, Z. Tang, and H. Li, "The state of the art of data science and engineering in structural health monitoring," *Engineering*, vol. 5, no. 2, pp. 234–242, 2019.

[2] A. Güemes, A. Fernandez-Lopez, A. R. Pozo, and J. Sierra-Pérez, "Structural health monitoring for advanced composite structures: A review," *Journal of Composites Science*, vol. 4, no. 1, p. 13, 2020.

[3] M. Azimi, A. D. Eslamlou, and G. Pekcan, "Data-driven structural health monitoring and damage detection through deep learning: State-of-the-art review," *Sensors*, vol. 20, no. 10, p. 2778, 2020.

[4] J. Ramli, J. Coulson, J. Martin, B. Nagaratnam, K. Poologanathan, and W. M. Cheung, "Crack detection and localisation in steel-fibre-reinforced self-compacting concrete using triaxial accelerometers," *Sensors*, vol. 21, no. 6, p. 2044, 2021.

[5] R. Mojidra, J. Li, A. Mohammadkhorasani, F. Moreu, C. Bennett, and W. Collins, "Vision-based fatigue crack detection using global motion compensation and video feature tracking," *Earthquake Engineering and Engineering Vibration*, pp. 1–21, 2023.

[6] Y. Li, Z. Han, H. Xu, L. Liu, X. Li, and K. Zhang, "Yolov3-lite: A lightweight crack detection network for aircraft structure based on depthwise separable convolutions," *Applied Sciences*, vol. 9, no. 18, p. 3781, 2019.

[7] B. Lin and X. Dong, "Ship hull inspection: A survey," *Ocean Engineering*, vol. 289, p. 116281, 2023.

[8] T. Ma, J. Shen, D. Song, and F. Xu, "A vibro-acoustic signals hybrid fusion model for blade crack detection," *Mechanical Systems and Signal Processing*, vol. 204, p. 110815, 2023.

[9] A. H. Rangel-Rodriguez, D. Granados-Lieberman, J. P. Amezquita-Sanchez, M. Bueno-Lopez, and M. Valtierra-Rodriguez, "Analysis of vibration signals based on machine learning for crack detection in a low-power wind turbine," *Entropy*, vol. 25, no. 8, p. 1188, 2023.

[10] Y. Chen, X. Liang, and M. J. Zuo, "An improved singular value decomposition-based method for gear tooth crack detection and severity assessment," *Journal of Sound and Vibration*, vol. 468, p. 115068, 2020.

[11] L. Sun, Z. Shang, Y. Xia, S. Bhowmick, and S. Nagarajaiah, "Review of bridge structural health monitoring aided by big data and artificial intelligence: From condition assessment to damage detection," *Journal of Structural Engineering*, vol. 146, no. 5, p. 04020073, 2020.

[12] K. Eltouny, M. Gomaa, and X. Liang, "Unsupervised learning methods for data-driven vibration-based structural health monitoring: A review," *Sensors*, vol. 23, no. 6, p. 3290, 2023.

[13] D. Posenato, F. Lanata, D. Inaudi, and I. F. Smith, "Model-free data interpretation for continuous monitoring of complex structures," *Advanced Engineering Informatics*, vol. 22, no. 1, pp. 135–144, 2008.

[14] Z. Ma, C.-B. Yun, H.-P. Wan, Y. Shen, F. Yu, and Y. Luo, "Probabilistic principal component analysis-based anomaly detection for structures with missing data," *Structural Control and Health Monitoring*, vol. 28, no. 5, p. e2698, 2021.

[15] X. Zhang, L. Li, and G. Qu, "Data-driven structural health monitoring: Leveraging amplitude-aware permutation entropy of time series model residuals for nonlinear damage diagnosis," *Sensors*, vol. 24, no. 2, p. 505, 2024.

[16] K. Kauss, V. Alves, F. Barbosa, and A. Cury, "Semi-supervised structural damage assessment via autoregressive models and evolutionary optimization," in *Structures*, vol. 59. Elsevier, 2024, p. 105762.

[17] A. Joshuva and V. Sugumaran, "Crack detection and localization on wind turbine blade using machine learning algorithms: A data mining approach," *Structural durability & health monitoring*, vol. 13, no. 2, p. 181, 2019.

[18] R. K. Vashisht and Q. Peng, "Crack detection in the rotor ball bearing system using switching control strategy and short time fourier transform," *Journal of Sound and Vibration*, vol. 432, pp. 502–529, 2018.

[19] Y. Liu, G. Yuan, J. Li, and S. Hu, "Fsdgnet: frequency and spatial dual guide network for crack detection," *Journal of Electronic Imaging*, vol. 33, no. 1, pp. 013 027–013 027, 2024.

[20] L.-F. Zhu, L.-L. Ke, X.-Q. Zhu, Y. Xiang, and Y.-S. Wang, "Crack identification of functionally graded beams using continuous wavelet transform," *Composite Structures*, vol. 210, pp. 473–485, 2019.

[21] T. Q. Nguyen, L. C. Vuong, C. M. Le, N. K. Ngo, and H. Nguyen-Xuan, "A data-driven approach based on wavelet analysis and deep learning for identification of multiple-cracked beam structures under moving load," *Measurement*, vol. 162, p. 107862, 2020.

[22] S. A. Taher, J. Li, J.-H. Jeong, S. Laflamme, H. Jo, C. Bennett, W. N. Collins, and A. R. Downey, "Structural health monitoring of fatigue cracks for steel bridges with wireless large-area strain sensors," *Sensors*, vol. 22, no. 14, p. 5076, 2022.

[23] P. Liu, H. Sohn, S. Yang, and H. J. Lim, "Baseline-free fatigue crack detection based on spectral correlation and nonlinear wave modulation," *Smart Materials and Structures*, vol. 25, no. 12, p. 125034, 2016.

[24] J. Prawin and A. Rama Mohan Rao, "Vibration-based breathing crack identification using non-linear intermodulation components under noisy environment," *Structural Health Monitoring*, vol. 19, no. 1, pp. 86–104, 2020.

[25] R. Indhu, G. R. Sundar, and H. S. Parveen, "A review of machine learning algorithms for vibration-based shm and vision-based shm," in *2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS)*. IEEE, 2022, pp. 418–422.

[26] M. H. Rafiei and H. Adeli, "A novel machine learning-based algorithm to detect damage in high-rise building structures," *The Structural Design of Tall and Special Buildings*, vol. 26, no. 18, p. e1400, 2017.

[27] D. Tibaduiza, M. Á. Torres-Arredondo, J. Vitola, M. Anaya, and F. Pozo, "A damage classification approach for structural health monitoring using machine learning," *Complexity*, vol. 2018, pp. 1–14, 2018.

[28] O. D. Singh, S. Gupta, and S. Dora, "Segmentation technique for the detection of micro cracks in solar cell using support vector machine," *Multimedia Tools and Applications*, pp. 1–26, 2023.

[29] L. Ali, S. Harous, N. Zaki, W. Khan, F. Alnajjar, and H. Al Jassmi, "Performance evaluation of different algorithms for crack detection in concrete structures," in *2021 2nd International Conference on Computation, Automation and Knowledge Management (ICCAKM)*. IEEE, 2021, pp. 53–58.

[30] S. D. Nguyen, T. S. Tran, V. P. Tran, H. J. Lee, M. J. Piran, and V. P. Le, "Deep learning-based crack detection: A survey," *International Journal of Pavement Research and Technology*, vol. 16, no. 4, pp. 943–967, 2023.

[31] Z. Ren, F. Fang, N. Yan, and Y. Wu, "State of the art in defect detection based on machine vision," *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 9, no. 2, pp. 661–691, 2022.

[32] J. J. Kim, A.-R. Kim, and S.-W. Lee, "Artificial neural network-based automated crack detection and analysis for the inspection of concrete structures," *Applied Sciences*, vol. 10, no. 22, p. 8105, 2020.

[33] J. Sun, Y. Liu, Z. Yao, and X. Zheng, "A data-driven multi-flaw detection strategy based on deep learning and boundary element method," *Computational Mechanics*, vol. 71, no. 3, pp. 517–542, 2023.

[34] Z. Liu, Y. Cao, Y. Wang, and W. Wang, "Computer vision-based concrete crack detection using u-net fully convolutional networks," *Automation in Construction*, vol. 104, pp. 129–139, 2019.

[35] J. Liu, X. Yang, S. Lau, X. Wang, S. Luo, V. C.-S. Lee, and L. Ding, "Automated pavement crack detection and segmentation based on two-step convolutional neural network," *Computer-Aided Civil and Infrastructure Engineering*, vol. 35, no. 11, pp. 1291–1305, 2020.

[36] M. A.-M. Khan, S.-H. Kee, and A.-A. Nahid, "Vision-based concrete-crack detection on railway sleepers using dense u-net model," *Algorithms*, vol. 16, no. 12, p. 568, 2023.

[37] H. Bae, K. Jang, and Y.-K. An, "Deep super resolution crack network (srcnet) for improving computer vision–based automated crack detectability in in situ bridges," *Structural Health Monitoring*, vol. 20, no. 4, pp. 1428–1442, 2021.

[38] Y. Ren, J. Huang, Z. Hong, W. Lu, J. Yin, L. Zou, and X. Shen, "Image-based concrete crack detection in tunnels using deep fully convolutional networks," *Construction and Building Materials*, vol. 234, p. 117367, 2020.

[39] R.-S. Rajadurai and S.-T. Kang, "Automated vision-based crack detection on concrete surfaces using deep learning," *Applied Sciences*, vol. 11, no. 11, p. 5229, 2021.

[40] S. Shim, J. Kim, G.-C. Cho, and S.-W. Lee, "Stereo-vision-based 3d concrete crack detection using adversarial learning with balanced ensemble discriminator networks," *Structural Health Monitoring*, vol. 22, no. 2, pp. 1353–1375, 2023.

[41] Z. Zhang, Z. Shen, J. Liu, J. Shu, and H. Zhang, "A binocular vision-based crack detection and measurement method incorporating semantic segmentation," *Sensors*, vol. 24, no. 1, p. 3, 2023.

[42] A. Zhang, K. C. Wang, Y. Fei, Y. Liu, S. Tao, C. Chen, J. Q. Li, and B. Li, "Deep learning–based fully automated pavement crack detection on 3d asphalt surfaces with an improved cracknet," *Journal of Computing in Civil Engineering*, vol. 32, no. 5, p. 04018041, 2018.

[43] C. V. Dung, H. Sekiya, S. Hirano, T. Okatani, and C. Miki, "A vision-based method for crack detection in gusset plate welded joints of steel bridges using deep convolutional neural networks," *Automation in Construction*, vol. 102, pp. 217–229, 2019.