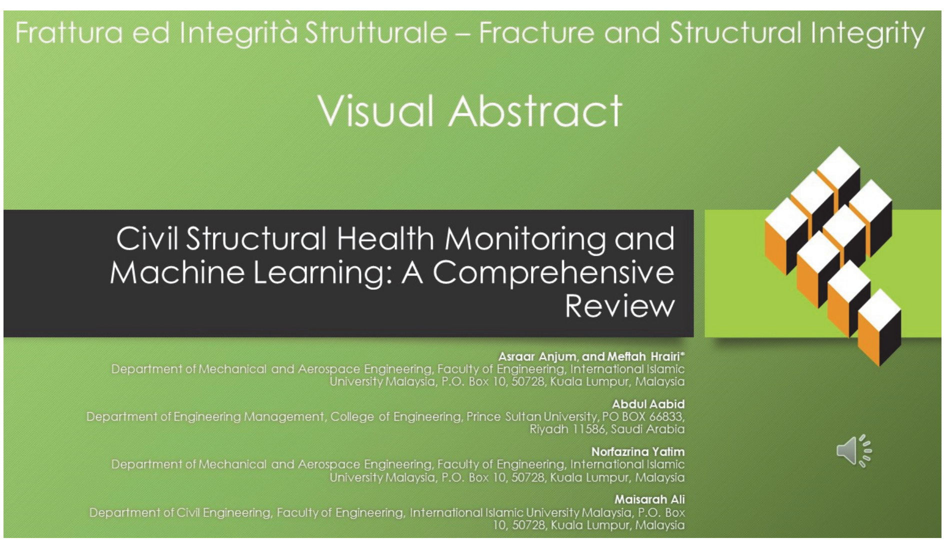
Civil structural health monitoring and machine learning: a comprehensive review

Asraar Anjum, Meftah Hrairi*
Department of Mechanical and Aerospace Engineering, Faculty of Engineering, International Islamic University Malaysia, P.O. Box 10, 50728, Kuala Lumpur, Malaysia
asraar.anjum@live.iium.edu.my and meftah@iium.edu.my

Abdul Aabid
Department of Engineering Management, College of Engineering, Prince Sultan University, PO BOX 66833, Riyadh 11586, Saudi Arabia
aaabid@psu.edu.sa, http://orcid.org/0000-0002-4355-9803

Norfazrina Yatim
Department of Mechanical and Aerospace Engineering, Faculty of Engineering, International Islamic University Malaysia, P.O. Box 10, 50728, Kuala Lumpur, Malaysia
noorfazrina@iium.edu.my

Maisarah Ali
Department of Civil Engineering, Faculty of Engineering, International Islamic University Malaysia, P.O. Box 10, 50728, Kuala Lumpur, Malaysia
maisarahali@iium.edu.my



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INTRODUCTION

Manual visual inspection is the primary approach for assessing the condition of civil infrastructure, ensuring it meets safety and serviceability standards. This process, carried out by qualified inspectors or structural engineers, involves identifying defects like cracks, damage, corrosion, and more in elements such as beams, columns, bridges, and roads [1]. It is conducted at regular intervals or following disasters to prevent accidents resulting from inadequate inspection. The gathered data helps predict future conditions, aids investment planning, and optimizes resource allocation for maintenance and repairs, ensuring ongoing infrastructure functionality.

Civil structures are vital for the global economy and people's daily lives but are aging and facing significant wear [2,3]. Replacing them is impractical due to cost and resource constraints. Engineers have developed strategies to enhance safety and structural integrity [4]. In the past decade, the adoption of computer vision methods in civil engineering has surged, thanks to affordable, high-quality visual sensing technology. This progress is evident in integrating computer vision modules in modern structural health monitoring (SHM) frameworks [5].

In computer science, SHM data analysis aims to transform sensor data into meaningful information and knowledge about structures. This knowledge is crucial for various applications, including life-cycle management and lifetime forecasting [6]. Two main approaches are used to assess the structural condition of civil engineering structures: physics-based and data-driven methods [7]. Physics-based methods create models based on the structure's physical characteristics and compare them with sensor data [8], demanding significant processing resources [9]. On the other hand, AI, which found early success in fields like robotics and data mining [10], has gained traction in civil engineering [11], offering knowledge-based systems, fuzzy logic algorithms, and artificial neural networks (ANNs) [12,13]. ML, a subset of AI, is also increasingly adopted, enhancing accuracy by understanding data structures and fitting them into models.

This review focuses on the increasing integration of machine learning and soft computing in civil engineering, specifically emphasizing energy efficiency and cost-effectiveness. It introduces this emerging trend and highlights its significance in addressing contemporary challenges. The section on machine learning explains its core principles and applicability in civil engineering contexts, including optimization and predictive analysis. The review explores the role of ML in SHM for concrete structures and its synergy. The critical analysis section delves into practical issues and challenges when implementing these techniques, offering insights into real-world applications. Investigations are categorized based on concrete types, structure types, and investigation methodologies. In conclusion, the review concisely summarizes its implications for promoting energy-efficient solutions and discusses potential future research directions in this dynamic field.

MACHINE LEARNING

ML forms the technological foundation for data mining, extracting implicit information from data [14]. While ML primarily focuses on prediction based on known features from training data, traditional regression analysis on experimental data is considered a rudimentary ML application. Still, it often fails in the discussed context due to its deviation from structural mechanics principles and limited applicability, resulting in overfitting. In contrast, the proposed techniques align with findings from structural mechanics investigations suitable for code-based design, offering a wealth of universally accepted, large-scale data ideal for modern data mining. Though their inner workings remain mysterious, these techniques can be validated using equilibrium equations and structural mechanics concepts, broadening their potential audience to practical engineers and academics. ML tools are provided to enhance SHM system capabilities and offer innovative solutions. This review aims to clarify the boundaries of ML relevant to contemporary SHM systems, thoroughly examining ML pipelines and providing summary tables and figures of popular techniques and algorithms. The future of SHM systems involves extensive sensing and big data processing in infrastructure [15]. More in-depth discussions can be found in critical references [16], and Miorelli et al. [17] comprehensively discussed managed learning methods for classification and regression applied to SHM issues (Fig. 1).

The system effectively combines physics-based and data-driven approaches by generating various training datasets from a calibrated FE model, conducting pretraining on a deep learning (DL) network, and transferring its learned knowledge to real-world monitoring and testing scenarios. Its efficacy is demonstrated in a challenging scenario involving the vibration-based identification of conditions in steel frame structures with bolted connection damage. The findings indicate that despite the training data originating from a different domain with distinct label types, the pretraining process enables learning intrinsic physics. As a result, transfer learning yields noticeable enhancements, with the accuracy of condition identification improving from 81.8% to 89.1% [18]. Similarly, for accessing the health state of another frame structure, the comparative and robustness evaluations are conducted, illustrating that the proposed method surpasses several machine learning and deep learning-based techniques such as time-series feature extractions, self-learning, graph neural network, and machine learning algorithms in terms of accuracy and resilience to noise and missing data [19]. The project centers on creating a real-time prediction model for structural health monitoring in case of shield tunnel structures. This model incorporates spatial and temporal correlations and external load data through an autoencoder network (ATENet) using SHM data. The autoencoder mechanism processes raw monitoring data from various spatial positions to obtain high-level representations. A recurrent neural network is also utilized to analyze the temporal correlation within the time series data of Form [20].

Moreover, four classification algorithms for SHM were introduced, leveraging the principles of the SVM algorithm. A laboratory experiment on a bridge structure at Western Sydney University aimed to validate these findings. The results were then compared with those of the standard SVM to assess the effectiveness of the proposed algorithms [21]. Also, numerical data is simulated, and real-world data from the KW51 bridge is utilized to evaluate its efficacy. A refined approach to assessing damage involves using an Exponentially Weighted Moving Average (EWMA) filter and a control chart-based threshold mechanism tools to help differentiate between structures in good condition and those experiencing gradual deterioration. This flexible method can be tailored to different monitoring setups and environmental factors. It remains reliable under changing operational conditions. The findings confirm that this approach can detect damage effectively even with a few sensors, thus offering a valuable means to improve bridge safety [22]. A method for multiclass classification of acceleration data gathered from an actual bridge is suggested, employing a recursive and easily understandable decision tree framework. The feature vectors utilized to train the random forest classifiers are determined based on comparable statistical features, simplifying the interpretation of the classifier models. This proposed framework demonstrates an ability to accurately classify non-anomalous (i.e., normal) time series within the test dataset, achieving an accuracy of 98% [23].

Acoustic emission (AE) simulates events using a pencil lead break as the source. Three models, including ANN and 1D and 2D convolutional neural networks, are trained and tested with AE signals generated by pencil lead break sources. The intention is that the DL methodology outlined will aid in the creation of a real-time monitoring system for rail inspection utilizing AE [24]. The analysis focuses on CNN-segmentation models trained using stochastic gradient descent (SGD) and adaptive moment estimation. These models are trained with varying learning rates—0.1, 0.01, and 0.0001—and evaluated across multiple metrics, including accuracy, intersection over union, precision, recall, and F1-score for concrete crack detection. InceptionV3 emerges as the top performer for defect classification, achieving an accuracy of 91.98% when utilizing the RMSprop optimizer. Specifically, the EfficientNetB3-based U-Net model stands out for crack segmentation, boasting an impressive F1 score of 95.66%. Meanwhile, the InceptionV3-based U-Net model excels in spalling segmentation, achieving an F1 score of 89.43%, surpassing the performance of all other algorithms [25].

Machine learning in civil structures applications

Over the last five years, several studies have been reported using ML algorithms. Therefore, in this section, previous work has been overviewed, and some information has been provided, considering the objectives, methodologies, outcomes, and challenges. ML was used to investigate many purposes apart from damage detection and repair studies. The other purposes have included measuring the quality, strength, optimum size, crack damages, optimum parameters, mechanical properties, and many other civil structures.

Zhu and Brilakis [26] employed a similar approach to assess the impact of cracks on concrete surfaces. Likewise, the same methodology was utilized to measure the surface roughness of concrete structures [27] and predict bridge cracks [28]. Furthermore, ML algorithms, including neural networks and 3D visualizations, were employed to quantify cracks and detect changes [29]. Another automated technique for detecting concrete fracture patterns from images was presented by analyzing structural and non-structural cracks, categorizing them as isolated or map patterns [30].

Karbassi et al. [31] employed a regression model with C4.5 decision tree algorithms to predict damage in RC buildings during future earthquake scenarios. Another two-phase decision tree method was developed based on seismic characteristics and structural features to detect damage in RC buildings [32]. RC structures have been a primary focus in civil applications for early prediction and long-term deflection estimation through data-driven ML models. These models were created and tested using an experimental dataset, employing the stratified 10-fold cross-validation technique [33]. Additionally, an ML model based on the observational corrosion-induced crack width distribution was used to establish a probabilistic assessment of the flexural loading capacity of existing RC structures [34].

An ML algorithm and image processing were employed to estimate internal loads like shear and moment loads in RC beams/slabs based on surface crack pattern images, allowing for quantitative damage and load level assessment in structures [35]. Additionally, an ML-based prediction model was used to assess the performance of RC concrete as a repair material for conventional concrete structures [36]. Further optimization models for RC structures have been developed, including a discrete gravitational search method and a metamodeling framework for reliability-based design optimization [37]. Specific

ML algorithms, such as ANN models, were utilized to predict the residual flexural strength of corroded RC beams [38]. ANN models were also applied to compute reduction factors to estimate the moment of inertia effectiveness in shape memory alloy RC beams [39]. To expedite the accurate design of RC columns and bridge piers, various ML-based functions were introduced. ANNs, in combination with well-constructed extensive training sets, can produce models with design accuracy that surpass traditional design charts and approach iterative section analysis techniques. This technique outperforms conventional design algorithms while maintaining stability, as demonstrated in a computational performance comparison [40].

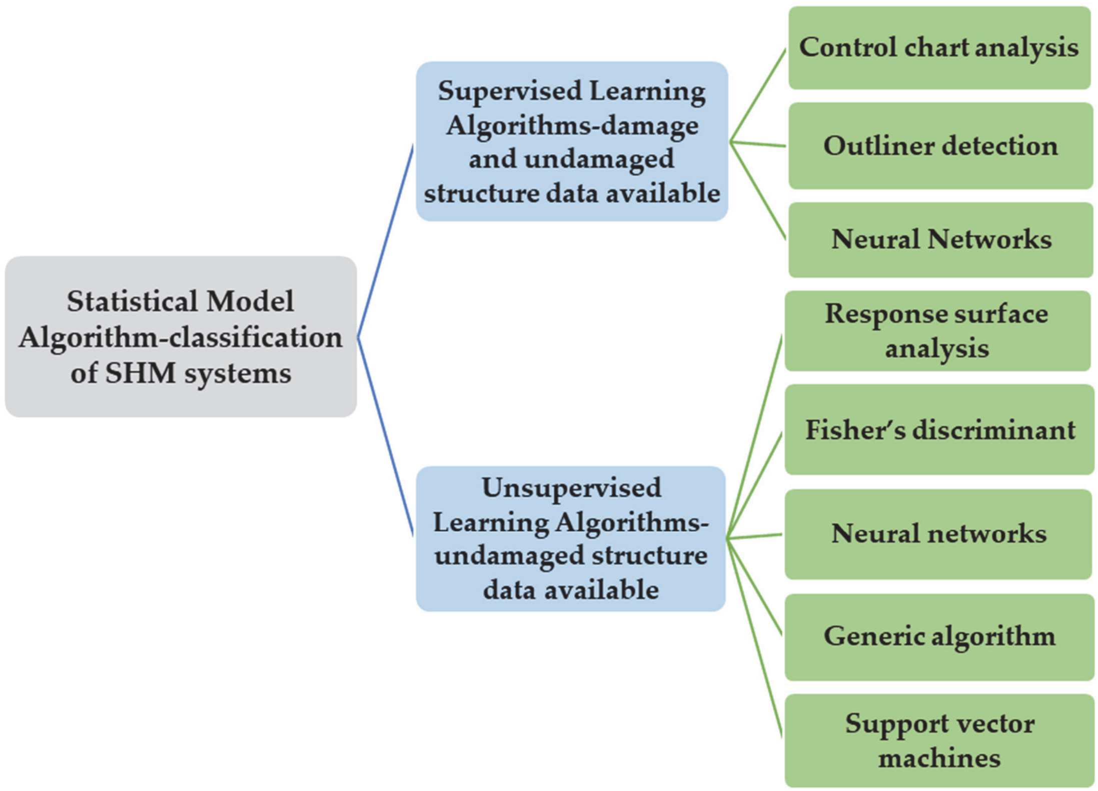

Figure 1. Classification of Algorithms for Statistical Model Development in SHM.

An ML method was implemented for automated crack detection in a concrete bridge, using a robust multifeatured classifier tailored for spatial adjustments. Results were displayed using a robotic bridge scanning system, effectively locating potential break areas even in noisy conditions and computing spatially customized visual characteristics [41]. Accurate anticipation of hygrothermal activity in concrete is crucial to making informed service-life extension decisions. An ANN-based hygrothermal prediction model was developed for assessing the temporal hygrothermal state in surface-protected concrete façade components [42]. Furthermore, ML techniques were employed to predict the shear strength and behavior of RC beams reinforced with externally bonded FRP sheets [43]. Existing shear design models for FRP-reinforced concrete structures tend to be overly conservative, increasing construction costs. An updated teeth model accounting for FRP reinforcement was optimized using a genetic algorithm and a database of longitudinally strengthened thin beams with FRP rebars, yielding a more accurate shear equation [44]. A model-free damage detection system based on ML approaches was also created for a simulated railway concrete bridge using a three-dimensional FE model [45].

This method analyses data collected from a structure in different states through a piezoelectric sensor network [46]. In the literature, an ML-based backbone curve model for RC columns subjected to cyclic loading reversals was found and utilized for predicting RC column strength [47]. ML was also employed for fracture mode categorization based on unlabelled acoustic emission waveform characteristics [48]. Additionally, when combined with unmanned aerial vehicles, an ML-based model enhanced the automation level of concrete infrastructure inspection by detecting surface fractures. This was achieved using a deep learning convolutional neural network (CNN) image classification technique to create the crack detection model [49]. Various crack models are illustrated in Fig. 2.

It was employed in a regression model for crack development and propagation to validate ML's applicability using inspection data from a concrete bridge. This process involves algorithm selection, innovative model development, and data analysis [50]. ML was also used to assess the condition rating of a concrete bridge through the analysis of impact echo data [51].

Using multiple non-destructive tests, a random forest-based assessment approach was applied to detect internal defects in RC structures [52]. ML was similarly found in applications like load-carrying capacity estimation and failure mode modelling of beam-column joint connections [53], rapid seismic damage assessment of bridge portfolios [54], and degree of concrete hydration [55]. Moreover, ML has contributed to the creation of three hybrid algorithms aimed at predicting the mechanical properties of plastic concrete samples with varying geometries [56], forecasting the self-healing capacity of bacteria-based concrete [57], and improving honeycomb detection in concrete through data aggregation [58].

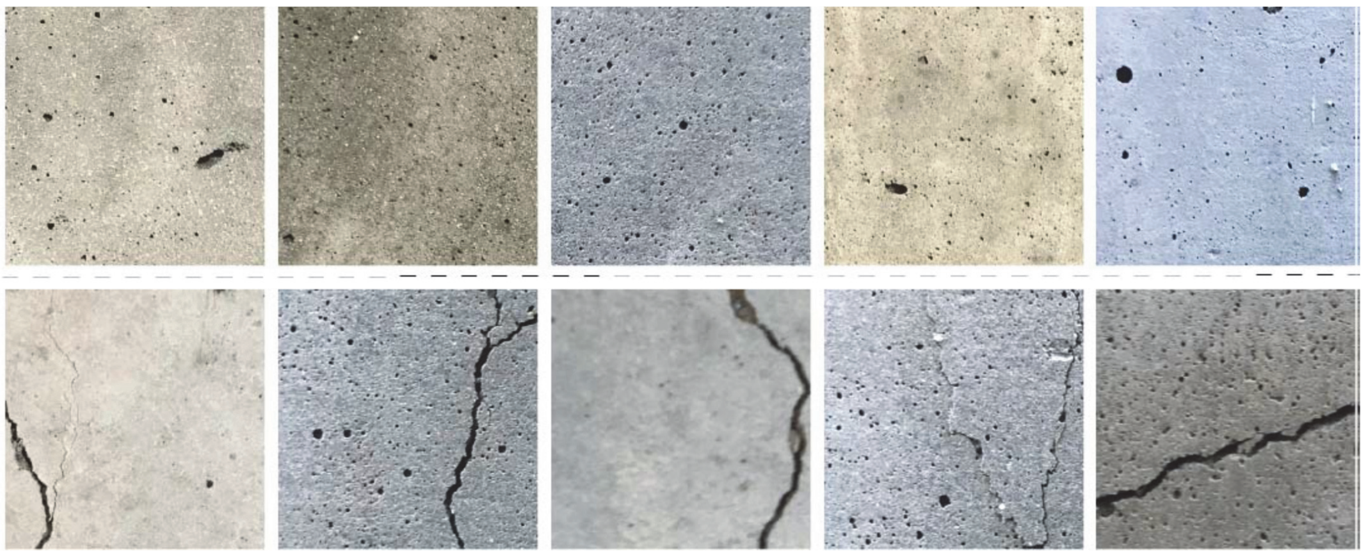

Figure 2. Crack detection in a concrete structure and classification [49]. Reprinted under the Creative Commons (CC) License (CC BY 4.0).

Stentoumis et al. [59] explored the 2D identification and 3D modeling of concrete tunnel fractures through visual cues, proposing a novel detection methodology to address shortcomings in existing crack evaluation methods. Significant advancements in this area encompass the integration of a hybrid technique for CNN detector initialization, adapting a modified census transformation for stereo matching, and combining two cutting-edge optimization approaches. Furthermore, a predictive model for assessing the tensile breakout capacity of concrete fastening systems was established, leveraging machine learning techniques, including Gaussian process regression (GPR) and support vector regression (SVR). [60]. These same ML techniques were applied to create a model for estimating building repair time, considering weight assignment methods and concrete strength [61]. Additionally, other ML methods, such as multilayer perceptron, gradient boosting regressor, extreme gradient boosting, and fuzzy-analytical hierarchy process, were utilized in case-based reasoning. Lastly, a prediction model was tested for the flexural strength of natural pozzolana and limestone-mixed concrete [62].

In civil engineering challenges, ML has played a pivotal role in analyzing complex problems using various algorithms, including ANN, regression, and random forest [63]. The effectiveness of MOGP (multi-objective genetic programming) is exemplified in simulating a demanding civil engineering issue: the long-term creep of concrete. The MOGP-derived creep model is noted for its simplicity, user-friendliness, and superior accuracy compared to previous prediction models [68]. Additionally, a collaborative ML-optimization technique is under development to improve the update of finite element models for civil engineering structures [64]. An ensemble ML model is employed to estimate corrosion initiation time in embedded steel-reinforced self-compacting concrete [65]. In civil engineering, ML has been applied to estimate seismic building structural types [66] and develop a carbonation prediction model for reinforced concrete [67].

Furthermore, the feasibility of using Support Vector Machines (SVM) to forecast the fresh characteristics of self-compacting concrete was explored. Some studies have utilized a sample numerical example to illustrate and visualize the risk-based active learning process, which was then applied to the Z24 Bridge benchmark. The case study findings reveal that risk-based active learning by a statistical classifier can significantly enhance decision-making processes for better outcomes [68].

Machine learning and SHM reinforced concrete structures.

Supervised Learning (SL) involves using labeled data to teach the machine about the characteristics associated with the provided labels, making it suitable for training models to address regression and classification challenges. For example, in the field of SHM, supervised learning can be utilized to identify and assess the type and severity of damage [69]. On the other hand, unsupervised learning focuses on unlabelled data, where datasets lack clear outputs but follow general patterns that can be summarized based on specific trends. The goal here is to obtain accurate and well-predicted results by the end of the process [2]. Recently, ML algorithms have demonstrated significant promise in SHM applications within structural engineering. These techniques are increasingly applied to detect damage in historic structures. Although ML was initially used for different designs and material properties of concrete, its application to legacy structures is relatively recent. Some of the most cutting-edge applications of ML techniques are being directly and indirectly employed in the context of historic buildings. Damage detection in concrete structures with impedance data and ML has been proven effective in optimizing the model [70]. Detecting surface-level damage on architectural landmarks is fundamental in structural engineering assessment. CNNs, a type of deep learning network, excel at tasks beyond the capabilities of simple ANNs, such as image classification. A typical CNN architecture comprises multiple convolutional blocks and a fully connected layer. Filters or kernels are employed to extract essential features for classification, such as edges and boundaries. Applying these filters with unique weight vectors across the image generates feature maps. CNN models are trained using various photos of the monument under different conditions, including varying lighting, shadows, and more [71]. The classification of ML is depicted in Fig. 3.

The SHM is an imaginative strategy for scholarly calculations to cross, mixing modern sensor advancements with a look at foundational strength issues [72]. Factual model creation is worried about the execution of calculations that utilize the extricated highlights to gauge the degree of the harmed structure. These calculations can be characterized into two classes. These calculations test factual circulations of deliberate or determined highlights to improve the harm discovery measure. A more extensive and more far-reaching conversation can be found [16,73], two critical writings for all individuals chipping away at SHM. In some studies, unsupervised learning was used to detect the presence and location of damage in specific experiments.

In contrast, supervised learning was used to identify the kind and severity of damage in SHM investigations [74]. Albuthbahak et al. [75] have demonstrated using supervised learning models to estimate concrete compressive strength using ultrasonic pulse velocity and mix factors. Lu et al. [76] proposed a robust technique for condition evaluation of real-life concrete structures for identifying tiny fractures at an early stage of development, which uses an unsupervised learning one-class support vector machine. A clustering method for bridge SHM [77] is shown in Fig. 4.

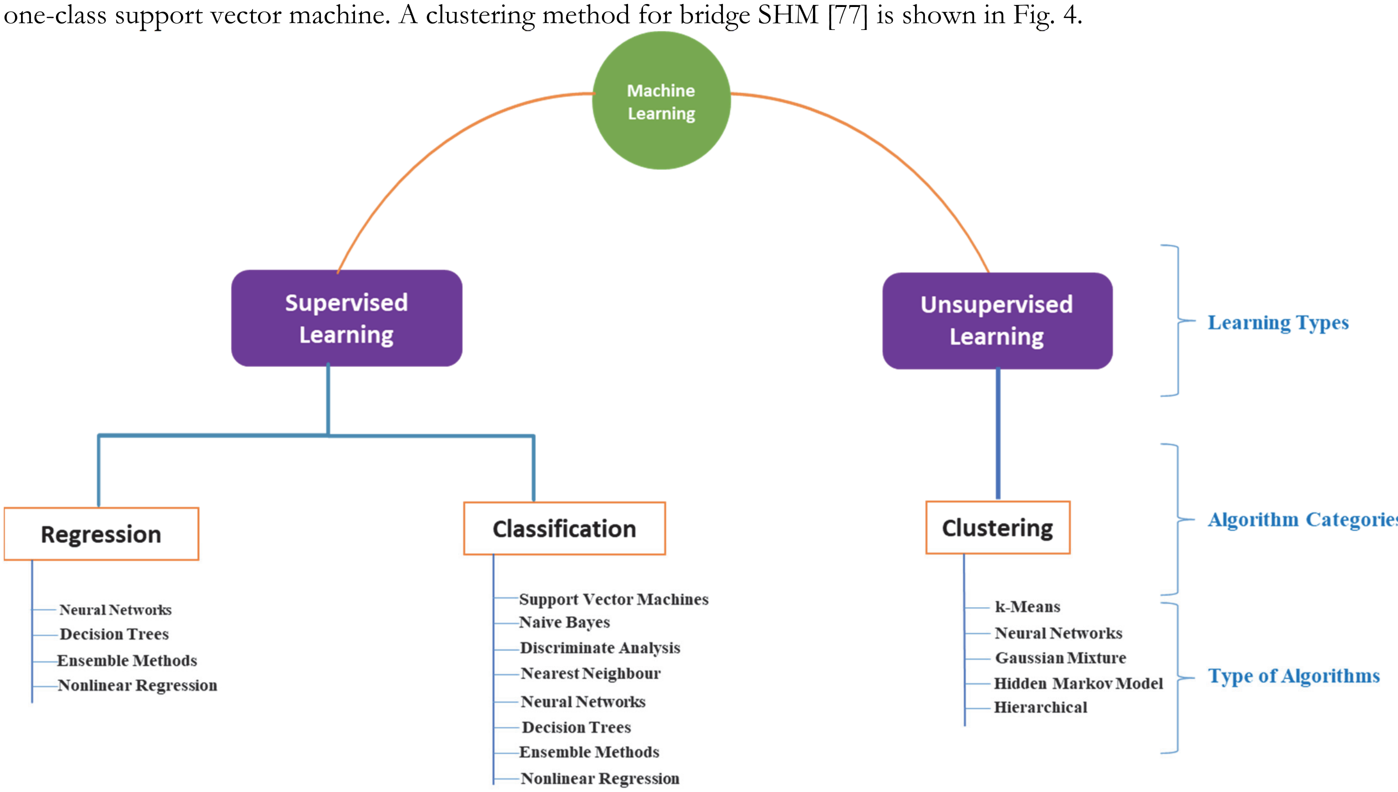

Figure 3. ML types with commonly adopted algorithms.

Various ML models, such as ANNs, SVM, decision trees, and evolutionary algorithms, can be applied to predict the mechanical properties of concrete [78]. ML is a technology widely used in pattern recognition, data extraction, natural language processing, and other areas, with three main types: supervised, unsupervised, and reinforcement learning. Among these, a multilayer perceptron-based feedforward neural network is a common choice for supervised learning. At the same time, support vector machines represent a standard optimization technique for specific types of single-layer networks [79]. However, this research focuses on detecting and repairing concrete structures through PZT-based EMI techniques.

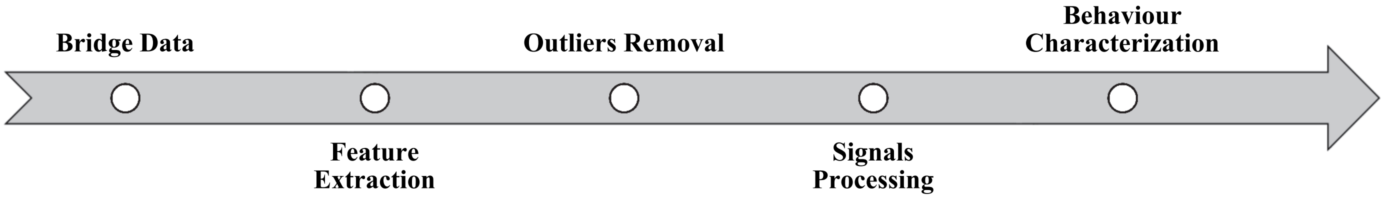

Figure 4. Diagram illustrating the suggested clustering-based strategy for SHM.

An IoT-based fiber Bragg grating (FBG) sensing method is applied for experimental validation to estimate the strain distribution profile at the bonding zone of the base plate from a central location [80]. EMI strategies offer cost-effective solutions for damage detection in various structures, with mathematical results validated through experiments or existing literature findings [81]. With the continuous advancements in composite technology, the complexity of components is on the rise, making the assurance of structural integrity increasingly critical and demanding effective and reliable non-destructive evaluation (NDE) techniques [82]. In the construction industry, building structures are widespread, but assessing the health state of truss structures under operational conditions remains challenging due to their diverse and structurally complex nature. An EMI technique is introduced to measure impedance spectra using PZT elements, accompanied by implementing a backpropagation neural network as a potent non-linear transformation tool to evaluate structural health [83].

Concrete structure cracking has a detrimental impact on performance and represents a significant durability concern. To maintain structural reliability and performance, promptly identifying and repairing cracks is crucial. This research focuses on vision-based crack detection systems that leverage deep convolutional neural networks to achieve superior classification rates in identifying and categorizing fractures [84]. Deep learning algorithms were also employed for crack recognition on concrete surfaces [85], and a multiscale and adversarial learning-based semi-supervised semantic segmentation approach was utilized to detect cracks in concrete structures [86].

CRITICAL ANALYSIS OF RELEVANT STUDIES

In this section, based on the existing work and its summarization, considering three possible aspects: objective, methodology, and outcome, a critical analysis is provided. For this, some review contents have been repeated to explore the research gap with an overview. Generally, ML is a computer-based investigation that does not require any practical work, and the researchers Koch et al. [1] explored the review based on computer vision damage detection in concrete structures. Additionally, they highlighted the concrete condition assessment. A similar idea of review work by changing the main object Almeida et al. [87] illustrated the several SHM statistical methodologies for the damage/crack detection in civil concrete structures. Several studies have been reported in ML-based SHM [2,69,88]; in each, there is a change in the defined problem and structure and the aim of the work, such as review based on challenges and opportunities [89] and application of ANNs and CNT/concrete composites [90]. Next to the ML, deep learning with SHM was also explored well by researchers in civil infrastructures [91].

Coming to an ML-based review, Taffese and Sistonen [92] reviewed the service life assessment and durability of civil concrete structures, focusing on recent studies and future work. Similarly, ML review has been performed considering specific problems of concrete structures such as crack pattern detection [93], model-based damage detection in bridges [94], concrete strength prediction [95], energy harvesting [96], and damage detection [97]. An image analysis method was also employed to determine the crack variation with a crack parameter such as width and length in reinforced concrete structures [98]. ML with an impedance-based technique for concrete infrastructure health monitoring and several studies in civil engineering have been explored well by previous researchers [99].

These previous reviews proved that numerous works have been done using a soft computing approach, and each of them shows that this can be a cost-effective method in determining health conditions, crack damage propagation, crack detection, crack prediction in damaged civil structures, and for healthy structures monitoring purposes. Some of the challenges researchers face in performing ML techniques are explored below. Fig. 5 illustrates the use of ML algorithms for different civil structures over the last years in percent. The data has been plotted based on the present investigation and review work considering different application purposes. Moreover, the mL algorithms are employed for case studies, but the chart shows the overall use of ML work for investigation in civil engineering applications/structures.

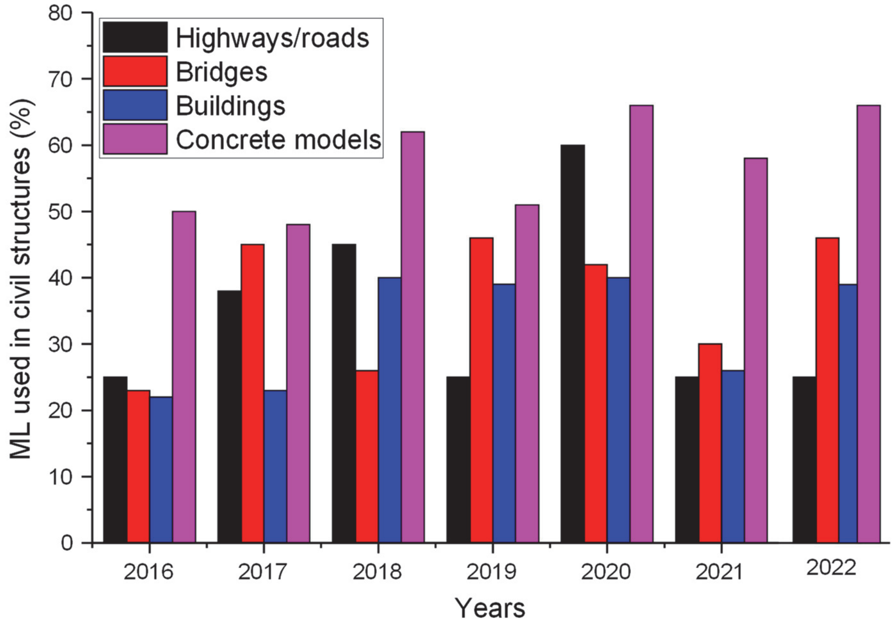

Figure 5. These are the types of concrete structures used in the ML approach in the last seven years.

Practical issues

Beams are the primary structural elements in reinforced concrete structures, bearing lateral loads applied to the structure's axis. These beams experience sustained loads, leading to deflection and, eventually, the development of cracks. Typically, these cracks initially appear in the tensile zones of the beams before extending into the compression zones. Flexural fractures in beams occur when the tensile strain reaches its critical point, typically when the bending moment surpasses the moment capacity. The stress that has built up in the concrete is released through these fractures, which may spread further with continued pressure. The crack width limitations may differ depending on the kind of structure. The reinforcements' performance, stiffness, ductility, and corrosion are all affected by fractures in concrete. Crack control is essential for the structure's effective operation because cracks appear on all concrete structures, signifying a loss of strength. There are two types of cracks: structural and non-structural. Typically, structural fractures occur early on because of design flaws or poor building methods—the internal tensions produced in the material utilized cause non-structural cracks [100].

Synchronizing planned and actual construction operations is a significant challenge in building engineering. To address this challenge, a database containing comparable processes in similar environmental conditions can be valuable for estimating essential process parameters like time, cost, and quality. While the available data may not be sufficient for ML applications, case-based reasoning within a hybrid advisory system can bridge the gap between rule-based reasoning and machine learning by drawing inferences from parallels with completed processes [101]. Predicting deflections in RC members is a complex task, as it involves nonlinear interactions among various factors, including mechanical properties of steel and concrete, cracking, and bond-slip between reinforcement and concrete. This complexity makes accurate deflection predictions for RC structures throughout their service life challenging [102]. When not addressed early in the design stage, long-term deflections in RC structures may result in delayed damage to non-structural components. Therefore, it is crucial to calculate these deflections during the initial design phase [103]. The width, length, type, and number of fractures in reinforced concrete structures significantly impact their deterioration levels and carrying capacity [104]. As a result, assessing fractures in concrete structures is critical for inspection, diagnosis, maintenance, and predicting the safety life of the structure. Visual inspection of cracks needs more incredible skill and specialized knowledge and is laborious, time-consuming, and subjective. Numerous issues have been raised regarding developing testing setups and data collection systems in different concrete structures for various applications.

CHALLENGES, LIMITATIONS AND RESEARCH GAP

ML is part of AI studies and has been utilized in numerous applications. ML is used to investigate innumerable data-driven purposes, and it needs a lot of information for training and testing. But, in this study, we have elaborated on some of the primary challenges in ML algorithms that are needed for civil engineering concrete structures.

- ML is classified mainly into supervised and unsupervised learning types and has several algorithms. Hence, knowing suitable algorithms based on the problem defined in concrete structures is vital.
- Experimentation in civil engineering requires more time, such as curing concrete blocks for testing purposes and collecting data for specific algorithms, which needs more time.
- When cracked structures are used, data optimization for health monitoring studies with the ML approach needs a high range of megapixel cameras to capture the crack length and thickness at different ranges, predict the damage propagation, and use other optimization methods.
- Based on the literature, it has also been noted that ML is utilized for different concrete structures such as buildings, roads, bridges, etc., and each has been predicted using ML algorithms. However, this required maximum information, and literature shows that in some cases, data has been collected from more than 1000 test data sets [88], and an average of 500-1000 data has been found in more studies [60,105].
- In recent studies, deep learning algorithms have become popular in many engineering applications, and this has been utilized in civil concrete structures in recent years [49,84,85].
- Large datasets are needed for training and testing ML models, which can be time-consuming and resource-intensive to collect, especially for high-resolution crack detection in concrete structures.
- Adapting ML models to handle diverse environmental conditions, varying surface geometries, and different materials is crucial for universal applicability and effectiveness in real-world scenarios.
- The enhancement of automation levels in defect identification and condition assessment to reduce human input and improve reliability and safety assessments.

Additionally, some of the other challenges have been found in experimental studies of civil structures considering ML-based work.

- To enable integrated condition evaluation of civil infrastructure, comprehensively identifying, measuring, and analyzing interacting defect patterns simultaneously is difficult to measure [1].
- Generalize existing detection models to handle environmental circumstances, such as shifting illumination conditions, varied surface geometries and materials, and different camera positions and distances effectively and universally.
- To raise the level of automation from inadequate defect identification to advanced defect and condition assessment, reduce the quantity of human user input.

Based on the comprehensive review conducted in this work, the research gap centers on the challenges and limitations (Tab. 1) of existing ML and soft computing methods in civil engineering for SHM and damage assessment. Despite the notable advancements and the application of various ML algorithms to enhance prediction accuracy, cost-effectiveness, and efficiency in civil engineering projects, several key challenges remain unaddressed.

Addressing these gaps requires interdisciplinary collaboration, improved data standardization protocols, and continuous learning in ML and soft computing fields among civil engineers. Further research is recommended to develop more robust, adaptable, and efficient ML models for civil engineering applications, focusing on reducing computational demands and aligning with sustainability goals.

The additional information on the research gap emphasizes the importance of developing ML models that are accurate but also interpretable and transparent in their decision-making processes. This is crucial for their acceptance and trustworthiness in critical civil engineering applications. Moreover, integrating machine learning with traditional civil engineering practices remains a significant challenge, requiring methodological innovations and educational curriculum changes to equip future engineers with the necessary skills. This review also points out the need for more comparative studies that evaluate the performance of different ML algorithms in various civil engineering tasks to guide practitioners in choosing the most appropriate method for their specific needs. Lastly, there is a sign for more interdisciplinary research that leverages advances in sensor technology, data analytics, and computational power to address the complex and dynamic nature of civil engineering projects.

The review uniquely integrates ML and soft computing in civil engineering, focusing on enhancing energy efficiency and cost-effectiveness. Unlike previous reviews, it offers a comprehensive exploration of ML-based methods and their synergy with soft computing techniques like fuzzy logic and the design of experiments. It critically examines practical challenges in implementing these technologies and navigates emerging research directions, synthesizing advanced artificial intelligence for new researchers. This review stands out by combining a variety of case examples, showcasing the versatility of ML and soft computing in structural reinforcement applications, and addressing integration difficulties, making it a valuable guide for the field.

Application of ML-based concrete structures

Over the last six years, ML has become popular in non-information technologies such as aerospace, civil and mechanical engineering. When we focussed on civil infrastructure work, several examples were found in recent years that used the concept of ML-based algorithms. However, this review extracted all the civil structure examples with different algorithms used by the previous researchers.

When considering application-based work for civil structures, most work has been found to determine the optimum methods to solve the defined problems in concrete highways.

- Type of concrete: Applications based on the kind of concrete have been found to have variations in different mechanical and structural properties. Some of the significant ML were used considering the type of concrete: reinforced concrete, non-reinforced concrete, concrete with CFRP, and composite concrete.
- Type of structures: Even though ML algorithms are also used in different types of civil structures to predict outcomes in healthy and unhealthy structures. Some of the civil structures in which ML and data-driven approaches are used are as follows: highways, buildings, columns, beams, bricks, brides, and other concrete models/blocks.
- Type of investigations: ML is used to investigate different purposes in civil structures for damaged and undamaged structures. Some of them have been considered necessary in this review, listed as damaged prediction, crack detections, healthy monitoring conditions, crack repair/control, suitable concrete model, optimum properties, parametric investigation, concrete structures design/model, etc.

ML algorithms have been used in tremendous studies with no limit in real-life applications. The algorithms fit any work/discipline. Indeed, this review is limited to civil infrastructures and structural models. Also, this review considered different approaches apart from ML-based algorithms to extract the soft computing method in civil engineering fields.

Structure type	Focus	Technique adopted	Outcome	Limitations	References
Concrete surface	Crack detection	Deep learning algorithms	A deep learning model is developed to classify images as cracked or not cracked, particularly those taken on concrete surfaces.	Crack detection problems on the surface	Rajadurai and Kang [84] and Le et al. [85]
Concrete structure surface	Detect concrete cracks	A semi-supervised semantic segmentation approach based on multiscale and adversarial learning.	A detection algorithm and learning method have been developed for segmenting crack areas in images, particularly those that can occur in underground concrete structures.	It is necessary to introduce a crack detection algorithm that is both highly accurate and efficient, as it will enhance the dependability of structural safety assessments.	Shim et al. [86]
Concrete structures-cored samples	Prediction of concrete carbonation depth	ML algorithms-ELM, SVM, MLR. Fuzzy logic-ANSIF	The results indicate that ANFIS-M2 enhanced prediction accuracy and model performance.	Various alternatives such as optimization techniques, hybrid models, and ensemble models may be applied to improve the model's performance.	Malami et al. [106]
Reinforced concrete structures-RC beams	Crack characterization	Experimental and data-driven numeric study	Structural designers and practitioners can employ the tool to achieve robust serviceability-based designs for reinforced concrete members and systems.	It is limited to the flexural crack behavior of RC beams.	Das et al. [100]

Concrete roads	Finding fractures in concrete roadways under different shooting, weather, and lighting circumstances	Pre-trained Faster R-CNN deep learning	It was acknowledged that illumination effects. On was relatively high for crack detection.	When photos captured at sunset and moonlight were processed to investigate the impact of illumination quality on crack detection, it became apparent that not all cracks were detectable.	K. Hacıefendioğlu and H. B. Başağa [107]
Concrete bridge	box confinement for crack detection	YOLOv5 with image processing technique	Quick and accurate bridge crack identification and quantification were achieved based on the actual engineering dataset.	The dataset is still minute and a more extensive dataset could significantly increase the suggested algorithm's accuracy in real-world applications.	L. Yu et al. [108]
10-story, 10-bay building	Framework for novelty detection for damage localization in massive constructions	time-dependent grid environment and a novel spatiotemporal composite autoencoder network	The framework successfully determined the structure's health state with average accuracy rates for damage detection and localization of 93% and 85%, respectively.	Despite the lack of damaged condition data, the SCAN design effectively uses deep learning and LSTM units.	K. A. Eltouny and X. Liang [109]
Beam and a bar planar truss	Identify structural damage and structural health monitoring	Slime mould algorithm and marine predators' algorithm	After accumulation noise, the suggested approach can accurately forecast the damage's position and extent.	To determine the sensitivity of the suggested indicator to the total number of modes considered in the analysis, single and multiple damage scenarios are analysed using various modes.	S. Tiachacht et al. [110]
Reinforced concrete column	Damage localization and quantifying concrete damage	3D damage segmentation and quantification model based on Mask R-CNN	It is possible to significantly increase the effectiveness of civil inspection work and the safety of inspection functions.	Because the cracks were not 3D rebuilt, cracks in concrete smaller than 10 mm could not be detected.	C. Yuan et al. [111]

Table 1: Overview and limitations in recent (2018-2022) studies of concrete structures.

CONCLUSION AND RECOMMENDATIONS

Civil engineering has witnessed a substantial surge in research concerning integrating machine learning algorithms and other soft computing methods. This exploration has delved into the core advantages of machine learning, strategies for enhancing its applicability and precision, and techniques for reducing computational demands. Machine learning algorithms have garnered substantial attention for their potential to identify, analyze, and even rehabilitate damage in civil engineering structures. We stand at the precipice of a technological transformation where artificial intelligence is poised to revolutionize structural health monitoring and asset management for aging civil structures. Within this paper, we have conducted a comprehensive review, discussion, and analysis of the principal approaches and algorithms featured in the open literature. We intend to provide readers with accessible insights into the extensive body of research in this domain through detailed tables, shedding light on the field's status.

Moreover, we have not shied away from highlighting these approaches' practical challenges and limitations, aiming to establish best practices for their utilization. We underscore the pressing need for further investigation by identifying existing

knowledge gaps. As a result of this critical evaluation, engineers will be better equipped to make informed decisions regarding integrating machine learning algorithms and soft computing methods in civil and structural engineering.
Several vital recommendations emerge based on the comprehensive discussion and analysis of machine learning in civil engineering. Firstly, interdisciplinary collaboration is essential, fostering partnerships between civil engineers, computer scientists, and data scientists, allowing for innovation and knowledge sharing. Implementing data standardization protocols is crucial to ensure data compatibility and consistency, enabling more effective data aggregation and analysis. Continuous learning and professional development in machine learning and soft computing should be promoted among civil engineers, ensuring they stay updated with the latest advancements to apply these technologies effectively. Additionally, ethical and privacy concerns related to data collection and machine learning applications must be addressed. Encouraging open data sharing within the civil engineering community is necessary for facilitating research, model development, and knowledge exchange. Sustainability should be a central focus, aligning machine learning applications with global efforts to reduce the environmental impact of infrastructure projects. Finally, developing machine learning models for risk assessment and predictive maintenance can aid in the proactive management of aging infrastructure, enhancing its reliability, safety, and sustainability.

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