

TOPICAL REVIEW

Artificial Intelligence and Structural Health Monitoring of Bridges: A Review of the State-of-the-Art

RAFFAELE ZINNO¹, SINA SHAFFIEE HAGHSHENAS², (Graduate Student Member, IEEE), GIUSEPPE GUIDO², (Member, IEEE), AND ALESSANDRO VITALE²

¹Department of Environmental Engineering, University of Calabria, 87036 Rende, Italy

²Department of Civil Engineering, University of Calabria, 87036 Rende, Italy

Corresponding author: Sina Shaffiee Haghshenas (sina.shaffieehaghshenas@unical.it)

ABSTRACT In the age of the smart city, things like the Internet of Things (IoT) and big data analytics are making big changes to the way traditional structural health monitoring (SHM) is done. Also, the capacity, flexibility, and robustness of artificial intelligence (AI) techniques for solving complex real-world problems have led to an increasing interest in applying these methods to SHM systems of infrastructures in recent years. Therefore, an analytical evaluation of recent advancements in SHM for infrastructures appears to be important. The bridge is one of the significant transportation infrastructures where existing environmental and destructive variables can have a negative impact on the structure's life and health. The SHM system for bridges in different stages of their life cycle, such as construction, development, management, and maintenance, is seen as a complementary part of intelligent transportation systems (ITS). The main goal of this study is to look at how AI can be used to improve the current state of the art in data-driven SHM systems for bridges, including conceptual frameworks, advantages, and challenges, as well as existing approaches. This article presents an overview of the role of AI in data-driven SHM systems for bridges in the future. Finally, some potential research possibilities in AI-assisted SHM are also emphasized and detailed.

INDEX TERMS Structural health monitoring, the Internet of Things, artificial intelligence, data-driven, bridge, intelligent transportation systems.

I. INTRODUCTION

With the increase in population growth rate in recent decades, the development of cities, villages and related infrastructure are among the undeniable needs. Infrastructure refers to the collection of systems, equipment, and services that a city, country, or region employs to conduct social, welfare, political, and economic affairs. In fact, infrastructure is a kind of artery of social life. Therefore, investment, design, construction, development and maintenance of infrastructure is one of the most important goals of economic and social development among countries that can be viewed in order to achieve the goals of sustainable development [1], [2], [3], [4], [5]. Bridges are one of the oldest infrastructures that humans have used to improve their transportation routes. However, in the subject of

urban management today, the bridge is seen as a structure for overcoming physical boundaries in order to maximize the use of available space for movement and access to destinations. Bridges are one of the relatively expensive infrastructures. Bridges may have a usable life of many decades, depending on the location and materials employed. The condition of bridges gets worse over time because of things like creep, corrosion, and cyclic loads, among others. However, with appropriate management and maintenance, they can last for hundreds of years [6], [7], [8]. A study issue that has received a great deal of interest throughout the years is the detection of structural problems in bridges. Most of the reason it has grown so popular is because the roads and trains are growing outdated and are no longer capable of handling the volume of traffic that they were intended to manage [9]. In transportation system, bridges are extensively employed in railway traffic, car traffic, and pedestrian traffic. They play an important

The associate editor coordinating the review of this manuscript and approving it for publication was Ines Domingues^{id}.

role in reducing travel time and increasing travel safety. Nowadays, as a result of sophisticated technologies for bridge building, which need significant financial investment, the relevance of researching the efficiency and performance of structures has increased more than ever. Lack of maintenance and monitoring of infrastructure such as bridges can lead to reduced efficiency, damage and their destruction. As a result, it can have a direct or indirect negative impact on the life and work of people who use these infrastructures. Bridges are affected by damaging effects over an extended period of time. These variables have an effect on bridges in both natural and unnatural ways. To make bridges last longer and be more efficient, they need to have a control and monitoring system [10], [11], [12], [13], [14]. So, structural health monitoring (SHM) can be a powerful tool and a reliable way to keep bridges safe. The SHM system is able to look at the bridge's workability, dependability, and ability to keep working in order to make it more durable [15], [16]. It is deemed critical to promptly identify damage, analyze the damaged element, and assess its health in order to reinforce and secure it to extend the bridge's lifespan. In the past, traditional methods were used to monitor, control, and test bridges, such as periodic visual inspections by technicians, magnetic method, mechanical wave (vibration) method. The great majority of in-service bridge data is still gathered by visual examination, despite the significant amount of academic research that has been done on bridge damage detection and identification. However, these procedures have been employed by bridge owners for a long time, but it has several drawbacks and isn't always effective due to the wide range of inspection abilities [17]. These types of controls are categorized in the form of non-destructive testing (NDT) or non-destructive evaluation (NDE). One of the most important drawbacks of these eye monitors is the lack of access and inspection of all parts of the bridge. Technicians and specialists are also used in this monitoring, but in any case, there is a possibility of human error or a lack of misdiagnosis of damage. Another difficulty is that, in some cases, it is necessary to stop the operation of the bridges for inspection and testing, which could have resulted in financial losses or not be possible to stop the operation. Also, some basic components are covered in bridges, and the breakdowns and damage may begin with the sections inside the element, and there is no possibility of visual inspection. In recent decades, with the significant advancement of technology and cooperation between several disciplines such as civil engineering, electronics, computer science, it has become possible to come up with new ways to monitor and analyze damage to bridges. On the other hand, the introduction of concepts such as the Internet of Things (IoT) has greatly contributed to the development of the technologies used in SHM. The integration of these sciences and the development of new technologies have increased the efficiency of the SHM system in monitoring, controlling, and evaluating bridges as accurately and efficiently as possible. Other advantages of using SHM for bridges can include providing basic information about the condition of bridges, quick

assessment of the damage, severity and level of damage, as well as the location of the damage (location where it is not possible to visually inspect). The mathematical or numerical models may be improved by including the structure's attributes into it, allowing for a better understanding of both its static and dynamic behaviors. Artificial intelligence (AI) techniques among the achievements of researchers who in recent decades have played a significant role in improving the SHM system in the areas of monitoring, control, evaluation and decision making.

The purpose of this study is to examine the use of AI in SHM systems, including its potential benefits, challenges, current approaches, and recent advancements. Another purpose of this study is to introduce researchers with tools that will aid them in developing a deeper knowledge of the monitoring systems found on bridges. In particular, a review and discussion of AI techniques will be conducted in order to evaluate SHM systems for bridges. In addition, future research in the field of AI and SHM systems are highlighted, as well as less-studied aspects of these approaches. The field of SHM has gained a great deal of attention throughout the last several decades, and numerous evaluations of the SHM literature are already available, but this work aims to give a broad and complete picture of present AI techniques with SHM systems as well as the most recent advancements and developing trends in this subject.

The remainder of this paper is structured as follows: Section 2 presents a brief overview on structural health monitoring system for bridge as well as definitions and conceptualizations. Section 3 describes AI methodologies. New research directions and developing trends in the use of AI in SHM are discussed in Section 4. Finally, Conclusions are then presented in Section 5.

II. STRUCTURAL HEALTH MONITORING (SHM) SYSTEM FOR BRIDGE

Many bridges today are carrying traffic loads that were never intended to be carried by such structures in the first place. Due to the growth in operating condition stresses, structural fatigue is no longer only a problem for a single structure, but a problem for the whole transportation network. Predicting and detecting failures in the future and those that have already occurred might lead to lower potential economic expenses as well as fewer human life deaths. As an example of the catastrophic, the I-35W bridge across the Mississippi River in Minneapolis, Minnesota, collapsed in the midst of rush hour in the summer of 2007. The collapse claimed the lives of 13 individuals and showed engineers the deteriorating infrastructure of the United States. This led to more and more engineers trying to control, retrieve, and improve that infrastructures [18]. In another example of a tragedy, the Polcevera viaduct (Ponte Morandi or Ponte delle Condotte) in Genoa collapsed in the summer of 2018. It was the consequence of structural flaws in the building's design, construction, and subsequent maintenance that led to corrosion in certain steel cables that eventually broke causing the collapse that claimed the lives



FIGURE 1. Some reasons to use SHM systems on bridges.

of 43 people. This caused the engineers to use new and smart technology and tools to monitor the health of the new bridge that was built in 2020 instead of the collapsed bridge in Genoa [19]. Static and dynamic forms of traffic-induced modal variation are also possible. Static variations are proportional to mass; however, traffic-induced dynamic variations have been demonstrated to be nonlinear and may reduce as the load impact increases. In addition, observed changes in a bridge's modal characteristics may actually be the result of the interaction response of a healthy bridge with a moving vehicle, making vibration-based monitoring of in-service bridges much more difficult to perform [17]. Hence, identifying structural deterioration is essential to this process. Also, it is important to figure out what kind of system is best for monitoring, controlling, and evaluating conditions [20]. Structural health monitoring SHM is a broad word that refers to a process that generates reliable data on the present condition of a structure, as well as its efficiency, which may be analyzed in the intermediate term. In order to properly diagnose and monitor bridge deterioration, it is necessary to consider two essential characteristics of the bridges: their physical state and structural function. Using a succession of continuous measurement sensors, SHM is an approach for detecting deterioration to a structure over an extended period of time. Numerous valuable studies have been conducted to investigate the reasons and how SHM systems are used to

monitor bridges, which have stated the reasons (Figure 1) [21], [22], [23], [24], [25].

In addition to receiving and collecting information from bridges, SHM is also capable of evaluating, analyzing, and predicting obtained data in order to determine appropriate actions for raising and enhancing the capacity and life-span of bridges. It is possible to classify SHM into two general categories: diagnostic and prognosis. Defects, locations of defects, and the degree of their spread are recognized using diagnostic techniques. But in contrast to this approach, prognostication makes use of diagnostic results to estimate how long a building will continue to stand. Figure 2 depicts an overview of the performance monitoring procedure for bridges that are equipped with the SHM system.

The term "damage" refers to alterations made to a system that have a negative impact on the system's present or future functioning. In order for damage to be meaningful, it must be measured in relation to a prior state of the system. "Initial state" is a term used to describe a system in its original form, without any alterations or damage [26]. Damage to bridges is often recognized using a vertical hierarchy. It is often necessary to have knowledge about the previous level in a hierarchical structure in order to accurately diagnose damage at the following level. There is a strong possibility that the success of each level will be influenced by how well the levels that came before it performed in relation to the current level.

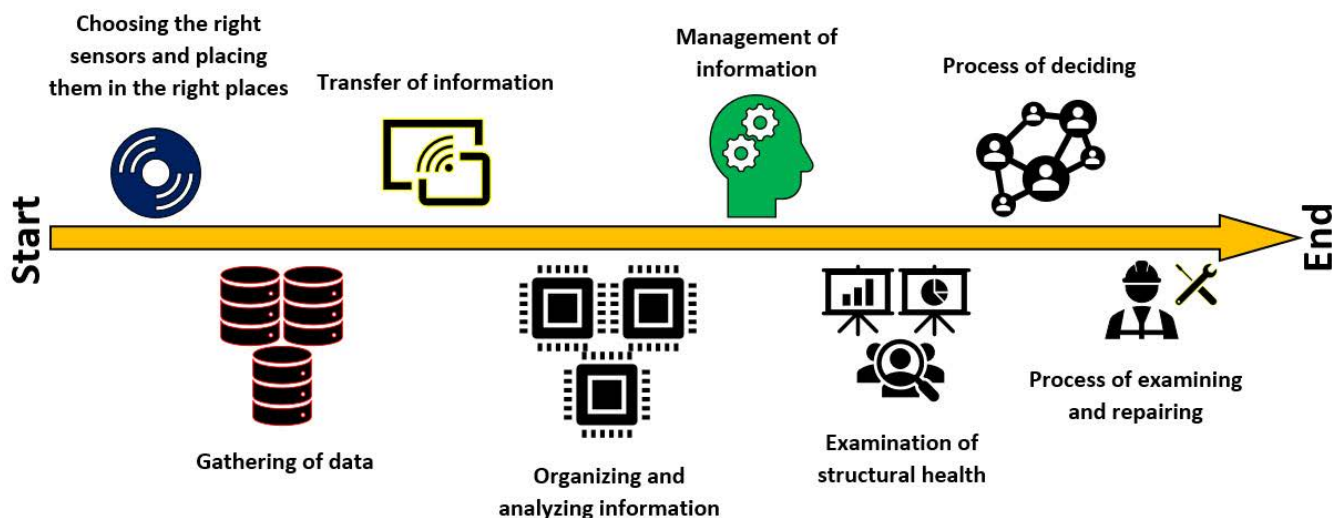


FIGURE 2. Overview of the performance monitoring process of bridges with the SHM system.

Some ground-breaking categorizations of damage introduced by researches [27]. According to the categorization scheme, damage can be broken down into five groups [28]:

- Level I (Damage detection): This level is identified when a damage event occurs.
- Level II (Damage location): This level is detected when damage occurs, and then the location and orientation of the damage are determined.
- Level III (Damage typification): This level is detected when damage occurs, the location and orientation of the damage, and then damage severity is determined, and the kind of damage is estimated.
- Level IV (Damage extent): This level considers the possibilities of limiting or postponing the extent of damage once previous levels have been completed.
- Level V (Damage prediction): After completing the previous four levels, this level assesses the bridge’s remaining usable life or its viability status, depending on the situation.

Table 1 contains the study’s acronyms and abbreviations, which makes it easier to read along.

III. CHALLENGING PROBLEMS OF SHM SYSTEM FOR BRIDGE

There are a number of factors that make SHM a difficult process to complete. The bulk of these challenges come as a result of the data that must be acquired, the imperfection and variety of sensor technologies, and the use of various methodologies for analyzing the data that has been collected. These challenges can be broken down into four general categories based on past research and a general summary as follows:

- Installation of equipment and sensors: One of the most basic challenges in SHM is the correct and appropriate selection, installation and commissioning of sensors. Selecting a project-appropriate sensor as well as considering the sensor performance in the project based on the importance of the project can be the first major challenge in SHM systems.

Sensors used in SHM, particularly for long-term monitoring, must be resistant to external conditions that influence performance, such as temperature, humidity, and corrosive compounds. Most sensors now in use need an external power source. Sensors that detect strain or stress in a structure may be located distant from the structure being monitored, necessitating the transmission of data to be processed and analyzed. Due to the requirement to link sensors to cables for power and data transmission, the SHM system is often more difficult to set up and maintain. There is also a direct or indirect influence on project costs since the whole structure may have to be modified to suit these sensor networks. As a result, more expenses may be incurred [29]. Given the relatively high cost of providing sensors, determining the minimum number of sensors is another challenge for SHM. So, the location of sensors is very important when it comes to making an effective SHM system. This is so that the number of sensors can be cut down and optimized, and then costs can be kept down at the same time with the best efficacy.

- Acquiring data and data fusion: Damage detection and evaluation in a SHM system might be complicated by measurement noise, poor boundary conditions, and vibrations from the environment [30]. How to ensure that data is normalized and processed under a broad variety of environmental loads or noise sources is one of the most critical concerns in the field of structural health monitoring. As a result, it is critical to adjust for or filter out these undesirable consequences. All sensor data is susceptible to some amount of imprecision and uncertainty in the readings, which is inherent in the data collection and provisioning process. In yet another challenge, data that comes from sensor networks can be qualitatively identical (homogeneous) or distinct (heterogeneous). Hence, some effective techniques are needed for data fusion. They must be suitable and efficient; otherwise, the data produced may not be proper [31].

TABLE 1. Summary of used acronyms and abbreviations.

Acronyms and abbreviations	Definition	Acronyms and abbreviations	Definition
AANN	Auto associative neural network	ITS	Intelligent transportation systems
AI	Artificial intelligence	KNN	K-nearest neighbors
ANN	Artificial neural network	LIN	Linear
ARMA	Auto-regressive moving average	MLP	Multilayer perceptron
CART	Classification and regression tree	ML	Machine learning
CEEMDAN-HHT	Complete ensemble empirical mode decomposition with adaptive noise- Hilbert Huang transform	NDT	Non-destructive testing
CHAID	Chi-squared automated interaction detection	NDE	Non-destructive evaluation
CNN	Convolutional neural network	POL	Polynomial
CRISP-DM	Cross Industry Standard Process for Data Mining	PSO	Particle swarm optimization
CS	Cuckoo search	PRNN	Pattern recognition neural network
DL	Deep Learning	PCA	Principal component analysis
DM	Data Mining	QUEST	Quick, unbiased, efficient statistical tree
DTEs	Decision tree ensembles	RBF	Radial basis function
ERA	Eigensystem realization algorithm	RBFNN	Radial basis function neural network
FEA	Finite element analysis	RCNN	Region Based Convolutional neural network
FNN	Feed-forward neural networks	ResNet	Residual Networks
FCM	Fuzzy c-means	RF	Random forest
FRF	Frequency response function	SDP	Structural damage prediction
GAN	Generative adversarial network	SHM	Structural health monitoring
GMM	Gaussian mixture models	SOM	Self-organizing map
GA	Genetic algorithm	SVM	Support vector machine
GK	Gustafson–Kessel	ULSCD	Uniform load surface curvature difference
ICA	Imperial competitive algorithm	VGGNet	Visual graphics group network
IoT	Internet of things	YOLO	You only look once

- Data analysis and processing framework: After overcoming the previous challenges, assuming complete and flawless information, the best results can be obtained by considering a framework for data analysis. But the important challenge in this case is to properly determine a framework for the analysis of the data. In the real world, things like unexpected problems and uncertainty, on the one hand, and things like high data volume, data type, and data reliability, on the other hand, have a direct and indirect impact on the results. So, when choosing an analytical system, attention to many of these factors is necessary.

- Operational scheduling and the best solution introduction: Having successfully completed and overcome on the previous challenges, the last challenge is to provide a suitable solution based on the analysis performed on the prepared data. In light of the results and how important each damage is, a set of appropriate steps should be taken for each one. Using reliability-based scheduling (RBS), the existing structural state may be represented by well-known performance measures, which is a more efficient technique of scheduling maintenance. Repair can be performed only when these indications exceed predetermined criteria. Modal-based metrics have been the traditional performance indicators utilized for monitoring purposes [32].

The hardware and software components of a SHM system must be considered together. Damage detection and damage modeling techniques make up the software components, while sensors and accompanying instruments comprise the hardware. Discussion of new improvements in hardware instruments may be beneficial; however, given this paper's emphasis is on artificial intelligence approaches as part of the software process in the SHM system, such a presentation will be left to future research.

IV. TYPES OF SHM SYSTEMS

As mentioned earlier, Bridges can be affected by natural and man-made events that happen over and over again. Since the vast majority of bridges are in constant use, any damage to them might result in a human tragedy. In order to determine how stable a bridge is, what hazards it poses, and how problems propagate over time, it is necessary to conduct regular inspections. The SHM system for bridges is one of the best ways to find and diagnose damage, look into changes caused by damage spreading, and figure out how healthy a bridge is overall. In SHM system, either assuming or developing the bridge's pre-damage state is required for damage detection. When diagnosing and determining the extent and location of the damage, it is vital to know the prior state of the structure in order to make an accurate assessment. In reality, the performance of this system is determined by analyzing and comparing new models with old models, as well as identifying and comparing discrepancies between two successive models. It is not feasible to apply this approach unless the damage that has already been done is known. In general, there are two systems for modeling in SHM, which include model-driven SHM and data-driven SHM. Using a

system identification paradigm, vibration data is processed for SHM or damage detection with the goal of figuring out the modal characteristics and keeping track of changes as a result of the process. Employing sensitivity matrices was considered by researchers to discover damage, which is now the foundation for the new discipline of model updating. Finite element analysis (FEA) models are often employed as a starting point in model-driven SHM. Sensitivity matrixes are used to update and modify them by adding the difference between FEA predictions and experiment results. Extensive studies have been conducted based on model-driven SHM on bridges [33], [34], [35], [36], [37]. However, with all the advantages of the Model-driven SHM, there are limitations to this approach. Among these limitations, it can be mentioned that model updates take time and that calculations in Model-driven are complex and should be validated with experimental results [38], [39], [40], [41]. Also, because of measurement noise, non-ideal boundary conditions, and environmental vibrations, it is almost impossible to perform damage detection and assessment in a SHM system with perfect precision. In contrast, data-driven techniques are very adept at handling ambiguity and unanticipated issues [42]. Particularly in the last few years, SMH has made a lot of progress thanks to the development of computational intelligence and the use of data-driven approaches based on methods of artificial intelligence and machine learning. Controlling uncertainty in SHM systems may be done in a variety of ways. Artificial intelligence and machine learning approaches are effective strategies that have lately gained a lot of traction. These techniques are powerful tools that have recently been used in a lot of research because of how well they work [43]. Data-driven techniques, alone or in combination with model-driven approaches, can detect building damages.

Insufficient data and uncertainty in modeling, measurement, and signal processing make SHM a complicated system. Therefore, artificial intelligence and machine learning approaches can play an effective role during the SHM process. In an investigation, Malekloo *et al.* showed eight steps during the SHM process that artificial intelligence and machine learning approaches could play a role base on Figure 3 [19], [31], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66].

V. APPLICATION OF ML IN PATTERN RECOGNITION

In the modern world, it is crucial to effectively analyze raw data and transform it into information that is insightful and clear. In the field of AI and machine learning applications, one area of study is the creation of systems that automatically sort data into groups and look for patterns that show what the data means. This Mechanism is referred to as pattern recognition. In truth, pattern recognition is both an ability and a body of knowledge that can be applied to the development of information-extracting systems from raw data [67], [68], [69], [70]. As shown in Figure 3, artificial intelligence solutions and machine learning algorithms can play a significant

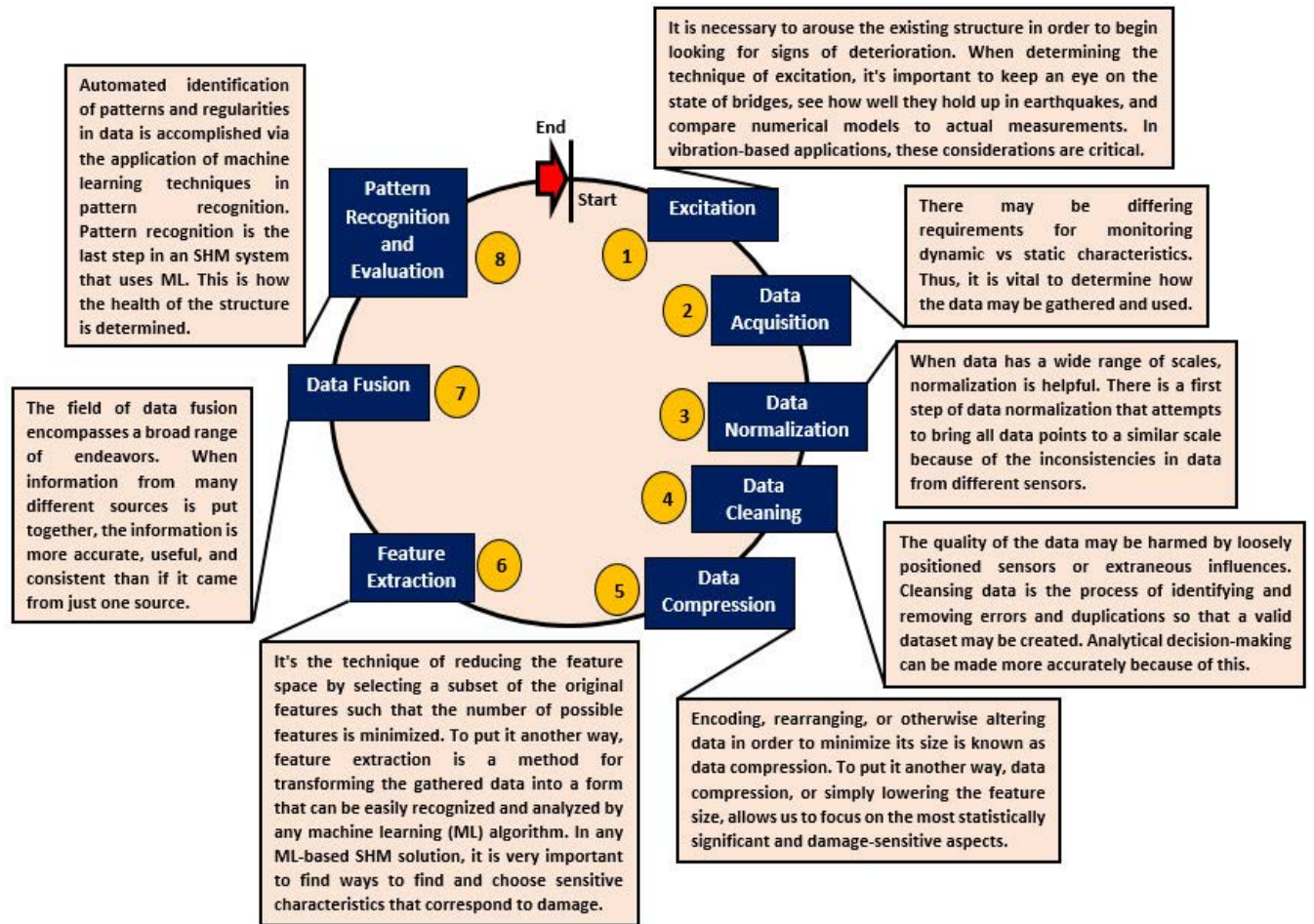


FIGURE 3. Overview of the processes involved in a data-driven SHM system in eight steps.

role in most of these eight steps based on the process of each of these steps. Pattern recognition is one of these eight steps, and machine learning algorithms play a big role in making this step more efficient [57]. Many machine learning approaches are put to use in pattern recognition, which is an extensively used subject. In an SHM system, a pattern recognition system needs information from sensors that are connected to the real world in order to work properly. This kind of system is able to analyze a wide variety of data types, including image, video, numbers, and text. Pattern recognition can be examined from several angles. One of the most important aspects of pattern recognition is pattern recognition analytical systems and algorithms. In general, these systems and analytical algorithms are divided into three general categories, including regression, classification, and clustering algorithms. In another way of looking at them, regression and classification algorithms are supervised learning techniques, while clustering algorithms are unsupervised learning techniques [71], [73], [73]. In fact, in order to get useful findings from the investigation, classification, regression, and clustering methods will be used, based on the information that is currently accessible pertaining to the problem.

Figure 4 provides an overview of the techniques used in pattern recognition.

1) FUZZY C-MEANS (FCM)

Fuzzy logic has the capacity to solve situations in which, as a result of the limited information and comprehension possessed by people, it is very challenging to identify and comprehend the system in question. One of the most significant applications of fuzzy logic in a variety of scientific fields is known as fuzzy clustering. One of the methods for clustering is known as fuzzy c-mean (FCM), and it was first introduced by Bezdek et al. [74], [75], [76]. This method is based on iterative optimization. With the FCM method, a data set is partitioned into N clusters, and each data point in the dataset is assigned to each cluster to a varying degree. In point of fact, fuzzy clustering methods are only an improved version of hard c-means clustering. In the FCM method, the degree to which data belongs to a cluster might have a value between 0 and 1, as opposed to the classic clustering method. The following is a condensed version of the four phases that make up the FCM clustering process [77]:

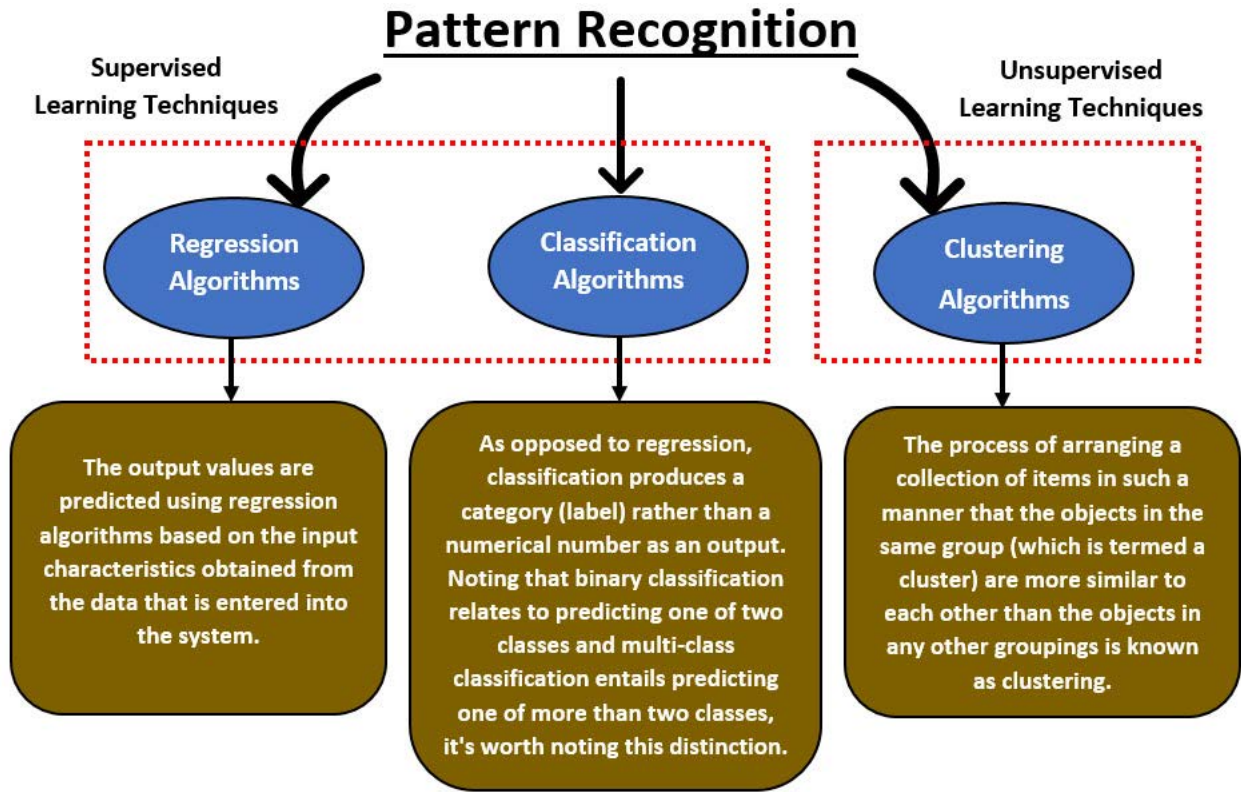


FIGURE 4. Overview of the pattern recognition techniques in a data-driven SHM system.

- In Step 1: the first thing that is done is to establish the total number of classes (C). It is important to point out that “ C ” has a numerical value that is either more than or equal to 2, and either lower than or equal to n (the number of data samples). After then, the significance of the weight parameter, denoted by the letter m' , must be figured out so that the correct level of fuzziness may be assigned to the clustering procedure. Within the context of the optimization process, the significance of this parameter cannot be overstated. The process of optimization that occurs inside the FCM algorithm may continue for a number of iterations (r), denoted by the notation “ $r = 0, 1, 2, \dots, n$.”

- Step 2 involves computing the locations of the cluster centers for each iteration.

- In Step 3: Eqs. 1 to 5 are used to modify and update the partitioned matrix for the r^{th} iteration into the form $\tilde{U}^{(r)}$ after discovering the cluster centers [77], [78].

$$\mu_{ik}^{(r+1)} = \left[\sum_{j=1}^c \left(\frac{d_{ik}^{(r)}}{d_{jk}^{(r)}} \right)^{\frac{2}{(m'-1)}} \right]^{-1} \text{ for } I_k = \varphi \quad (1)$$

$$\mu_{ik}^{(r+1)} = 0 \text{ for all classes } i \text{ where } i \in \tilde{I}_k \quad (2)$$

$$I_k = \{i | 2 \leq C < n; d_{ik}^{(r)} = 0\} \quad (3)$$

$$\tilde{I}_k = \{1, 2, \dots, c\} - I_k \quad (4)$$

$$\sum_{i \in I_k} \mu_{ik}^{(r+1)} = 1 \quad (5)$$

where d_{ik} represents the Euclidean distance between the center of the i^{th} cluster and the k^{th} data, and $\mu_{ik}^{(r+1)}$ represents the membership degree of k^{th} data in the i^{th} cluster for the $r + 1$ iteration of the algorithm.

Step 4: Finally, the clustering accuracy must be assessed. The minimal acceptance precision (r^{th}) is specified in this scenario, and the process will finish only if Eq. 6 is met. If it isn't, the algorithm returns to the second phase and repeats the optimization process until the desired degree of accuracy is achieved [78].

$$\| \tilde{U}^{(r+1)} - \tilde{U}^{(r)} \| = \varepsilon_L \quad (6)$$

The study by Yu *et al.*, is one of the studies that looked at how fuzzy clustering could be used to monitor the structural health of bridges. They investigated how vibrations may be utilized to detect deterioration in a truss bridge model and suggested a novel approach based on fuzzy clustering and reduced frequency response function (FRF) data using principal component projection. For structural damage identification, the FCM clustering technique was employed to classify features for structural damage detection. By loosening the bolted joints of the truss bridge structure to simulate damage, the results showed that the proposed method could find the damage to the bridge [79].

2) K-MEANS CLUSTERING (LLOYD'S ALGORITHM)

In the fields of machine learning and data science, the K-Means algorithm is a kind of unsupervised learning

technique that is used to tackle clustering issues. K-Means, which can be found on the list of the best clustering algorithms, is most likely the one that is the simplest to use [80], [81], [82]. K-mean clustering is a collection of partitioning clustering algorithms with a computational cost that depends on some characteristics such as the number of objects (n), the dimension of attributes (d), and the number of clusters (k). Also, the algorithm's time complexity depends on the number of iterations (i). When doing k-mean clustering, it is necessary to optimize an object function. The goal function may be minimized or maximized in this approach to conduct clustering answers. This indicates that the objective function will be based on minimization if the criteria is the "distance measure" between objects [83]. Finding clusters with the shortest distances between items is the solution to the clustering problem. To determine how different two items are from one another, the dissimilarity function may be utilized. In this case, however, the target function is set in order to maximize the clustering response [84]. In an investigation, Park *et al.*, established wireless SHM based on electromechanical impedance. PCA-based data compression, and k-means clustering-based pattern identification were used. The PCA technique was used to the raw impedance data collected from the MFC patch to improve the on-board active sensor system's local data processing capacity, preserving vital vibration features while removing undesirable sounds via data compression. The outcome of the root-mean square-deviation (RMSD)-based damage identification using PCA-compressed impedances was then compared to the raw impedance data without PCA preprocessing. In addition, just two main components were used in k-means clustering-based unsupervised pattern identification. Experimental research consisting of checking loose bolts in a bolt-jointed aluminum structure was used to verify the efficiency of the suggested methodologies for the practical usage of the electromechanical impedance-based wireless SHM. The results showed the good performances of the suggested methodologies [85].

3) ARTIFICIAL NEURAL NETWORKS (ANNs)

Artificial neural networks (ANNs) are a kind of technology derived from brain and nervous system research. ANNs are computer networks that are inspired by biology. These networks are modeled after biological neural networks, although they only utilize a subset of biological neural system ideas. By imitating the way, the human brain works, artificial neural networks can be taught to find patterns and group information in the same way that humans can. ANN models, for example, replicate brain and nervous system electrical activity [86], [87], [88], [89], [90]. A neurode or a perceptron are processing elements that are coupled to other processing units. The neurons are often stacked in a layer or vector, with one layer's output acting as the input to the next layer and maybe further layers. A neurode may be linked to all or a subset of the neurons in the next layer, replicating brain synaptic connections [91], [92]. When weighted data signals come into a neurode, they simulate the electrical stimulation

of nerve cells and, as a result, the transfer of information in the network or brain. In another word, an adaptive system that learns by employing linked nodes or neurons in a layered structure that mimics a human brain is known as a neural network (also known as an artificial neural network). A neural network simplifies the input by dividing it into many levels of abstraction. It is possible to teach it to identify patterns in speech or pictures by providing it with numerous instances to study. Its behavior is determined by the manner in which its many components are linked to one another as well as the strength, or weight, of those connections. During training, these weights are modified in accordance with a predetermined learning rule in an automated process [93], [94]. This process continues until the artificial neural network successfully completes the job at hand. The innovative structure of the information processing system is an important part of this concept. ANNs have been used in a variety of applications. A neural network may be taught to identify patterns, classify data, and predict future events by learning from data [95]. It's important to note that artificial neural networks can use either supervised or unsupervised learning methods, depending on what they're being used for. There is a wide range of artificial neural networks that are used in various parts of the SHM system, especially in pattern recognition, such as self-organizing maps (SOM), multilayer perceptron (MLP), and radial basis function (RBF). There has been a significant amount of investigation carried out towards the use of the ANNs algorithms in SHM of bridges.

4) K-NEAREST NEIGHBOR (KNN)

The K-Nearest Neighbors method, often known as the KNN algorithm, is one of the supervised learning techniques that is considered to be both one of the simplest and most commonly used in the area of machine learning [96], [97]. KNN is a technique that is used in data mining, machine learning, and pattern recognition. It is not a parametric approach. Both classification and regression issues are amenable to being solved using the k-nearest neighbor approach. On the other hand, it is often used for purposes of categorization. According to Wu *et al.*, KNN is considered to be one of the best 10 algorithms in the field of data mining because of how easy it is to use, how effective it is, and how easily it can be implemented. Also, in order to determine the distance between neighbors while dealing with issues pertaining to regression, kNN makes use of three distance functions (Eqs 7-9), which may be written as follows [98], [99]:

$$\text{Euclidean Function} : \sqrt{\sum_{i=1}^f (x_i - y_i)^2} \quad (7)$$

$$\text{Manhattan Function} : \sum_{i=1}^f |x_i - y_i| \quad (8)$$

$$\text{Minkowski Function} : \left(\sum_{i=1}^f (|x_i - y_i|^q) \right)^{1/q} \quad (9)$$

Noise in the data influences the number of neighbors to consider. The amount of data needed to train for low-dimensional feature space is less. Higher training data is needed in SHM instances with large feature dimensions, resulting in a computationally costly approach. Extensive research has been conducted on the use of the KNN algorithm in SHM of bridges [100], [101], [102], [103]. Feng *et al.*, introduced a k-Nearest Neighbors (kNN) technique based on time-varying forced frequencies from driving trucks to locate and quantify bridge deterioration. They used a time–frequency signal processing technique to assess the acceleration caused by the crossing of a test car in order to acquire the instantaneous frequencies. The kNN algorithm then looks for the patterns of forced eigenfrequencies that are nearest to the on-site immediate frequencies in order to estimate the location of the damage as well as its severity. Their findings demonstrated that damage may be identified, and in the best situations, localized and quantified, with some obvious unfavorable areas close to the supports [104].

5) SUPPORT VECTOR MACHINE (SVM)

Support vector machines, sometimes known as SVMs, are an efficient approach of machine learning that was first developed by Cortes and Vapnik [105]. SVMs are a kind of supervised learning algorithm that may be used to a variety of modeling tasks, including regression and classification. This type of modeling is very widespread. The support vector machine (SVM) is a linear two-class classifier that seeks to maximize the margin between the two classes in order to build a classification hyperplane in the center of the largest margin. It offers a wide variety of hyperplanes, while the support vector machine seeks to locate the one hyperplane that is superior to the others in n-dimensional space. There are two labels that are taken into consideration for this classification: label +1 is taken into consideration for instances that are regarded to be above the hyperplane, while label -1 is assigned to cases that are deemed to be below the hyperplane. A subset of the sample set that is used in the process of classifying learning data is shown by Eq. 10 [106], [107].

$$S = \left\{ (x_i, y_i)_{i=1}^n \mid x_i \in R^N, y_i \in \{-1, 1\}, i = 1, 2, \dots, n \right\} \quad (10)$$

where y_i is the observed i -th sample's target variable. The i -th sample data is likewise supposed to be presented by x_i . Following the construction of hyperplanes, one of them is designated as the ideal hyperplane since it has the largest margin. The current support vectors and limitations define this optimal hyperplane. The limitations are shown in Eqs. 11 and 12 [107].

$$\text{Min } \frac{1}{2} \|w\|^2 \quad (11)$$

$$\text{s.t. } y_i (wx_i + b) \geq 1 \quad (12)$$

where w and b are the weight vector and the bias vector, correspondingly. Then, considering an error coefficient,

the constraints are rewritten and corrected according to Eqs 13 and 14. This error coefficient is intended to ensure a more accurate classification. Where c is the penalty coefficient. Then, based on Eq. 15, SVM classification problems are looked at as the following dual optimization problem using the Lagrange method [107], [108].

$$\text{Min } \frac{1}{2} \|w\|^2 + c \sum_{i=1}^n \varepsilon_i (\varepsilon_i \geq 0) \quad (13)$$

$$\text{s.t. } \begin{cases} y_i (wx_i + b) \geq 1 - \varepsilon_i & (i = 1, 2, 3, \dots, n) \\ c \geq 0 \end{cases} \quad (14)$$

$$\begin{cases} W(a) = \sum_{i=1}^n a_i - \frac{1}{2} \sum_{i,j=1}^n a_i a_j y_i y_j K(x_i, x_j) \\ \text{s.t. } \sum_{i=1}^n a_i y_i = 0 \quad (0 \leq a_i \leq c; i = 1, 2, 3, \dots, n) \end{cases} \quad (15)$$

where K is the so-called kernel function in mathematics. As illustrated in Table 2, there are a variety of kernel functions, including linear, the radial basis function (RBF), and polynomial. Kernel types are defined by gamma (γ) and d . RBF and POL both employ gamma (γ), and “ d ” is only required for the POL kernel function to indicate the term of polynomial degree. Most importantly, the kernel function takes the dataset and transforms it into the appropriate format. The quality of a category may be influenced by an individual's understanding of how distinct kernel functions are used in related circumstances [109], [110].

Numerous studies have been conducted to use the SVM in SHM of bridges [111], [112], [113], [114], [115], [116], [117]. Li *et al.* applied particle swarm optimization-based SVM to classify cable surface defects of cable-stayed bridges. The particle swarm optimization technique (PSO) was used to get the punish factor c and the kernel parameter g of the SVM model, resulting in the PSO-SVM approach, which improved the SVM classification performance. Finally, the classification of real surface fault photos of bridge cables was implemented using our PSO-SVM classification model. The PSO-SVM model improved the classification performance of surface defects, according to the experimental data [118].

6) DECISION TREE

In data mining, decision trees are among the most commonly used algorithms. Predictive models such as the decision tree may be used for both regression and stratified models in data mining [119]. The decision tree is a nonparametric technique with a straightforward structure, cheap processing costs, and the capacity to be represented graphically. DTs have been shown to be effective for a variety of tasks, including classification, decision-making, and establishing a link between independent and dependent variables. The term “classification decision tree” refers to a technique used for classification issues, while the term “regression decision tree” refers to a technique used for regression issues. Decision trees are a subset of the larger family of algorithms

known as supervised learning algorithms. Entropy is the basis for their quantification. Alternative methods exist for gaining insight into the decision tree, though. There are many different forms of decision trees, including classification and regression trees (CART), Chi-squared automated interaction detection (CHAID), C4.5, and ID3, which are quick, unbiased, and efficient statistical trees (QUEST) [120], [121]. According to a recent research, Mariniello *et al.* investigated decision tree ensembles' (DTEs) capacities for identifying and localizing damage in SHM. Numerical models and physically recorded data were used to evaluate their suggested approach to determine damage in three distinct ways. These experiments were considered at a variety of damage scenarios, including single and multiple damages, various kinds and amounts of damage, and the random noise levels associated with dynamic property acquisition. The accuracy, confidence in probabilistic predictions, and measurements of physical distances in localization errors were all used to judge how well the proposed method worked [122].

7) RANDOM FORESTS ALGORITHM

There are nonparametric and tree-based ensemble techniques known as random forests that were proposed by Breiman [123]. Instead of parametric models, random forests use a variety of decision tree models that are straightforward to understand. Combining information from many decision tree models allows for more accurate forecasting [124], [125]. Random Forest is an easy-to-use machine learning technique that typically produces excellent results. To create each ensemble member, RF employs the bagging approach, which is used to gather data from many training datasets. In a random manner, bagging samples forecast from the space of DTs very identically. For classification and regression, this method is one of the most often used machine learning algorithms. It is a supervised learning method and creates a random forest. When dividing a "node," the algorithm doesn't seek for the most essential attributes, but rather the best properties in a random selection of properties. This results in a wide range of options and a superior model in the long run [126], [127], [128]. In a recent study, Li *et al.* used an ensemble-based machine learning technique to quantify structural damage at the elemental level, with acceleration reactions from the structures. In order to forecast various output variables, such as the structure's vector of elemental level damage quantification data, their proposed approach used a random forest as a regressor. The drop in the stiffness parameters of the elements was shown to be an indicator of damage severity. Their results showed that less sensors were needed to measure acceleration responses in order to figure out where damage is and how bad it is. Also, an effective training approach yielded good identification results. Compared to neural network training methods, the proposed method for identifying damage could get good results quickly and with much less computational work and time [129].

8) DEEP LEARNING

Deep learning is a machine learning approach that is basically a neural network with at least three layers. With the help of deep learning, computers can "learn" from a large amount of data and do so with great precision since it mimics the way human brains operate [130], [131], [132]. Even though digital image processing is one of the most popular areas of deep learning, these methods can also work well with numerical datasets. In contrast to other types of machine learning algorithms, deep learning algorithms use a diverse set of models [133]. This is due to the fact that deep learning algorithms can be used in a variety of ways when creating a model that is always evolving. There are many different architectures for deep learning. AlexNet, Visual Graphics Group, GoogleNet, Residual Networks, ResNeXt, Region Based CNN, You Only Look Once, SqueezeNet, SegNet, and Generative Adversarial Network are 10 of the most important and advanced [134]. Also, the convolutional neural network (CNN) is an interesting and commonly used deep learning architecture that is often used to find images and objects and classify them. CNN is a feed-forward neural network which has neurons with trainable biases and weights. There are also many layers to CNN. Convolutional, pooling, ReLU correction, and fully-connected layers are the four main kinds of CNN layers, in that order. With the use of a neural network, CNNs can analyze images by analyzing their two-dimensional structure. A traditional CNN structure for classification is shown in Fig. 5 [135].

The high capability and efficiency of deep learning networks in adapting to various issues and complexities in SHM of bridges, as well as their ability to function properly in learning from large amounts of data, has led to valuable studies in this field in recent years [136], [137], [138], [139], [140], [141], [142], [143], [144]. For bridge damage detection, Fernandez-Navamuel *et al.*, developed a supervised deep learning strategy that incorporates Finite Element models to enhance the training phase of a deep neural network. Their ultimate aim was to figure out where the damage was and how severe the damage was by measuring how the structure moved. They examined the suggested approach on two full-scale instrumented bridges to see how it performed. The technique accurately predicted the damage situation on one of the bridges for two realistic damage scenarios of increasing severity [145]. In another study, using Deep Learning Enhanced Principal Component Analysis, Fernandez-Navamuel *et al.* were able to identify outliers in the structural state of bridges. The monitoring data from two bridges were used to apply the suggested strategy, and the results were compared before and after residual connections were added. Results revealed that the network's capacity to recognize outliers is improved by the inclusion of residual connections, enabling it to detect mild damage [146].

Also, Table 2 shows a summary of the research that has been done in the field of SHM over the past few years using machine learning algorithms. In the sections that follow, some of the most common pattern recognition algorithms used in

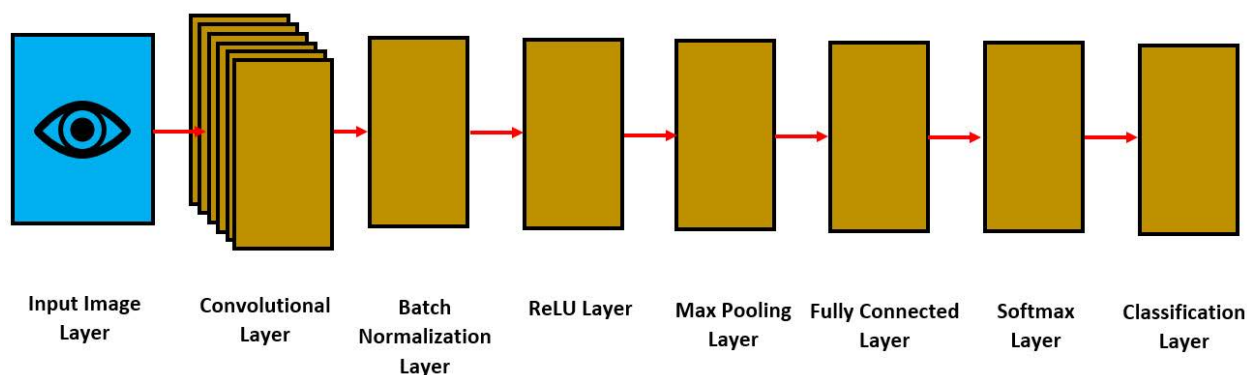


FIGURE 5. Typical multi-layered CNN structure for classification.

the SHM system will be discussed. These algorithms use either supervised or unsupervised learning techniques.

VI. OBSERVATION AND DISCUSSION

Examining past studies as well as examining the capabilities of machine learning methods, it can be concluded that machine learning approaches will be an integral part of SHM systems in the data processing and pattern recognition in bridge health monitoring because of their self-adaptation for pattern detection based on data. Compared to classic and older approaches, machine learning is accurate and efficient. In summary, specific items can be stated or improved based on reviews of past studies, and for future studies, certain suggestions may be examined:

- As mentioned earlier, SHM systems give information about the health, reliability, damage, and structural integrity of a structure. In fact, SHM is a technique for acquiring real-time, reliable information on structural health and performance. In the SHM process, the first step in pattern recognition by artificial intelligence algorithms for data analysis with numerical data or visual data is to set up a database with enough real-time data that is accurate [167], [168]. Hence, the acquisition of precise and correct data, as well as the analysis and correctness of this data, are two critical parts of the SHM process. As a result of scientific advancements in recent decades, remote monitoring technologies have recently been created. One of these techniques is the use of sensors to monitor structures. However, the cost of providing these sensors is relatively high, and their economic cost should also be considered for projects. Therefore, selecting the installation locations of these sensors in order to obtain the maximum and best amount of data is very important. Because by determining the most suitable locations for installing sensors, it is possible to optimize their number. So, the best amount of information can be gathered with the fewest number of sensors. Therefore, despite the valuable studies of recent years, it is suggested that more extensive studies be conducted to find the optimal number and locations of sensors on bridges. It is also suggested that future studies lead to the creation of new protocols and codes

to figure out how many sensors should be used and where they should be placed. These can be added to the regulations and standards for using sensors to check on the health of bridges.

- As mentioned, due to the relatively high cost of sensors, more studies should be done to determine the optimal number of sensors and their location. However, with the Internet of Things being a relatively new technology, other rapidly growing tools and technologies may be utilized as substitutes or complementary tools instead of sensors to monitor and gather data. Drone technology is one of the most significant of these technologies. There are several advantages to deploying drones in SHM, including time and cost savings; rapid and repeatable access to project data; access to hard-to-reach regions; and remote access to the present status of the project [169], [170]. Also, drone technology, along with the IoT and different ways to use AI to control and operate drones, can be a very useful tool for monitoring the health of bridges. Although studies have been conducted in this area, due to the innovation of the subject as well as the smaller amount of research compared to other new technologies in SHM, it is suggested that more extensive studies on the combination of these technologies and approaches in monitoring the health of bridges be done.

- Many approaches to damage detection have been successfully implemented using artificial intelligence, such as artificial neural networks. However, these systems still have issues. The first issue is the network's sensitivity to input changes. In fact, artificial neural networks may not work as well in places like bridges where there is a lot of noise and the environment is always changing. The second issue is that as the amount of data falls, so does their accuracy. With the rise of new phenomena and technologies like the Internet of Things, 5G and 6G Internet, which have made it much easier to send data, and sensor technology, large amounts of data that may not be important for traditional machine learning methods are being collected and sent. However, for some new generations, machine learning techniques like deep learning are very important. In comparison to traditional artificial neural networks, deep learning methods are a sort of neural network that have the most layers and parameters

TABLE 2. Review of machine learning-based studies in the area of SHM.

References	ML Technique	Supervised Learning Techniques	Unsupervised Learning Techniques	Description
da Silva et al., [147]	GK, FCM		✓	They developed an alternate technique to structural health monitoring and demonstrated its efficacy using the Los Alamos National Laboratory data. The technique just required a measurement of the intact system, not a mathematical model. Principal component analysis (PCA) data reduction was used to speed up the classification process. ARMA models were built utilizing undamaged structural data under multiple operation circumstances. Comparing ARMA model output with a fuzzy clustering approach determined the structure's health. Fuzzy c-means (FCM) and Gustafson–Kessel (GK) clustering were examined. Both fuzzy clustering techniques function, although the GK algorithm is somewhat superior.
Santos et al., [148]	K-means, GMM, SVC, SOM		✓	They evaluated the effectiveness of numerous clustering methods in vibration-based damage identification under operational and environmental conditions. Multiple clustering techniques have been suggested for statistical modeling and feature categorization. Standard data sets from the Tamar Suspension Bridge in England and the Z-24 Bridge in Switzerland were used to conduct the research. The algorithms might be utilized with the suggested clustering methodologies for discovering damage, according to their findings.
Nick et al., [149]	SVM, FNN, K-means, SOM	✓	✓	They employed some unsupervised learning techniques to detect the damage's existence and location. Meanwhile, they used some supervised learning techniques to determine its kind and severity. For every approach except self-organizing map (SOM), they evaluated PCA variants to decrease data dimension. These machine learning approaches have different properties.
Liu et al., [150]	FCM		✓	They proposed a two-stage scheme for damage identification using the ratios of modal frequency changes and uniform load surface curvature difference (ULSCD) in the damage region. The FCM algorithm, which had been improved by the particle swarm optimization (PSO) algorithm, was used to find damage and estimate how bad it was. Damage identification results for a typical bridge with an irregular shape showed that the two-stage damage identification method is a fast and accurate way to find out where and how much structural damage has happened.
Marcy et al., [151]	SOM		✓	They developed a machine learning technique for SHM. This was motivated by the rising number of slender structures that are more vulnerable to vibrations and by worries about the performance and degeneration of historic buildings. For this purpose, they used self-organizing maps in a SHM to detect structure damage. The results indicated the SOM algorithm had good performance as an implemented method to detect relatively small structural changes.
Yu and Zhu [152]	FCM		✓	Yu and Zhu proposed developing an integrated technique by integrating damage-sensitive feature extraction, greater

TABLE 2. (Continued.) Review of machine learning-based studies in the area of SHM.

				statistical moments of structural reactions, and the FCM clustering algorithm with the classic time-series analysis-based structural damage prediction (SDP) method. The findings revealed that the suggested integrated SDP approach may effectively detect damage to a truss bridge with end connector bolts.
Yang et al., [153]	ERA, FCM		✓	They used an automated operational modal analysis methodology based on an eigensystem realization algorithm and a two-stage clustering strategy for SHM processes of bridges.
Tran-Ngoc et al., [154]	ANN, CS		✓	They used an artificial neural network (ANN) and a cuckoo search (CS) algorithm to develop a novel method for detecting structural deterioration. Two numerical models were used to assess the robustness of the proposed approach. The proposed technique showed high performance for damage identification and reduced the computational time.
Mao et al., [155]	PCA, K-means, hierarchical clustering		✓	Using a method called parametric modal identification, they used some well-known machine learning algorithms in an automated framework to get structural modal parameters from the stabilization diagram. The results demonstrated that the proposed framework is capable of accurately and reliably extracting structural modal characteristics. This makes it a solid technical support for long-span bridge in-service monitoring.
Lei et al., [156]	KNN		✓	For bridge health monitoring data, they proposed a single variable pattern anomaly detection approach based on K-nearest neighbors (KNN) distance, as well as a multivariate time series anomaly detection method based on the covariance matrix and singular value decomposition.
Lei et al., [157]	RF		✓	Using the random forest approach, they investigated vibration-based seismic damage states for regional concrete beam bridges. Their findings demonstrated that their suggested model had an excellent prediction performance, with over 90% accuracy.
Gordan et al., [158]	ANN, ICA		✓	They proposed a data mining-based damage identification procedure for SHM. In the learning process of ANN, the Imperial competitive algorithm (ICA) was used to predict the severity and location of multiple damage cases found through experimental modal analysis of bridge structures that were both intact and damaged.
Gordan et al., [159]	SVM, CART	ANN,	✓	They used inverse analysis for data mining-based damage identification of a slab-on-girder bridge. Then, they proposed a hybrid algorithm in the deployment step of the Cross Industry Standard Process for Data Mining (CRISP-DM) model. Their suggested algorithm outperformed other techniques, according to the findings.
Mousavi et al., [160]	MLP		✓	They tested how well a combined CEEMDAN-HT-ANN model, which is a mix of data analysis and machine learning, could find the presence, location, and severity of damage on a model steel truss bridge in a lab.
Zhang, and Sun [161]	MLP		✓	The results showed that the proposed method could recognize multiple data outliers with a very high degree of accuracy and at a low cost to calculate. This shows that it can be used for field monitoring.

TABLE 2. (Continued.) Review of machine learning-based studies in the area of SHM.

Baptista et al., [162]	SOM, MLP	✓	✓	They proposed a neural network-based approach. A self-organizing map (SOM) identified the regimes, and a multi-layer perceptron normalized the sensor data. Their methodology could create equivalent results to conventional approaches without specifying the number of regimes and explicitly computing hold-out dataset statistics.
Sharma, and Sen [163]	AANN, RBFNN	✓		They proposed a two-step data-driven method for incorporating temperature effects into vibration-based damage identification and localisation, as long as the temperature was also monitored. The suggested approach was numerically evaluated on a multispan bridge structure with measurement errors. It was seen that the proposed data-based approach worked well to find a problem, even when the temperature changed.
Kwon et al., [164]	MLP	✓		In order to identify anomalies in bridge SHM, they developed and presented an ANN-based detection framework. The suggested system was able to accurately forecast how the bridge would react under a variety of different loading scenarios. For comparison, the projected outcomes were compared to the observed findings. The suggested method uses the results of this comparison to find abnormalities in bridge behavior.
Gao et al., [165]	ANN	✓		They proposed a data anomaly detection system based on pattern recognition. This approach consists of three steps: extracting features from long time-series data samples, training a pattern recognition neural network (PRNN) using the retrieved features, and finally detecting abnormalities in the data.
Gordan et al., [166]	ANN, ICA, GA	✓		They used a bridge monitoring approach to investigate the link between enhanced computational intelligence and the establishment of SHM solutions. Based on a comparison of the results, the used evolutionary algorithms could improve the accuracy of the pre-built network's predictions by making the ANN's learning process better.

TABLE 3. Equations relating to a variety of kernel functions.

No	Type of Kernel Function	Equations
1	Linear (LIN)	$G(x_i, x_j) = x_i^t x_j$
2	Radial basis function (RBF)	$G(x_i, x_j) = \exp(-\gamma \ x_i - x_j\ ^2)$
3	Polynomial (POL)	$G(x_i, x_j) = (-\gamma x_i^t x + 1)^d$

and can learn from databases with a lot of data. In recent years, we have seen the use of deep learning methods in various parts of the SHM process [171], [171], [172], [173], [174], [175]. But even though deep learning techniques have many benefits, there are limitations. Some researchers have done research in this issue. As an example, it's still difficult for vibration- or vision-based DL algorithms to match how people view things, despite the many advancements in the

field since DL was originally presented. Furthermore, generalized numerical models cannot accurately mimic environmental challenges [176]. So, in future studies, the capabilities of machine learning approaches, especially deep learning techniques, should be taken into account, and each case study should pay attention to how these models are being built and developed.

- Finally, after studying and reviewing the published articles on bridge health monitoring and the applications of artificial intelligence in this regard, we can point to a very important point: system security. With the growing number of people, cars, and cities, there is no doubt that there will be a greater push to turn cities into "smart cities." Even if all urban systems do not become smart city systems, it will still be inevitable that some of these systems will become smart systems. Intelligent transportation systems can be one of these sectors. With SHM sensors and IoT, the ITS systems can get information on the health of a bridge for ITS

applications [177]. Bridges are considered one of the most important urban and interurban infrastructures. When using IoT platforms with artificial intelligence platforms to monitor the health of the structure, special attention should be paid to data retention. Even though these new technologies make bridge health monitoring systems work better, they also make it easier for persons to get to data in many ways. This data can be used in specific situations to damage urban infrastructure. Because of this, there needs to be more research done on network security in bridge health monitoring systems that use IoT and AI software and platforms.

VII. CONCLUSION

An in-depth analysis of AI's role in SHM systems, as well as its relationship to other emerging technologies, was offered in this article. In this review, the focus is on machine learning (ML) and the data-driven advances that are changing the way SHM systems in bridges are being researched. A taxonomy of the ways that machine learning can be used in pattern recognition was examined, and each category's challenges, theoretical frameworks, and algorithms related to this field were also reviewed. These explanations demonstrate unequivocally that applications of AI in SHM significantly boosted the system's performance and provided researchers with new avenues of investigation. Also, applications of AI in SHM research are getting more and more prevalent, as seen by this review. In fact, this issue leads researchers in various fields of science, such as civil engineering, electronics, mechanics, and computer sciences who are involved in the subject of SHM to use more and more artificial intelligence methods, especially machine learning techniques, in their research. On the other hand, with the emergence of new phenomena and technologies in recent years, such as the Internet of Things and the Internet, 5G and 6G, along with sensor technologies, we are facing an increase in the quantity and quality of data. Deep learning, which is one of the most important and modern approaches to machine learning and artificial intelligence, can be used as a powerful and reliable tool. In fact, a SHM system can predict trends and needs with the help of metadata and the analytical and interpretive skills of deep learning. This lets the system offer customized options and personalized responses. As a result, we can see the proper performance of SHM systems. Finally, it is hoped that this study will help researchers in this field by giving an overview of the current state of SHM research and a review of the range of ways that artificial intelligence methods can be used in SHM.

ACKNOWLEDGMENT

The authors would like to express their deepest thanks to Mahdi Ghaem for his excellent advice.

REFERENCES

- [1] P. Prus and M. Sikora, "The impact of transport infrastructure on the sustainable development of the region—Case study," *Agriculture*, vol. 11, no. 4, p. 279, Mar. 2021.

- [2] N. Sharma, F. Nocera, and P. Gardoni, "Classification and mathematical modeling of infrastructure interdependencies," *Sustain. Resilient Infrastruct.*, vol. 6, nos. 1–2, pp. 4–25, Mar. 2021.
- [3] R. Osei-Kyei, V. Tam, M. Ma, and F. Mashiri, "Critical review of the threats affecting the building of critical infrastructure resilience," *Int. J. Disaster Risk Reduction*, vol. 60, Jun. 2021, Art. no. 102316.
- [4] C. Magazzino and M. Mele, "On the relationship between transportation infrastructure and economic development in China," *Res. Transp. Econ.*, vol. 88, Sep. 2021, Art. no. 100947.
- [5] J. Boakye, R. Guidotti, P. Gardoni, and C. Murphy, "The role of transportation infrastructure on the impact of natural hazards on communities," *Rel. Eng. Syst. Saf.*, vol. 219, Mar. 2022, Art. no. 108184.
- [6] A. C. Estes and D. M. Frangopol, "Bridge lifetime system reliability under multiple limit states," *J. Bridge Eng.*, vol. 6, no. 6, pp. 523–528, Dec. 2001.
- [7] F. Greco, P. Lonetti, and R. Zinno, "An analytical delamination model for laminated plates including bridging effects," *Int. J. Solids Struct.*, vol. 39, no. 9, pp. 2435–2463, May 2002.
- [8] P. D. Thompson, K. M. Ford, M. H. R. Arman, S. Labi, K. C. Sinha, and A. M. Shirole, "Estimating life expectancies of highway assets," Purdue Univ., West Lafayette, IN, USA, NCHRP Rep. 713, 2012.
- [9] J. R. Casas and J. J. Moughty, "Bridge damage detection based on vibration data: Past and new developments," *Frontiers Built Environ.*, vol. 3, p. 4, Feb. 2017.
- [10] S. Artese, J. L. Lerma, G. Zagari, and R. Zinno, "The survey, the representation and the structural modeling of a dated bridge," in *Proc. 8th Int. Congr. Archaeol., Comput. Graph., Cultural Heritage Innov.*, Sep. 2016, pp. 162–168.
- [11] F. Khosravikia, "Seismic vulnerability and post-event actions for Texas bridge infrastructure," Univ. Texas Austin Centre Transp. Res., Austin, TX, USA, Tech. Rep. FHWA/TX-18/0-6916-1, 2018.
- [12] L. Liu, D. M. Frangopol, A. Mondoro, and D. Y. Yang, "Sustainability-informed bridge ranking under scour based on transportation network performance and multiattribute utility," *J. Bridge Eng.*, vol. 23, no. 10, Oct. 2018, Art. no. 04018082.
- [13] N. Cavalagli, A. Kita, S. Falco, F. Trillo, M. Costantini, and F. Ubertini, "Satellite radar interferometry and *in-situ* measurements for static monitoring of historical monuments: The case of Gubbio, Italy," *Remote Sens. Environ.*, vol. 235, Dec. 2019, Art. no. 111453.
- [14] S. Somy, R. Shafaei, and R. Ramezani, "Resilience-based mathematical model to restore disrupted road-bridge transportation networks," *Struct. Infrastruct. Eng.*, vol. 18, no. 9, pp. 1334–1349, Sep. 2022.
- [15] H. Sousa, C. Félix, J. Bento, and J. Figueiras, "Design and implementation of a monitoring system applied to a long-span prestressed concrete bridge," *Struct. Concrete*, vol. 12, no. 2, pp. 82–93, Jun. 2011.
- [16] R. Zinno, S. Artese, G. Clausi, F. Magarò, S. Meduri, A. Miceli, and A. Venneri, "Structural health monitoring (SHM)," in *The Internet of Things for Smart Urban Ecosystems*. Cham, Switzerland: Springer, 2019, pp. 225–249.
- [17] J. J. Moughty and J. R. Casas, "A state of the art review of modal-based damage detection in bridges: Development, challenges, and solutions," *Appl. Sci.*, vol. 7, no. 5, p. 510, May 2017.
- [18] J. Collins, G. Mullins, C. Lewis, and D. Winters, "State of the practice and art for structural health monitoring of bridge substructures," Federal Highway Admin. Office Infrastruct. Res. Develop., McLean, VA, USA, Tech. Rep. FHWA-HRT-09-040, 2014.
- [19] P. Milillo, G. Giardina, D. Perissin, G. Milillo, A. Coletta, and C. Terranova, "Pre-collapse space geodetic observations of critical infrastructure: The Morandi Bridge, Genoa, Italy," *Remote Sens.*, vol. 11, no. 12, p. 1403, Jun. 2019.
- [20] A. Malekloo, E. Ozer, M. Alhamaydeh, and M. Girolami, "Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights," *Struct. Health Monit.*, vol. 21, no. 4, pp. 1–50, Aug. 2021.
- [21] R. M. Moss and S. L. Matthews, "In-service structural monitoring. A state-of-the-art review," *Struct. Engineer*, vol. 73, no. 2, pp. 23–31, Jan. 1995.
- [22] J. Ko and Y. Ni, "Technology developments in structural health monitoring of large-scale bridges," *Eng. Struct.*, vol. 27, no. 12, pp. 1715–1725, 2005.
- [23] H. K. Mohamed, O. Salah, A. Elbaz, M. A. K. Hawwas, O. A. Elnawawy, and M. A. H. Tayel, "State of the art review of structural health monitoring for bridges using wireless system techniques," *Eng. Struct.*, vol. 27, pp. 1715–1725, Aug. 2005.

- [24] K. Heiza, A. Khalil, and O. El Nawawy, "State of the art review on bridges structural health monitoring (model testing)," in *Proc. Int. Conf. Civil Archit. Eng.*, 2016, vol. 11, no. 11, pp. 1–21.
- [25] D. Lydon, M. Lydon, R. Kromanis, C.-Z. Dong, N. Catbas, and S. Taylor, "Bridge damage detection approach using a roving camera technique," *Sensors*, vol. 21, no. 4, p. 1246, Feb. 2021.
- [26] H. Sohn *et al.*, "A review of structural health monitoring literature: 1996–2001," Los Alamos Nat. Lab., Los Alamos, NM, USA, Tech. Rep. LA-13976-MS, 2004.
- [27] A. Rytter, "Vibration based inspection of civil engineering structures," Ph.D. dissertation, Dept. Building Technol. Struct. Eng., Aalborg Univ., Aalborg, Denmark, 1993.
- [28] N. Haritos and J. S. Owen, "The use of vibration data for damage detection in bridges: A comparison of system identification and pattern recognition approaches," *Struct. Health Monitor.*, vol. 3, no. 2, pp. 141–163, Jun. 2004.
- [29] A. Deivasigamani, A. Daliri, C. H. Wang, and S. John, "A review of passive wireless sensors for structural health monitoring," *Modern Appl. Sci.*, vol. 7, no. 2, pp. 57–76, Jan. 2013.
- [30] Y. Yang, Y. Zhang, and X. Tan, "Review on vibration-based structural health monitoring techniques and technical codes," *Symmetry*, vol. 13, no. 11, p. 1998, Oct. 2021.
- [31] B. Khaleghi, A. Khamis, F. O. Karray, and S. N. Razavi, "Multisensor data fusion: A review of the state-of-the-art," *Inf. Fusion*, vol. 14, no. 1, pp. 28–44, Jan. 2013.
- [32] G. Barone and D. M. Frangopol, "Reliability, risk and lifetime distributions as performance indicators for life-cycle maintenance of deteriorating structures," *Rel. Eng. Syst. Saf.*, vol. 123, pp. 21–37, Mar. 2014.
- [33] A. A. Ezzat, J. Tang, and Y. Ding, "A model-based calibration approach for structural fault diagnosis using piezoelectric impedance measurements and a finite element model," *Struct. Health*, vol. 19, no. 6, pp. 1839–1855, Jan. 2020.
- [34] X. Fan and J. Li, "Damage identification in plate structures using sparse regularization based electromechanical impedance technique," *Sensors*, vol. 20, no. 24, p. 7069, Dec. 2020.
- [35] A. Sivasuriyan, D. S. Vijayan, A. LeemaRose, J. Revathy, S. Gayathri Monicka, U. R. Adithya, and J. J. Daniel, "Development of smart sensing technology approaches in structural health monitoring of bridge structures," *Adv. Mater. Sci. Eng.*, vol. 2021, Aug. 2021, Art. no. 2615029.
- [36] L. Xu, K. Wang, X. Yang, Y. Su, J. Yang, Y. Liao, P. Zhou, and Z. Su, "Model-driven fatigue crack characterization and growth prediction: A two-step, 3-D fatigue damage modeling framework for structural health monitoring," *Int. J. Mech. Sci.*, vol. 195, Apr. 2021, Art. no. 106226.
- [37] A. Moallemi, A. Burrello, D. Brunelli, and L. Benini, "Model-based vs. data-driven approaches for anomaly detection in structural health monitoring: A case study," in *Proc. IEEE Int. Instrum. Meas. Technol. Conf. (IMTC)*, May 2021, pp. 1–6.
- [38] C. B. Brooker, "Field experimentation and finite element analysis of prominent drive-by bridge inspection techniques," Doctoral dissertation, Dept. Civil Eng., Ohio Univ., Athens, OH, USA, 2021.
- [39] M. Torti, I. Venanzi, S. Laflamme, and F. Ubertaini, "Life-cycle management cost analysis of transportation bridges equipped with seismic structural health monitoring systems," *Struct. Health Monitor.*, vol. 21, no. 1, pp. 100–117, Jan. 2022.
- [40] A. Sukamta, A. Alfianur, S. A. Widyanto, and H. A. Lie, "Development experimental investigations of truss bridge model for vibration-based structural health monitoring," in *Proc. 5th Int. Conf. Sustain. Civil Eng. Struct. Construct. Mater.*, in Lecture Notes in Civil Engineering. Singapore: Springer, 2022, pp. 137–153.
- [41] R. J. Barthorpe, A. J. Hughes, and P. Gardner, "A forward model driven structural health monitoring paradigm: Damage detection," in *Model Validation Uncertainty Quantification*, vol. 3. Cham, Switzerland: Springer, 2022, pp. 119–126.
- [42] K. Worden, W. J. Staszewski, and J. J. Hensman, "Natural computing for mechanical systems research: A tutorial overview," *Mech. Syst. Signal Process.*, vol. 25, no. 1, pp. 4–111, 2011.
- [43] S. Jahan, Y. Hoseinzadeh, and A. Mojtahedi, "Steel bridges structural health monitoring based on operational modal analysis accommodating evaluation of uncertainty," *J. Struct. Construct. Eng.*, vol. 4, no. 3, pp. 5–17, 2017.
- [44] C. R. Farrar, T. A. Duffy, P. J. Cornwell, and S. W. Doebling, "Excitation methods for bridge structures," Los Alamos Nat. Lab., Los Alamos, NM, USA, Tech. Rep. LA-UR-98-4579, 1999.
- [45] M. Gul and F. N. Catbas, "Statistical pattern recognition for structural health monitoring using time series modeling: Theory and experimental verifications," *Mech. Syst. Signal Process.*, vol. 23, no. 7, pp. 2192–2204, Oct. 2009.
- [46] S. Theodoridis and K. Koutroumbas, "Pattern recognition and neural networks," in *Machine Learning and its Applications*. Berlin, Germany: Springer, 2001, pp. 169–195.
- [47] H. Li, S. Li, J. Ou, and H. Li, "Modal identification of bridges under varying environmental conditions: Temperature and wind effects," *Struct. Control Health Monitor.*, vol. 17, no. 5, pp. 495–512, Aug. 2009.
- [48] V. L. Junior, V. Steffen, and M. A. Savi, *Dynamics of Smart Systems and Structures*. Cham, Switzerland: Springer, 2016.
- [49] J.-X. Mao, H. Wang, D.-M. Feng, T.-Y. Tao, and W.-Z. Zheng, "Investigation of dynamic properties of long-span cable-stayed bridges based on one-year monitoring data under normal operating condition," *Struct. Control Health Monitor.*, vol. 25, no. 5, p. e2146, May 2018.
- [50] J.-Z. Huang, D.-S. Li, H.-N. Li, G.-B. Song, and Y. Liang, "Damage identification of a large cable-stayed bridge with novel cointegrated Kalman filter method under changing environments," *Struct. Control Health Monitor.*, vol. 25, no. 5, p. e2152, May 2018.
- [51] C. Cremona and J. Santos, "Structural health monitoring as a big-data problem," *Struct. Eng. Int.*, vol. 28, no. 3, pp. 243–254, Jul. 2018.
- [52] Y. Cheng, H. Zhu, J. Wu, and X. Shao, "Machine health monitoring using adaptive kernel spectral clustering and deep long short-term memory recurrent neural networks," *IEEE Trans. Ind. Informat.*, vol. 15, no. 2, pp. 987–997, Feb. 2019.
- [53] O. Ovcharenko, V. Kazei, M. Kalita, D. Peter, and T. Alkhalifah, "Deep learning for low-frequency extrapolation from multioffset seismic data," *Geophysics*, vol. 84, no. 6, pp. R989–R1001, Nov. 2019.
- [54] L. A. Bull, T. J. Rogers, C. Wickramarachchi, E. J. Cross, K. Worden, and N. Dervilis, "Probabilistic active learning: An online framework for structural health monitoring," *Mech. Syst. Signal Process.*, vol. 134, Dec. 2019, Art. no. 106294.
- [55] C. Bigoni, Z. Zhang, and J. S. Hesthaven, "Systematic sensor placement for structural anomaly detection in the absence of damaged states," *Comput. Methods Appl. Mech. Eng.*, vol. 371, Nov. 2020, Art. no. 113315.
- [56] X. Chai, G. Tang, S. Wang, K. Lin, and R. Peng, "Deep learning for irregularly and regularly missing 3-D data reconstruction," *IEEE Trans. Geosci. Remote Sens.*, vol. 59, no. 7, pp. 6244–6265, Jul. 2021.
- [57] A. Malekloo, E. Ozer, and F. Al-Turjman, "Combination of GIS and SHM in prognosis and diagnosis of bridges in earthquake-prone locations," in *Smart Grid in IoT-Enabled Spaces: The Road to Intelligence in Power*. Boca Raton, FL, USA: CRC Press, 2020.
- [58] H. Shokravi, H. Shokravi, N. Bakhary, M. Heidarrezaei, S. S. Rahimian Koloor, and M. Petr , "Vehicle-assisted techniques for health monitoring of bridges," *Sensors*, vol. 20, no. 12, p. 3460, Jun. 2020.
- [59] H. Miao and F. Li, "Shear horizontal wave transducers for structural health monitoring and nondestructive testing: A review," *Ultrasonics*, vol. 114, Jul. 2021, Art. no. 106355.
- [60] M. A. Becerra, C. Tob n, A. E. Castro-Ospina, and D. H. Peluffo-Ord n ez, "Information quality assessment for data fusion systems," *Data*, vol. 6, no. 6, p. 60, Jun. 2021.
- [61] X. Lai, M. Furkan, I. Bartoli, A. E. Aktan, and K. Grimmelsman, "Bridge weigh-in-motion using augmented Kalman filter and model updating," *J. Civil Struct. Health Monitor.*, vol. 12, no. 3, pp. 593–610, Jun. 2022.
- [62] M. O. Yano, S. da Silva, E. Figueiredo, and L. G. G. Villani, "Damage quantification using transfer component analysis combined with Gaussian process regression," *Struct. Health Monitor.*, May 2022, Art. no. 147592172210945.
- [63] A. F. G. Tenreiro, A. M. Lopes, and L. F. da Silva, "A review of structural health monitoring of bonded structures using electromechanical impedance spectroscopy," *Struct. Health Monitor.*, vol. 21, no. 2, pp. 228–249, Mar. 2022.
- [64] F. Parisi, A. M. Mangini, M. P. Fanti, and J. M. Adam, "Automated location of steel truss bridge damage using machine learning and raw strain sensor data," *Autom. Construct.*, vol. 138, Jun. 2022, Art. no. 104249.
- [65] A. C. Neves, I. Gonz lez, and R. Karoumi, "Development and validation of a data-based SHM method for railway bridges," in *Structural Integrity*. Cham, Switzerland: Springer, 2022, pp. 95–116.
- [66] C. Zhang, A. A. Mousavi, S. F. Masri, G. Gholipour, K. Yan, and X. Li, "Vibration feature extraction using signal processing techniques for structural health monitoring: A review," *Mech. Syst. Signal Process.*, vol. 177, Sep. 2022, Art. no. 109175.

- [67] C. M. Bishop and N. M. Nasrabadi, *Pattern Recognition and Machine Learning*, vol. 4. New York, NY, USA: Springer, 2006.
- [68] X.-Y. Zhang, C.-L. Liu, and C. Y. Suen, "Towards robust pattern recognition: A review," *Proc. IEEE*, vol. 108, no. 6, pp. 894–922, Jun. 2020.
- [69] M. Paolanti and E. Frontoni, "Multidisciplinary pattern recognition applications: A review," *Comput. Sci. Rev.*, vol. 37, Aug. 2020, Art. no. 100276.
- [70] A. Entezami, H. Sarmadi, B. Behkamal, and S. Mariani, "Big data analytics and structural health monitoring: A statistical pattern recognition-based approach," *Sensors*, vol. 20, no. 8, p. 2328, Apr. 2020.
- [71] H. Sohn, C. R. Farrar, F. M. Hemez, D. D. Shunk, D. W. Stinemates, B. R. Nadler, and J. J. Czarnecki, "A review of structural health monitoring literature: 1996–2001," Los Alamos Nat. Lab., Santa Fe, NM, USA, Tech. Rep. LA-UR-02-2095, 1996, vol. 1.
- [72] S. U. N. Li-Min, S. H. A. N. G. Zhi-Qiang, and X. I. A. Ye, "Development and prospect of bridge structural health monitoring in the context of big data," *China J. Highway Transp.*, vol. 32, no. 11, pp. 1–11, Nov. 2019.
- [73] E. Figueiredo and J. Brownjohn, "Three decades of statistical pattern recognition paradigm for SHM of bridges," *Struct. Health Monitor.*, Mar. 2022, Art. no. 147592172210752, doi: [10.1177/14759217221075241](https://doi.org/10.1177/14759217221075241).
- [74] J. C. Bezdek, R. J. Hathaway, M. J. Sabin, and W. T. Tucker, "Convergence theory for fuzzy C-means: Counterexamples and repairs," *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-17, no. 5, pp. 873–877, Oct. 1987.
- [75] R. Mikaeil, S. S. Haghshenas, S. S. Haghshenas, and M. Ataei, "Performance prediction of circular saw machine using imperialist competitive algorithm and fuzzy clustering technique," *Neural Comput. Appl.*, vol. 29, no. 6, pp. 283–292, Mar. 2018.
- [76] R. Mikaeil, S. S. Haghshenas, Y. Ozcelik, and H. H. Gharehgheshlagh, "Performance evaluation of adaptive neuro-fuzzy inference system and group method of data handling-type neural network for estimating wear rate of diamond wire saw," *Geotech. Geol. Eng.*, vol. 36, no. 6, pp. 3779–3791, Dec. 2018.
- [77] R. Mikaeil, S. S. Haghshenas, and Z. Sedaghati, "Geotechnical risk evaluation of tunneling projects using optimization techniques (case study: The second part of Emamzade Hashem tunnel)," *Natural Hazards*, vol. 97, no. 3, pp. 1099–1113, Jul. 2019.
- [78] R. S. Faradonbeh, S. S. Haghshenas, A. Taheri, and R. Mikaeil, "Application of self-organizing map and fuzzy c-mean techniques for rockburst clustering in deep underground projects," *Neural Comput. Appl.*, vol. 32, no. 12, pp. 8545–8559, Jun. 2020.
- [79] L. Yu, J.-H. Zhu, and L.-L. Yu, "Structural damage detection in a truss bridge model using fuzzy clustering and measured FRF data reduced by principal component projection," *Adv. Struct. Eng.*, vol. 16, no. 1, pp. 207–217, Jan. 2013.
- [80] A. Aryafar, R. Mikaeil, S. S. Haghshenas, and S. S. Haghshenas, "Application of Metaheuristic algorithms to optimal clustering of sawing machine vibration," *Measurement*, vol. 124, pp. 20–31, Aug. 2018.
- [81] A. Salemi, R. Mikaeil, and S. S. Haghshenas, "Integration of finite difference method and genetic algorithm to seismic analysis of circular shallow tunnels (case study: Tabriz urban railway tunnels)," *KSCSE J. Civil Eng.*, vol. 22, no. 5, pp. 1978–1990, May 2018.
- [82] S. S. Haghshenas, S. S. Haghshenas, Z. W. Geem, T.-H. Kim, R. Mikaeil, L. Pugliese, and A. Troncone, "Application of harmony search algorithm to slope stability analysis," *Land*, vol. 10, no. 11, p. 1250, Nov. 2021.
- [83] R. Mikaeil, S. S. Haghshenas, and S. H. Hoseinie, "Rock penetrability classification using artificial bee colony (ABC) algorithm and self-organizing map," *Geotech. Geol. Eng.*, vol. 36, pp. 1309–1318, Oct. 2017.
- [84] G. Guido, S. S. Haghshenas, S. S. Haghshenas, A. Vitale, V. Astarita, and A. S. Haghshenas, "Feasibility of stochastic models for evaluation of potential factors for safety: A case study in southern Italy," *Sustainability*, vol. 12, no. 18, p. 7541, Sep. 2020.
- [85] S. Park, J.-J. Lee, C.-B. Yun, and D. J. Inman, "Electro-mechanical impedance-based wireless structural health monitoring using PCA-data compression and K-means clustering algorithms," *J. Intell. Mater. Syst. Struct.*, vol. 19, no. 4, pp. 509–520, Apr. 2008.
- [86] R. Mikaeil, S. S. Haghshenas, Y. Ozcelik, and S. Haghshenas, "Development of intelligent systems to predict diamond wire saw performance," *J. Soft Comput. Civil*, vol. 1, no. 2, pp. 52–69, Oct. 2017.
- [87] H. Naderpour, A. H. Rafiean, and P. Fakharian, "Compressive strength prediction of environmentally friendly concrete using artificial neural networks," *J. Building Eng.*, vol. 16, pp. 213–219, Mar. 2018.
- [88] A. F. Morosini, S. S. Haghshenas, S. S. Haghshenas, D. Y. Choi, and Z. W. Geem, "Sensitivity analysis for performance evaluation of a real water distribution system by a pressure," *Water*, vol. 13, no. 8, p. 1116, Apr. 2021.
- [89] D. R. Eidgahee, H. Jahangir, N. Solatifar, P. Fakharian, and M. Rezaeemanesh, "Data-driven estimation models of asphalt mixtures dynamic modulus using ANN, GP and combinatorial GMDH approaches," *Neural Comput. Appl.*, pp. 1–26, May 2022, doi: [10.1007/s00521-022-07382-3](https://doi.org/10.1007/s00521-022-07382-3).
- [90] Y. S. Park and S. Lek, "Developments in environmental modelling," *Ecological*, vol. 28, pp. 1–268, Apr. 2016.
- [91] K. A. Barber and M. Krarti, "A review of optimization based tools for design and control of building energy systems," *Renew. Sustain. Energy Rev.*, vol. 160, May 2022, Art. no. 112359.
- [92] S. Lek and Y. S. Park, "Artificial neural networks," in *Encyclopedia of Ecology*. Amsterdam, The Netherlands: Elsevier, 2008, pp. 237–245.
- [93] Y.-S. Park and T.-S. Chon, "Artificial neural networks: Temporal networks," in *Encyclopedia of Ecology*. Amsterdam, The Netherlands: Elsevier, 2008, pp. 245–254.
- [94] A. Malekian and N. Chitsaz, "Concepts, procedures, and applications of artificial neural network models in streamflow forecasting," in *Advances in Streamflow Forecasting*. Amsterdam, The Netherlands: Elsevier, 2021, pp. 115–147.
- [95] C. M. Shufflebarger, "What is a neural network?" *Ann. Emerg. Med.*, vol. 21, no. 12, pp. 1461–1462, 1992.
- [96] A. R. F. Quiros, R. A. Bedruz, A. C. Uy, A. Abad, A. Bandala, E. P. Dadios, and A. Fernando, "A kNN-based approach for the machine vision of character recognition of license plate numbers," in *Proc. IEEE Region 10th Conf. TENCON*, Nov. 2017, pp. 1081–1086.
- [97] H. Xu, J. Zhou, P. G. Asteris, D. Jahed Armaghani, and M. M. Tahir, "Supervised machine learning techniques to the prediction of tunnel boring machine penetration rate," *Appl. Sci.*, vol. 9, no. 18, p. 3715, Sep. 2019.
- [98] Z. Karami and R. Kashef, "Smart transportation planning: Data, models, and algorithms," *Transp. Eng.*, vol. 2, Dec. 2020, Art. no. 100013.
- [99] M. Koopialipoor, P. G. Asteris, A. S. Mohammed, D. E. Alexakis, A. Mamou, and D. J. Armaghani, "Introducing stacking machine learning approaches for the prediction of rock deformation," *Transp. Geotech.*, vol. 34, May 2022, Art. no. 100756.
- [100] A. Diez, N. L. D. Khoa, M. Makki Alamdari, Y. Wang, F. Chen, and P. Runcie, "A clustering approach for structural health monitoring on bridges," *J. Civil Struct. Health Monitor.*, vol. 6, no. 3, pp. 429–445, Jul. 2016.
- [101] J. Peng, S. Zhang, D. Peng, and K. Liang, "Application of machine learning method in bridge health monitoring," in *Proc. 2nd Int. Conf. Rel. Syst. Eng. (ICRSE)*, Jul. 2017, pp. 1–7.
- [102] A. G. Mohapatra, A. Khanna, D. Gupta, M. Mohanty, and V. H. C. de Albuquerque, "An experimental approach to evaluate machine learning models for the estimation of load distribution on suspension bridge using FBG sensors and IoT," *Comput. Intell.*, vol. 38, no. 3, pp. 747–769, Jun. 2022.
- [103] H. Sarmadi and A. Karamodin, "A novel anomaly detection method based on adaptive mahalanobis-squared distance and one-class kNN rule for structural health monitoring under environmental effects," *Mech. Syst. Signal Process.*, vol. 140, Jun. 2020, Art. no. 106495.
- [104] K. Feng, A. González, and M. Casero, "A kNN algorithm for locating and quantifying stiffness loss in a bridge from the forced vibration due to a truck crossing at low speed," *Mech. Syst. Signal Process.*, vol. 154, Jun. 2021, Art. no. 107599.
- [105] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, Jan. 1995.
- [106] W.-H. Chen, S.-H. Hsu, and H.-P. Shen, "Application of SVM and ANN for intrusion detection," *Comput. Oper. Res.*, vol. 32, no. 10, pp. 2617–2634, 2005.
- [107] S. Maldonado, J. López, A. Jimenez-Molina, and H. Lira, "Simultaneous feature selection and heterogeneity control for SVM classification: An application to mental workload assessment," *Expert Syst. Appl.*, vol. 143, Apr. 2020, Art. no. 112988.
- [108] J. Zhou, Y. Qiu, S. Zhu, D. J. Armaghani, C. Li, H. Nguyen, and S. Yagiz, "Optimization of support vector machine through the use of Metaheuristic algorithms in forecasting TBM advance rate," *Eng. Appl. Artif. Intell.*, vol. 97, Jan. 2021, Art. no. 104015.

- [109] J. Zeng, P. C. Roussis, A. S. Mohammed, C. Maraveas, S. A. Fatemi, D. J. Armaghani, and P. G. Asteris, "Prediction of peak particle velocity caused by blasting through the combinations of boosted-CHAID and SVM models with various kernels," *Appl. Sci.*, vol. 11, no. 8, p. 3705, Apr. 2021.
- [110] G. Guido, S. S. Haghshenas, S. S. Haghshenas, A. Vitale, V. Astarita, Y. Park, and Z. W. Geem, "Evaluation of contributing factors affecting number of vehicles involved in crashes using machine learning techniques in rural roads of Cosenza, Italy," *Safety*, vol. 8, no. 2, p. 28, Apr. 2022.
- [111] M. Akbarzadeh, S. Shaffiee Haghshenas, S. M. E. Jalali, S. Zare, and R. Mikaeil, "Developing the rule of thumb for evaluating penetration rate of TBM, using binary classification," *Geotech. Geol. Eng.*, pp. 1–19, May 2022, doi: 10.1177/147592172211075241.
- [112] H. Hasni, A. H. Alavi, P. Jiao, and N. Lajnef, "Detection of fatigue cracking in steel bridge girders: A support vector machine approach," *Arch. Civil Mech. Eng.*, vol. 17, no. 3, pp. 609–622, May 2017.
- [113] H. Pan, M. Azimi, F. Yan, and Z. Lin, "Time-frequency-based data-driven structural diagnosis and damage detection for cable-stayed bridges," *J. Bridge Eng.*, vol. 23, no. 6, Jun. 2018, Art. no. 04018033.
- [114] H. B. Bisheh, G. G. Amiri, M. Nekooei, and E. Darvishan, "Damage detection of a cable-stayed bridge using feature extraction and selection methods," *Struct. Infrastruct. Eng.*, vol. 15, no. 9, pp. 1165–1177, Sep. 2019.
- [115] M. Gordan, S. R. Sabbagh-Yazdi, Z. Ismail, K. Ghaedi, and H. H. Ghayeb, "Data mining-based structural damage identification of composite bridge using support vector machine," *J. AI Data Mining*, vol. 9, no. 4, pp. 415–423, 2021.
- [116] Z. Sun, J. Santos, and E. Caetano, "Data-driven prediction and interpretation of fatigue damage in a road-rail suspension bridge considering multiple loads," *Struct. Control Health Monit.*, vol. 12, p. e2997, May 2022.
- [117] Z. Sun, J. Santos, and E. Caetano, "Vision and support vector machine-based train classification using weigh-in-motion data," *J. Bridge Eng.*, vol. 27, no. 6, Jun. 2022, Art. no. 06022001.
- [118] X. Li, Y. Guo, and Y. Li, "Particle swarm optimization-based SVM for classification of cable surface defects of the cable-stayed bridges," *IEEE Access*, vol. 8, pp. 44485–44492, 2020.
- [119] R. S. Faradonbeh and A. Taheri, "Long-term prediction of rockburst hazard in deep underground openings using three robust data mining techniques," *Eng. Comput.*, vol. 35, no. 2, pp. 659–675, Apr. 2019.
- [120] A. Gordon, L. Breiman, J. Friedman, R. Olshen, and C. Stone, "Classification and regression trees," *Biometrics*, vol. 40, no. 3, p. 874, Sep. 1984.
- [121] A. Salimi, R. S. Faradonbeh, M. Monjezi, and C. Moormann, "TBM performance estimation using a classification and regression tree (CART) technique," *Bull. Eng. Geol. Environ.*, vol. 77, no. 1, pp. 429–440, Feb. 2018.
- [122] G. Mariniello, T. Pastore, C. Menna, P. Festa, and D. Asprone, "Structural damage detection and localization using decision tree ensemble and vibration data," *Comput.-Aided Civil Infrastruct. Eng.*, vol. 36, no. 9, pp. 1129–1149, Sep. 2021.
- [123] L. Breiman, "Bagging predictors," *Mach. Learn.*, vol. 24, no. 2, pp. 123–140, 1996.
- [124] J. Zhou, X. Li, and H. S. Mitri, "Comparative performance of six supervised learning methods for the development of models of hard rock pillar stability prediction," *Natural Hazards*, vol. 79, no. 1, pp. 291–316, 2015.
- [125] S. Adusumilli, D. Bhatt, H. Wang, P. Bhattacharya, and V. Devabhaktuni, "A low-cost INS/GPS integration methodology based on random forest regression," *Expert Syst. Appl.*, vol. 40, no. 11, pp. 4653–4659, Sep. 2013.
- [126] J. Zhou, X. Shi, K. Du, X. Qiu, X. Li, and H. S. Mitri, "Feasibility of random-forest approach for prediction of ground settlements induced by the construction of a shield-driven tunnel," *Int. J. Geomechanics*, vol. 17, no. 6, Jun. 2017, Art. no. 04016129.
- [127] J. Zhou, E. Li, H. Wei, C. Li, Q. Qiao, and D. J. Armaghani, "Random forests and cubist algorithms for predicting shear strengths of rockfill materials," *Appl. Sci.*, vol. 9, no. 8, p. 1621, Apr. 2019.
- [128] J. Zhou, P. G. Asteris, D. J. Armaghani, and B. T. Pham, "Prediction of ground vibration induced by blasting operations through the use of the Bayesian network and random forest models," *Soil Dyn. Earthq. Eng.*, vol. 139, Dec. 2020, Art. no. 106390.
- [129] J. Li, H. Hao, R. Wang, and L. Li, "Development and application of random forest technique for element level structural damage quantification," *Struct. Control Health Monit.*, vol. 28, no. 3, pp. 1–10, Mar. 2021.
- [130] H. Schulz and S. Behnke, "Deep learning: Layer-wise learning of feature hierarchies," *KI, Künstliche Intell.*, vol. 26, no. 4, pp. 357–363, Nov. 2012.
- [131] IBM Cloud Education. (May 1, 2020). *What is Deep Learning?* Accessed: Jul. 14, 2022. [Online]. Available: <https://www.ibm.com/cloud/learn/deep-learning>
- [132] B. Gan, Y. Chen, Q. Dong, J. Guo, and R. Wang, "A convolutional neural network intrusion detection method based on data imbalance," *J. Supercomput.*, vol. 12, pp. 1–34, Jun. 2022.
- [133] *10 Advanced Architecture Concepts*. Accessed: Jun. 20, 2022. [Online]. Available: <https://b.fdrs.ir/3e3>
- [134] S. Abbas, Y. Alhwaiti, A. Fatima, M. A. Khan, M. A. Khan, T. M. Ghazal, A. Kanwal, M. Ahmad, and N. S. Elmitwally, "Convolutional neural network based intelligent handwritten document recognition," *Comput., Mater. Continua*, vol. 70, no. 3, pp. 4563–4581, 2022.
- [135] Y. Bao, Z. Tang, H. Li, and Y. Zhang, "Computer vision and deep learning-based data anomaly detection method for structural health monitoring," *Struct. Health Monitor.*, vol. 18, no. 2, pp. 401–421, Mar. 2019.
- [136] J. Yang, F. Yang, Y. Zhou, D. Wang, R. Li, G. Wang, and W. Chen, "A data-driven structural damage detection framework based on parallel convolutional neural network and bidirectional gated recurrent unit," *Inf. Sci.*, vol. 566, pp. 103–117, Aug. 2021.
- [137] A. Entezami, H. Sarmadi, and S. Mariani, "An unsupervised learning approach for early damage detection by time series analysis and deep neural network to deal with output-only (big) data," in *Proc. 7th Int. Electron. Conf. Sensors Appl.*, Nov. 2020, pp. 1–19.
- [138] H. Liu, Y. L. Ding, H. W. Zhao, M. Y. Wang, and F. F. Geng, "Deep learning-based recovery method for missing structural temperature data using LSTM network," *Struct. Monit.*, vol. 7, no. 2, pp. 109–124, 2020.
- [139] 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," *J. Struct. Eng.*, vol. 146, no. 5, May 2020, Art. no. 04020073.
- [140] S. Li, L. Jin, Y. Qiu, M. Zhang, and J. Wang, "Signal anomaly detection of bridge SHM system based on two-stage deep convolutional neural networks," *Struct. Eng. Int.*, vol. 1, pp. 1–10, Oct. 2021.
- [141] H. Son, Y. Jang, S.-E. Kim, D. Kim, and J.-W. Park, "Deep learning-based anomaly detection to classify inaccurate data and damaged condition of a cable-stayed bridge," *IEEE Access*, vol. 9, pp. 124549–124559, 2021.
- [142] Y. Li, T. Bao, H. Chen, K. Zhang, X. Shu, Z. Chen, and Y. Hu, "A large-scale sensor missing data imputation framework for dams using deep learning and transfer learning strategy," *Measurement*, vol. 178, Jun. 2021, Art. no. 109377.
- [143] Z. Yue, Y. Ding, H. Zhao, and Z. Wang, "Case study of deep learning model of temperature-induced deflection of a cable-stayed bridge driven by data knowledge," *Symmetry*, vol. 13, no. 12, p. 2293, Dec. 2021.
- [144] Z. Li, H. Zhu, and M. Huang, "A deep learning-based fine crack segmentation network on full-scale steel bridge images with complicated backgrounds," *IEEE Access*, vol. 9, pp. 114989–114997, 2021.
- [145] A. Fernandez-Navamuel, D. Zamora-Sánchez, Á. J. Omella, D. Pardo, D. Garcia-Sanchez, and F. Magalhães, "Supervised deep learning with finite element simulations for damage identification in bridges," *Eng. Struct.*, vol. 257, Jul. 2022, Art. no. 114016.
- [146] A. Fernandez-Navamuel, F. Magalhães, D. Zamora-Sánchez, Á. J. Omella, D. Garcia-Sanchez, and D. Pardo, "Deep learning enhanced principal component analysis for structural health monitoring," *Struct. Health Monitor.*, vol. 21, no. 4, pp. 1710–1722, Jul. 2022.
- [147] S. da Silva, M. D. Júnior, V. L. Junior, and M. J. Brennan, "Structural damage detection by fuzzy clustering," *Mech. Syst. Signal Process.*, vol. 22, no. 7, pp. 1636–1649, Oct. 2008.
- [148] A. Santos, E. Figueiredo, and J. Costa, "Clustering studies for damage detection in bridges: A comparison study," *Struct. Health Monitor.*, vol. 2, pp. 1–25, Sep. 2015.
- [149] W. Nick, K. Asamene, G. Bullock, A. Esterline, and M. Sundaresan, "A study of machine learning techniques for detecting and classifying structural damage," *Int. J. Mach. Learn. Comput.*, vol. 5, no. 4, pp. 313–318, Aug. 2015.
- [150] Y. Jiao, H. Liu, and X. Wang, "Damage identification for irregular-shaped bridge based on fuzzy C-means clustering improved by particle swarm optimization algorithm," *J. Vibroeng.*, vol. 18, no. 4, pp. 2149–2166, Jun. 2016.
- [151] M. Marcy, G. Doz, F. Magalhães, and A. Cunha, "Monitoring of the Infante D. Henrique Bridge with self-organizing maps," in *Maintenance, Monitoring, Safety, Risk and Resilience of Bridges and Bridge Networks*. Boca Raton, FL, USA: CRC Press, 2016, p. 239.

- [152] L. Yu and J. H. Zhu, "Structural damage prognosis on truss bridges with end connector bolts," *J. Eng. Mech.*, vol. 143, no. 3, Mar. 2017, Art. no. B4016002.
- [153] X.-M. Yang, T.-H. Yi, C.-X. Qu, H.-N. Li, and H. Liu, "Automated eigensystem realization algorithm for operational modal identification of bridge structures," *J. Aerosp. Eng.*, vol. 32, no. 2, Mar. 2019, Art. no. 04018148.
- [154] H. Tran-Ngoc, S. Khatir, G. De Roeck, T. Bui-Tien, and M. A. Wahab, "An efficient artificial neural network for damage detection in bridges and beam-like structures by improving training parameters using cuckoo search algorithm," *Eng. Struct.*, vol. 199, Nov. 2019, Art. no. 109637.
- [155] J.-X. Mao, H. Wang, Y.-G. Fu, and B. F. Spencer, Jr., "Automated modal identification using principal component and cluster analysis: Application to a long-span cable-stayed bridge," *Struct. Contr. Health Monit.*, vol. 26, no. 10, p. e2430, Aug. 2019.
- [156] Z. Lei, L. Zhu, Y. Fang, X. Li, and B. Liu, "Anomaly detection of bridge health monitoring data based on kNN algorithm," *J. Intell. Fuzzy Syst.*, vol. 39, no. 4, pp. 5243–5252, Oct. 2020.
- [157] X. Lei, L. Sun, Y. Xia, and T. He, "Vibration-based seismic damage states evaluation for regional concrete beam bridges using random forest method," *Sustainability*, vol. 12, no. 12, p. 5106, Jun. 2020.
- [158] M. Gordan, H. A. Razak, Z. Ismail, K. Ghaedi, Z. X. Tan, and H. H. Ghayeb, "A hybrid ANN-based imperial competitive algorithm methodology for structural damage identification of slab-on-girder bridge using data mining," *Appl. Soft Comput.*, vol. 88, Mar. 2020, Art. no. 106013.
- [159] M. Gordan, Z. Ismail, H. A. Razak, K. Ghaedi, Z. Ibrahim, Z. X. Tan, and H. H. Ghayeb, "Data mining-based damage identification of a slab-on-girder bridge using inverse analysis," *Measurement*, vol. 151, Feb. 2020, Art. no. 107175.
- [160] A. A. Mousavi, C. Zhang, S. F. Masri, and G. Gholipour, "Structural damage localization and quantification based on a CEEMDAN Hilbert transform neural network approach: A model steel truss bridge case study," *Sensors*, vol. 20, no. 5, p. 1271, Feb. 2020.
- [161] Z. Zhang and C. Sun, "Structural damage identification via physics-guided machine learning: A methodology integrating pattern recognition with finite element model updating," *Struct. Health Monit.*, vol. 20, no. 4, pp. 1675–1688, 2021.
- [162] M. L. Baptista, E. M. P. Henriques, and K. Goebel, "A self-organizing map and a normalizing multi-layer perceptron approach to baselining in prognostics under dynamic regimes," *Neurocomputing*, vol. 456, pp. 268–287, Aug. 2021.
- [163] S. Sharma and S. Sen, "Bridge damage detection in presence of varying temperature using two-step neural network approach," *J. Bridge Eng.*, vol. 26, no. 6, Jun. 2021, Art. no. 04021027.
- [164] T. H. Kwon, S. H. Park, S. I. Park, and S.-H. Lee, "Correction to: Building information modeling-based bridge health monitoring for anomaly detection under complex loading conditions using artificial neural networks," *J. Civ. Struct. Health Monit.*, vol. 12, no. 2, p. 483, 2022.
- [165] K. Gao, Z. D. Chen, S. Weng, H. P. Zhu, and L. Y. Wu, "Detection of multi-type data anomaly for structural health monitoring using pattern recognition neural network," *Smart Struct. Syst.*, vol. 29, no. 1, pp. 129–140, 2022.
- [166] M. Gordan, O. Z. Chao, S.-R. Sabbagh-Yazdi, L. K. Wee, K. Ghaedi, and Z. Ismail, "From cognitive bias toward advanced computational intelligence for smart infrastructure monitoring," *Frontiers Psychol.*, vol. 13, Mar. 2022, Art. no. 846610.
- [167] A. Santos, E. Figueiredo, M. F. M. Silva, C. S. Sales, and J. C. W. A. Costa, "Machine learning algorithms for damage detection: Kernel-based approaches," *J. Sound Vib.*, vol. 363, pp. 584–599, Feb. 2016.
- [168] F. Ni, J. Zhang, and M. N. Noori, "Deep learning for data anomaly detection and data compression of a long-span suspension bridge," *Comput.-Aided Civil Infrastruct. Eng.*, vol. 35, no. 7, pp. 685–700, Jul. 2020.
- [169] Y. Tian, C. Chen, K. Sagoe-Crentsil, J. Zhang, and W. Duan, "Intelligent robotic systems for structural health monitoring: Applications and future trends," *Autom. Construct.*, vol. 139, Jul. 2022, Art. no. 104273.
- [170] S. Sony, S. Laventure, and A. Sadhu, "A literature review of next-generation smart sensing technology in structural health monitoring," *Struct. Control Health Monitor.*, vol. 26, no. 3, p. e2321, Mar. 2019.
- [171] 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.
- [172] D. S. Ásgrímsson, I. González, G. Salvi, and R. Karoumi, "Bayesian deep learning for vibration-based bridge damage detection," in *Structural Integrity*. Cham, Switzerland: Springer, 2022, pp. 27–43.
- [173] E. M. Tronci, H. Beigi, M. Q. Feng, and R. Betti, "A transfer learning SHM strategy for bridges enriched by the use of speaker recognition X-vectors," *J. Civil Struct. Health Monitor.*, vol. 12, pp. 1–4, Jun. 2022.
- [174] H. Zhang, J. Lin, J. Hua, F. Gao, and T. Tong, "Data anomaly detection for bridge SHM based on CNN combined with statistic features," *J. Non-destruct. Eval.*, vol. 41, no. 1, pp. 1–3, Mar. 2022.
- [175] D. Hajializadeh, "Deep learning-based indirect bridge damage identification system," *Struct. Health Monitor.*, vol. 3, May 2022, Art. no. 147592172210871.
- [176] T. Zhang, S. Biswal, and Y. Wang, "SHMNet: Condition assessment of bolted connection with beyond human-level performance," *Struct. Health Monitor.*, vol. 19, no. 4, pp. 1188–1201, Jul. 2020.
- [177] H. Malik and W. Zatar, "Software agents to support structural health monitoring (SHM)-informed intelligent transportation system (ITS) for bridge condition assessment," *Proc. Comput. Sci.*, vol. 130, pp. 675–682, May 2018.



RAFFAELE ZINNO received the master's degree in civil engineering and the Ph.D. degree in chemical technologies and new materials from the University of Calabria, Italy, in 1988 and 1995, respectively.

From 1992 to 1994, he was a Visiting Doctoral Student with the Department of Mechanical and Aerospace Engineering, West Virginia University, Morgantown, WV, USA. From 1997 to 1998, he was a Researcher at the CNR—Central Institute for Industrialization and Building Technology, Rome. Since 1998, he has been an Associate Professor of strength of materials and structural engineering with the Department of Environmental Engineering, University of Calabria. In 2018, he obtained the Italian National Scientific Qualification (ASN) as a Full Professor in his scientific area. His main research interests include structural health monitoring (SHM), structural uses of wood and related experiments, theoretical analysis of structures in composite material (problems of damage in composite material, bending and buckling of structures in ordinary and advanced materials, etc.), experiments on innovative materials (composites, fiber-reinforced or high-performance concretes, self-diagnostic, smart, etc.) and on structures made with them, design of structures in innovative material, and problems of dynamic analysis of structures. He founded and directs the SMART Laboratory (Structural Monitoring, structural Advanced materials, structural Rehabilitation, structural Testing Laboratory) at the University of Calabria.



SINA SHAFFIE HAGHSHEENAS (Graduate Student Member, IEEE) was born in Rasht, Guilan, Iran, in 1985. He received the B.S. degree in civil engineering from Islamic Azad University, Bandar Anzali, Iran, in 2006, the M.S. degree in geotechnics with a focus on rock mechanics from Islamic Azad University, Arak, Iran, in 2012, and the second master's degree in transportation engineering from the University of Calabria, Rende, Italy, in 2021, where he is currently pursuing the

Ph.D. degree in transportation engineering with the Department of Civil Engineering.

From 2009 to 2019, he was a Supervisor Engineer on over eight civil engineering projects. Since 2012, he had extensive cooperation with research teams in the universities of Iran, Turkey, Australia, South Korea, and Italy, and this cooperation is continuing until today. As a result of these collaborations, more than 70 articles have been written and published in ISI journals and at international conferences. His research interests include transportation engineering, road safety, traffic safety, intelligent transportation systems, smart cities, structure health monitoring, geotechnics, tunneling, sustainable development, risk assessment, risk management, artificial intelligence, meta heuristic algorithms, and deep learning.



GIUSEPPE GUIDO (Member, IEEE) received the M.Sc. degree in civil engineering and the Ph.D. degree from the University of Calabria (UNICAL), Italy. He has been an Associate Professor of transportation engineering with the Department of Civil Engineering, University of Calabria, since 2015. He is also the Mobility Manager with the University of Calabria. He is a Co-Founder of the academic spin-off Smart-Oriented Mobility Solutions (SOMOS), an innovative startup offering innovative

solutions on IoT applications for transport and logistics. He has authored or coauthored more than 120 international journal articles. His research

interests include road traffic simulation, road safety, information and communication technologies for traffic analysis, intelligent transportation systems, transit systems, mobility management, mobility modeling, and users' behavior modeling. He is a member of the Italy Section of the IEEE, the IEEE ITSS Italian Chapter, the Cosenza Association of Professional Engineer, the Italian Society of Transport Engineering Professors, and the Italian Association for Traffic and Transport Engineering. He is a co-founder and a member of the Working Group on Systems Engineering for Infrastructure and Building Systems.



ALESSANDRO VITALE graduated in transportation engineering at the University of Calabria, in 2002, where he is currently pursuing the Ph.D. degree in environmental technologies and planning. He is also a Research Fellow with the Department of Territorial Planning (now Department of Civil Engineering), University of Calabria, where he is also a Technical Coordinator of the Research Laboratory of Management of Interventions in Environmental Emergencies Conditions, Department of Civil Engineering.

In September 2018, he obtained the National Scientific Qualification for the functions of an Associate Professor in infrastructure and transport systems. He participated in numerous scientific research projects at national and international level and he is the coauthor of several international publications on the development and application of innovative methodologies and technologies to emergencies scenarios, urban planning and transport planning, and management. He is an article editor, a guest editor, and a referee of numerous prestigious international journals.

• • •