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Review article

Emerging artificial intelligence methods in structural engineering

Hadi Salehi[a], Rigoberto Burgueño[a,b,*]

[a] Department of Civil and Environmental Engineering, Michigan State University, East Lansing, MI, USA
[b] Department of Mechanical Engineering, Michigan State University, East Lansing, MI, USA

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ABSTRACT

Artificial intelligence (AI) is proving to be an efficient alternative approach to classical modeling techniques. AI refers to the branch of computer science that develops machines and software with human-like intelligence. Compared to traditional methods, AI offers advantages to deal with problems associated with uncertainties and is an effective aid to solve such complex problems. In addition, AI-based solutions are good alternatives to determine engineering design parameters when testing is not possible, thus resulting in significant savings in terms of human time and effort spent in experiments. AI is also able to make the process of decision making faster, decrease error rates, and increase computational efficiency. Among the different AI techniques, machine learning (ML), pattern recognition (PR), and deep learning (DL) have recently acquired considerable attention and are establishing themselves as a new class of intelligent methods for use in structural engineering. The objective of this review paper is to summarize techniques concerning applications of the noted AI methods in structural engineering developed over the last decade. First, a general introduction to AI is presented and the importance of AI in structural engineering is described. Thereafter, a review of recent applications of ML, PR, and DL in the field is provided, and the capability of such methods to address the restrictions of conventional models are discussed. Further, the advantages of employing such algorithmic methods are discussed in detail. Finally, potential research avenues and emerging trends for employing ML, PR, and DL are presented, and their limitations are discussed.

1. Introduction

Civil engineering is fraught with problems that defy solution via traditional computational techniques. However, they can often be solved by an expert with proper training. Classical artificial intelligence (AI) has targeted this class of problems by capturing the essence of human cognition at the highest level. The term "AI" was introduced at a workshop held in Dartmouth college in 1956 [1]. AI is a computational method attempting to simulate human cognition capability through symbol manipulation and symbolically structured knowledge bases to solve engineering problems that defy solution using conventional methods. AI has been developed based on the interaction of various disciplines; namely, computer science, information theory, cybernetics, linguistic, and neurophysiology.

Several terms referring to artificial intelligence can be found in the literature, and they need to be identified to further elaborate on the state of the art. One of those terms is machine intelligence (MI). AI and MI are almost identical terms [2,3] and are often used interchangeably. MI is often considered a synonym of AI; yet it deals with different types of intelligent problems, e.g., clustering, classifications, computer vision, etc. In general, MI refers to machines with human-like intelligent behavior and reasoning, while AI refers to a machine's ability to mimic the cognitive functions of humans to perform tasks in a smart manner. Another important term is cognitive computing (CC), which is inspired by human mind's capabilities [4]. Cognitive systems are able to solve problems in a form mimicking humans thinking and reasoning. Such systems are based on the ability of machines to measure, reason, and adapt using learned experience [4,5]. The main characteristics of CC systems are their ability to interpret big data, dynamic training and adaptive learning, probabilistic discovery of relevant patterns. Technically, AI refers to computers and machines that can behave intelligently, while CC concentrates on solving the problems using humanlike thinking. The most significant difference between AI and CC can be defined in terms of interacting normally with humans. For any AI system, there is an agent that decides what actions need to be taken. However, CC systems learn, reason, and interact like humans. Therefore, it can be concluded that CC is essentially an AI agent, and as such CC is considered a sub-set of AI. Expert systems, on the other hand, is a

* Corresponding author at: Department of Civil and Environmental Engineering, Michigan State University, 428 S. Shaw Lane, Engineering Building, East Lansing, MI 48824-1226, USA.
E-mail address: burgueno@msu.edu (R. Burgueño).

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branch of AI. As noted, AI is defined as the ability of a machine to mimic intelligent human behavior, seeking to use human-inspired algorithms to solve problems. Similarly, an expert system is defined as a computer program attempting to mimic human experts to solve problems demanding human/expert knowledge. It follows from the noted definitions that AI includes different branches such as expert systems, machine learning, pattern recognition, and fuzzy logic.

In recent years, there has been a growing interest in the use of AI in all engineering domains, and it has fueled many visions and hopes. While the civil engineering community has witnessed an extensive growth in the use of different AI branches/methods in its diverse areas, the present study concentrates on the AI methods that have gained significant attention over the last decade, namely machine learning (ML), pattern recognition (PR), and deep learning (DL) with a focus on their application to the structural engineering discipline. The scope of the review is to summarize the theoretical background of the methods, provide a historical context on their use, summarize the latest research developments, and discuss promising paths for future research.

The use of AI in civil engineering has been the topic of previous review articles. Adeli et al. [6] presented a multiparadigm learning technique, where the authors demonstrated that the performance can be notably enhanced by skillful integration of different AI branches, including neural networks, genetic algorithms, fuzzy sets, and parallel processing. An extensive study of evolutionary computation, a branch of AI, in the context of structural design was conducted by Kicinger et al. [7]. Lio et al. [8] carried out a review of studies concerning the application of metaheuristics as optimization techniques to address issues faced in the lifetime of a construction or engineering project. A survey on different AI methods (e.g., fuzzy logic, evolutionary computation, neural networks, swarm intelligence, expert systems, etc.) for civil engineering was conducted by Lu et al. [9]. Shahin et al. [10] studied applications of AI in geotechnical engineering; and Saka et al. [11] conducted a survey on mathematical and metaheuristic algorithms in design optimization of steel frame structures. Adeli et al. [12] carried out a review on progress in the optimization of high-rise buildings; and a survey on the applications and methodologies of the fuzzy multiple criteria decision-making techniques was conducted by Mardani et al. [13].

Recently, a survey on the application of multi-criteria decision making methods for the analysis of suspension bridges was conducted by Garcia-Segura et al. [14]; Sanchez et al. [15] presented a review on the applications of artificial neural networks, a branch of AI, for civil infrastructure that includes structural health monitoring, structural system identification, structural design and optimization, etc.; and a comprehensive state-of-the-art overview of sustainable structural design in green buildings rating systems and building codes was conducted by Pongiglione et al. [16]. Further, a survey on different AI methods (e.g., artificial neural networks, Bayesian, genetic algorithms, case-based reasoning, and fuzzy logic) for the field of fracture mechanics was performed by Khosravani et al. [17], while a literature review of application of multi-criteria decision analysis for aging-dam management was carried out by Mieza et al. [18]. Additionally, Sierra et al. [19] conducted a review on multi-criteria assessment of the social sustainability of infrastructures and Zavadskas et al. [20] surveyed the state-of-the-art methods applied to sustainable decision-making in civil engineering, construction, and building technology.

Although the noted review articles highlighted applications of AI in civil engineering structures/infrastructure, they mainly focused on traditional techniques and do not cover recent methods, such as PR, ML, and DL. Yet, these intelligent methods have experienced notable developments and increased use in structural engineering during the last few years. Therefore, this review paper presents a broad perspective of research efforts on the use of such emerging AI methods (i.e., PR, ML, and DL) in structural engineering during the last decade. Due to space limitations, the review emphasis for each paper was on the problem/issue being addressed, the domain and case structure being considered, and the AI method being used. The contributions of this review paper are: (1) study and summarize techniques concerning the applications of PR, ML, and DL in structural engineering over the last decade, (2) identify future directions and emerging trends for employing PR, ML, and DL in structural engineering applications, and (3) highlight current limitations of the reviewed AI methods in structural engineering.

The review paper is structured as follows. Section 2 presents the approach followed for selecting the reviewed literature and conducting the content analysis. A general introduction to AI is presented in Section 3, and the significance of AI in structural engineering is also described. New AI techniques (namely ML, PR, and DL) are introduced and highlighted in Section 4, where the differences of these techniques are elaborated. Section 5 reviews the application of such techniques in structural engineering. Further, Section 6 identifies potential research avenues and emerging trends for using the noted AI methods in future innovations, while highlighting the current limitations of such methods. Finally, conclusions are provided in Section 7.

2. Research method

The present study used content analysis [21] to select the reviewed literature. Content analysis is commonly used to objectively make valid inferences according to collected data with the aim of disclosing central aspects of previous studies. It further allows for qualitative and quantitative operations. As a result, content analysis is able to provide an inclusive disclosure of AI applications in structural engineering, leading to reliable results from the study.

Sample collection was performed in this study through the search and selection of peer-reviewed articles. Articles were collected from prominent and well-accepted academic databases. The procedure of literature search and selection for this study can be summarized as follows:

- The academic databases Web of Science, Scopus, Science Direct, ASCE Library, Engineering Village, Wiley Online Library, Sage, and Emerald were used for article search and selection.
- Keywords such as “artificial intelligence”, “artificial intelligence in civil and structural engineering”, “pattern recognition structural engineering”, “machine learning structural engineering”, “deep learning structural engineering”, “convolutional neural networks structural engineering”, and “computational intelligence” were used to search the databases. This resulted in the identification of academic articles concerning the application of AI methods in structural engineering. The time period under review was from 2009 to 2017, which led to the identification of approximately 430 candidate articles.
- The criteria for selecting the identified articles was the application of pattern recognition, machine learning, and deep learning in structural engineering. In accordance with such criteria, a two-round article selection technique was employed. That is, titles, abstract, and keywords of the noted articles were checked in the first round to ascertain if they meet the criteria. The second round consisted of reading and analyzing the entire article, thus ensuring that all of the selected papers were closely related to the review objective. Finally, 282 articles were selected and used for the present review.

For the review, qualitative and quantitative analyses were performed to identify the applications of emerging AI methods in structural engineering, the AI algorithms used for such applications, and analyze the applicability of these algorithms for the noted applications. This approach led to the identification of the most promising applications of emerging AI techniques and future research directions.

3. Overview of artificial intelligence

In general, there are two types of machine intelligence: hard computing and soft computing methods. Hard computing, which is based on binary logic, crisp systems, and numerical analysis, requires a precisely stated analytical model and is capable of producing precise answers. Soft computing differs from conventional computing in that, unlike hard computing, it can deal with ambiguous and noisy data, incorporates stochastic information, and allows parallel computations. Soft computing is based on fuzzy logic, neural nets, and probabilistic reasoning; where the methods are able to evolve their own programs and yield approximate answers [22].

Soft computing is commonly considered a synonym of computational intelligence (CI). In fact, CI or soft computing can be expressed by the capability of a computer to learn a specific task from sample data or experimental observation. Mathematical or conventional modelling are useless in many complex real-life problems due to factors such as: complexity of the processes for mathematical reasoning, uncertainties during the process, and the stochastic nature of the process. The set of nature-inspired computational techniques defining CI provides solutions for such problems [23]. CI uses a combination of supplementary techniques such as artificial neural networks, fuzzy logic, learning theory, evolutionary computing, and probabilistic methods, and is capable of solving and approximating nonlinear problems while introducing human knowledge into the areas of computing.

Artificial intelligence (AI) is essentially defined as the ability of a machine to mimic intelligent human behavior, thus seeking to use human-inspired algorithms for approximating conventionally defiant problems. The main goals of AI research involve knowledge representation, reasoning, automated planning, learning, natural language processing, perception, robotics, and general intelligence [24–28]. Although AI and CI/soft computing pursue a similar goal, there is a slight difference between them. According to Bezdek [24], CI is a subset of AI. It is also important to distinguish AI from data science and big data. There is indeed a substantial overlap among these methods. Data mining/science is a cross-disciplinary field used to discover valuable insights and trends in a data set. Data mining techniques focus on the discovery of unknown properties in an area where there is limited knowledge. The data set, on the other hand, is called big data if it is big in terms of volume (i.e., number of data points or features per data point), velocity (i.e., large portions of data arriving in a small amount of time for analysis and mining), or variety (i.e., different types of data such as text, speech, and images). Big data thus refers to large or complex data sets that are difficult to represent using conventional data processing techniques. Machine learning, a subfield of AI, is used to design a model to learn the trends, thus focusing on prediction based on known properties learned from the training data. Deep learning, a subset of machine learning, is a tool that concentrates on learning the representations and features of the data. Fig. 1 schematically presents the noted different intelligent techniques and their correlation.

In the field of structural engineering, there are numerous problems that are influenced by uncertainties, e.g., those related to design, analysis, condition monitoring, construction management, decision making, etc. Such problems need mathematics, physics, and mechanics calculations to be solved, and their solution strongly depends on the practitioners' experience. It can be further said that computers are yet to be fully utilized for many tasks. This is essentially because of the need for logical reasoning, problems tend to be unique, feasibility constraints, and the need to use prior experiences in the analysis and design process. However, AI techniques can be effectively used to enhance these efforts and can also be considered to check the general validity of laboratory or field test results. AI methods can also help minimize (and potentially avoid) time-consuming laboratory or field tests to determine design parameters.

Uncertainties are an unavoidable part of structural engineering problems. For example, in seismic design earthquake demands are not known with precision. In structural health monitoring there are uncertainties in the amplitude of the input excitation, measurement noise, and spatial density of measurements. Many uncertainties also exist in the models used to predict structural response, as well as those defining constitutive behavior. Geotechnical information for foundation design purposes is determined with limited information and/or based on laboratory tests with high levels of uncertainty. All of the aforementioned problems can be modeled and treated as uncertainties [29]. AI is able to deal with such uncertainty problems. For instance, AI methods have been used to solve uncertainty problems defined within the context of damage detection and system identification using finite element model updating [30]. Model updating can be used to identify physical parameters (e.g., stiffness of a structural component) for which a reduction in value is taken to indicate damage. However, such reduction may be simply due to statistical uncertainty. Thus, it is of importance to compute the uncertainty of the estimation to distinguish whether the reduction of a parameter is due to actual damage. The use of AI methods can also result in significant time and cost savings, as well as increasing computational efficiency in many structural engineering tasks.

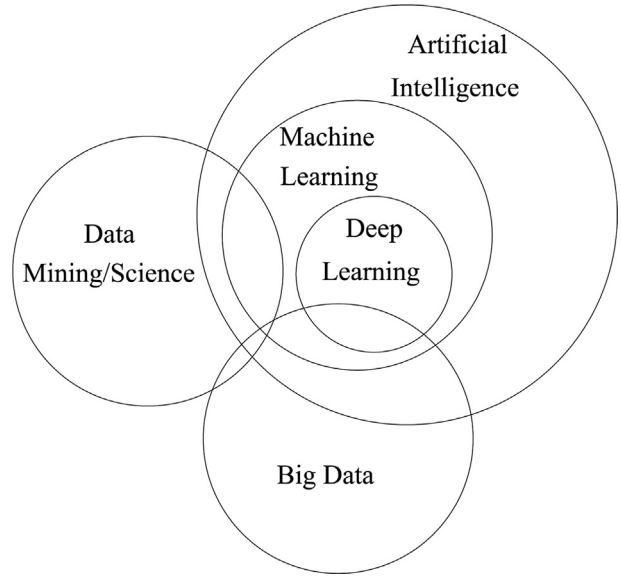

Fig. 1. Illustration of the interrelation of different intelligent computational techniques.

Many of the AI branches, such as machine learning (ML), pattern recognition (PR), neural networks, fuzzy logic, evolutionary computation, deep learning (DL), expert systems, probability theory, discriminant analysis, swarm optimization, metaheuristic optimization, and decision trees, have been used in structural engineering. The number of research publications showing the use of these AI methods in structural engineering over the last decade is presented in Fig. 2. As can be seen, the use of most methods has increased during the last decade. Nevertheless, the number of studies featuring techniques such as evolutionary computation, fuzzy logic, and expert systems has not had a notable change. Even though the use of neural networks has drawn a great attention from researchers, new studies on the use of such method has also remained rather constant over the last decade. In contrast, the significant increase in studies featuring the use of ML and PR is evident. Further, deep learning architectures, e.g., convolutional neural networks (CNNs), are gaining remarkable attention among the research community over the last few years. These observations motivated the authors to concentrate this review on ML, PR, and DL, as they are emerging as the new computational intelligence paradigms in structural engineering.

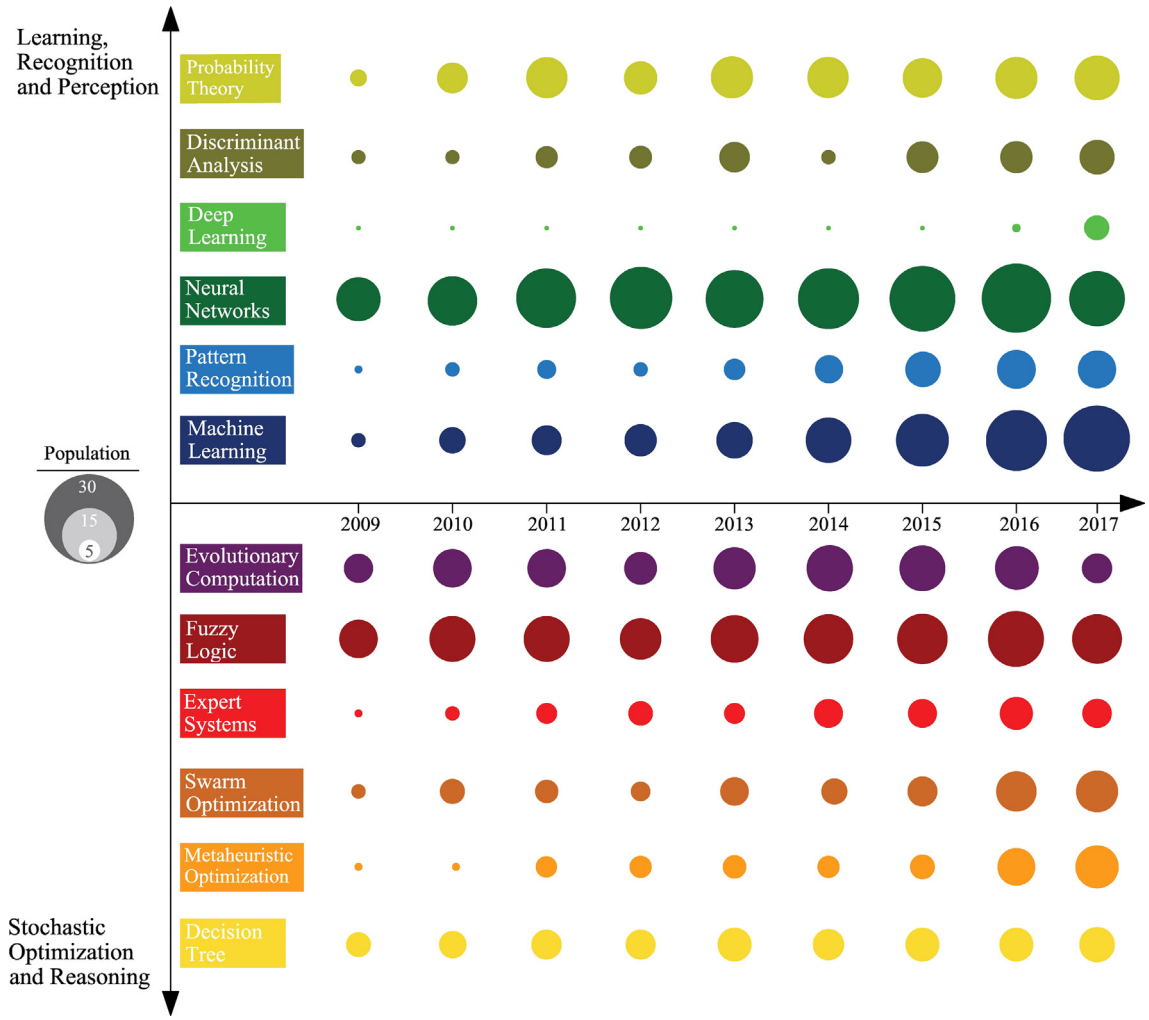

Fig. 2. Research publications on the use of different AI branches in structural engineering.

4. Emerging AI methods

As previously discussed, pattern recognition, machine learning, and deep learning are among the new artificial intelligence methods that are increasingly emerging as reliable and efficient tools in the field of structural engineering. This section provides technical background on the noted methods and insight regarding the use of such algorithms for structural engineering problems.

4.1. Pattern recognition

Pattern recognition (PR) is a technique in which the main goal is to classify objects into a number of classes or categories. The objects, depending on the applications, could be images, signals, hand writing, speech, or measurements to be classified [31,32]. In PR, a pattern is represented by a set of features. Concepts from statistical decision theory are used to establish decision boundaries between pattern classes. The recognition system in PR consists of two modes, namely learning (training) and classification (testing), as shown in Fig. 3. In the learning/training mode the proper features for representing the input patterns are discovered by means of the feature extraction/selection module, and the classifier is trained/calibrated to partition the feature space. In the classification mode the input patterns are assigned to one of the classes using the trained classifier; while the performance of the designed classifier, i.e., classification error rate, is evaluated by the system evaluation module.

In general, PR methods can be categorized into two main categories: *supervised* PR and *unsupervised* PR. The *supervised* term refers to the condition when a set of labeled training samples are available. When there is no prior information regarding the class labels and the training data are not labeled, this is known as *unsupervised* PR, or clustering. These terms are further discussed in the following section. Another difference in PR methods is that of *generative* models versus *discriminative* models. If the aim is to discover the distribution of patterns in the model, this denotes the *generative* models in PR. The task for this case is to find out how the patterns can be modeled in the class. In this regard, the density function needs to be determined based on training data. On the other hand, the goal in *discriminative* PR models is to determine the model that discovers the decision boundary, thus learning the function and parameters of the decision boundary. Generative and discriminative PR models along with the algorithms used are shown in Fig. 4.

4.2. Machine learning

Machine learning (ML) is a major subfield of artificial intelligence (AI) (see Fig. 1) dealing with the study, design, and development of algorithms that can learn from the data itself and make predictions using learned data [33–36]. In fact, ML refers to the capability of computers to learn without being explicitly programmed. ML based models can be predictive or descriptive to achieve knowledge from the data [37,38]. The scope and potential of ML is much more general than other AI methods, although it is a subset of AI and used in various disciplines; including computer science, information theory, control

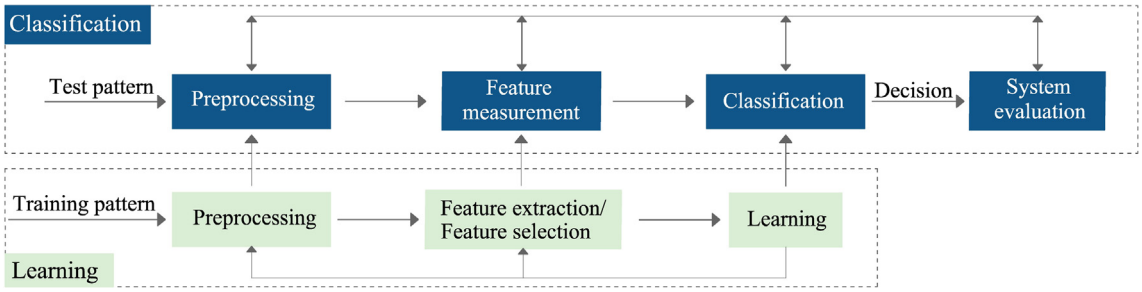

Fig. 3. Schematic of a pattern recognition system.

computational complexity, probability and statistics, financial market, and theory and philosophy [35]. It is of importance to differentiate ML from other similar AI subsets including pattern recognition (PR) and deep learning (DL). In general, PR and ML are closely related areas, as they fundamentally overlap in their scope. However, PR deals with methods for classification tasks, while ML focuses on algorithms utilized for learning. In fact, the major task of PR is recognition of patterns in data and to classify them, and it does not necessarily imply learning. ML systems, on the other hand, are designed to learn by themselves. Further, DL is considered a subset of ML (see Fig. 1), in which the system has the ability to learn features from the data. Deep learning, in fact, is a tool to learn the representation of data. Once the representation is determined, the ML problem can be solved. Indeed, deep learning transforms a problem/representation with high dimensionality to a lower dimensional representation. Depending on the resources of the training dataset, ML can be categorized as supervised, unsupervised, or reinforcement learning [33,36].

4.2.1. Supervised learning

The goal of supervised learning is to build a model/function to accurately predict the unknown target output of future examples. Training samples in supervised learning are labeled and the key characteristic of the learning is the existence of a *teacher* that provides a cost or category label for each pattern in a training dataset, thus seeking to decrease the added cost for these patterns. If the objective of the ML model is to forecast continuous target variables, the task is said to be *regression*. However, if the aim is to predict discrete target variables the task is known as *classification*.

4.2.2. Unsupervised learning

The objective of unsupervised learning is to separate the training dataset into clusters such that the data in all clusters exhibits a high level of proximity. Unlike supervised learning, the labels for data are unavailable and there is no explicit teacher. Thus, the system itself forms the clusters from the input patterns.

4.2.3. Reinforcement learning

In reinforcement learning, or learning with a critic, no information is given regarding the desired category signal or explicit goals. Reinforcement algorithms are forced to learn optimal goals through trial and error. In fact, in order to maximize the model's performance, reinforcement learning allows an agent to determine the ideal behavior within a specific context. Agents receive a numerical reward as a reinforcement signal encoding the success of an action's outcome. The goal for the agent is then to learn to select actions maximizing the accumulated reward over time.

Recent research reveals the successful practical applications of ML in different fields, such as: computer vision and image processing [39–44], speech recognition [45–50], computational finance [51–53], energy production [54–56], and computational biology [57–59]. In a machine learning domain an algorithm has to be developed to solve problems. Different methods from various fields have been adopted for such a purpose [60,61]. Therefore, ML enables exploiting the interaction form all these fields, which in turn leads to robust solutions using various domains of knowledge. Fig. 5 illustrates some of most prominent algorithms used in the ML domain.

4.3. Deep learning

Deep learning (DL), a branch of machine learning, is composed of networks that can learn unsupervised from unstructured/unlabeled data. DL architecture aims to learn the feature representation of the input data. In fact, DL is based on deep neural networks, i.e., neural networks with more than one hidden layer. In such an architecture, increasing the number of layers results in a deeper network. Examples of DL architectures include convolutional neural networks (CNNs), recurrent neural networks (RNNs), autoencoders, deep belief nets, etc. Among these, CNNs are the DL architectures that have gained the most attention among the structural engineering community during last few years. CNNs are inspired by the visual cortex of animals [62]. They have been mainly used in computer science and engineering for image recognition [63–68]. Unlike standard neural networks, CNNs are capable of capturing the 2D topology of pixels, while demanding fewer

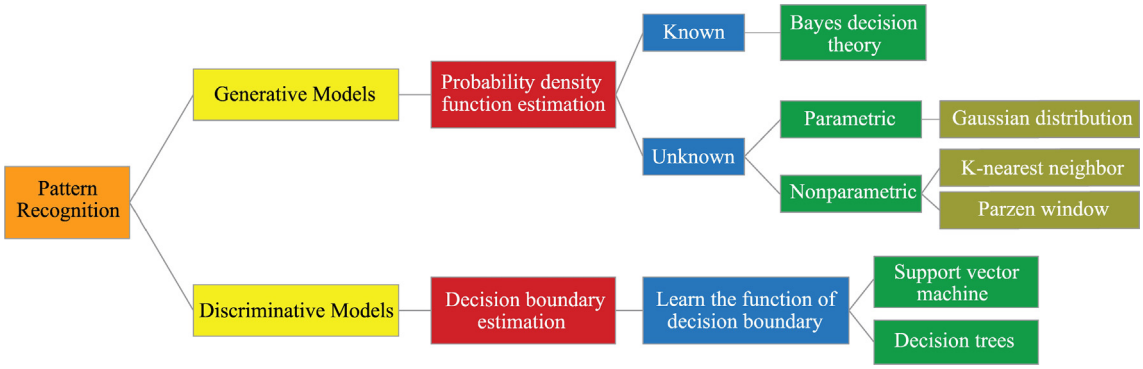

Fig. 4. Tree structure of generative and discriminative pattern recognition models and algorithms.

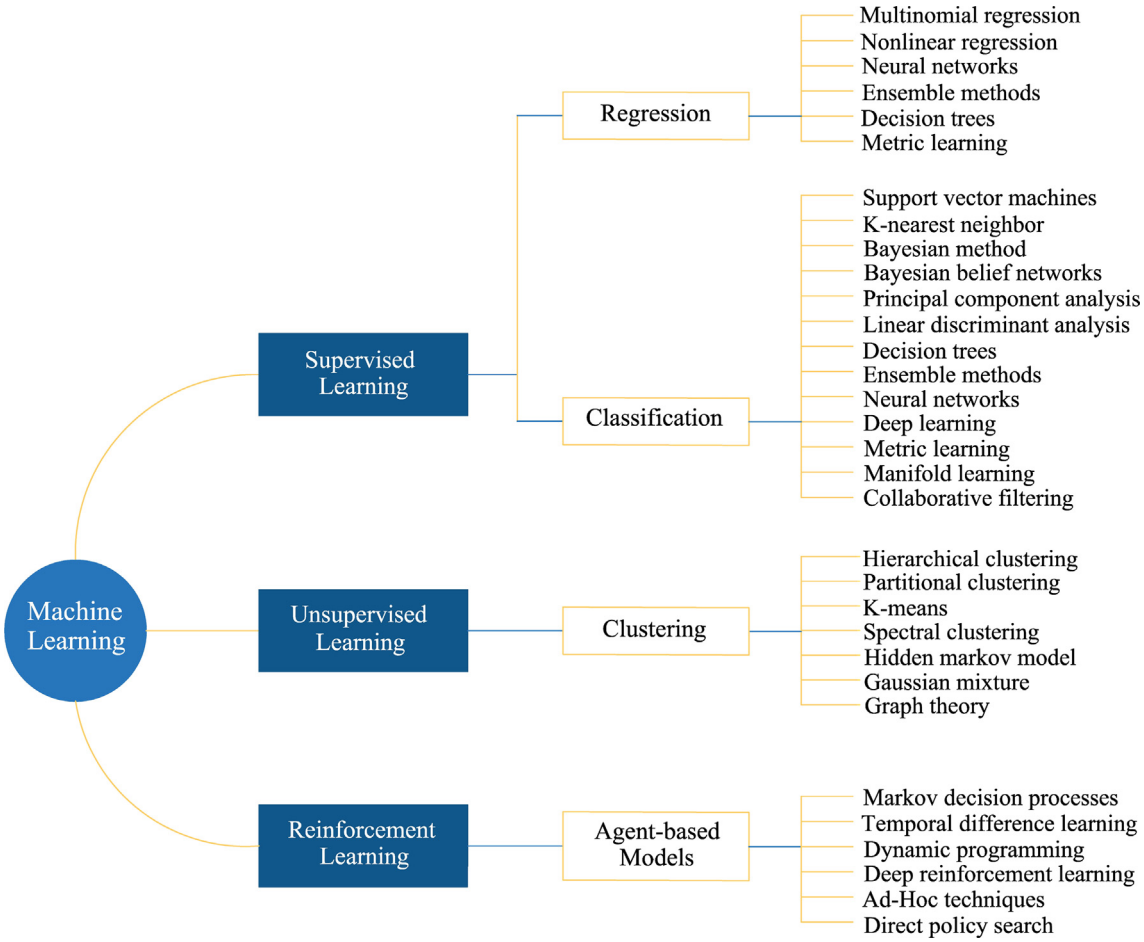

Fig. 5. Machine learning categories with commonly adopted algorithms.

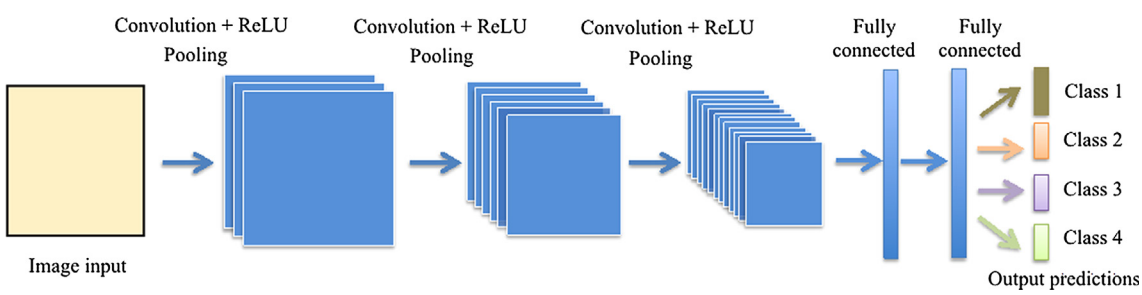

Fig. 6. Schematic of a typical CNN architecture.

computations because of a pooling process and sparsely connected neurons. Further, CNNs are able to simultaneously extract and learn optimal features from the raw data. Recent studies [69,70] have demonstrated that CNNs can outperform conventional artificial intelligence methods in both accuracy and speed. Generally, CNNs leverage the following ideas: local connectivity, parameter sharing, and pooling/subsampling of hidden units. The network consists of three layer types, namely convolution, pooling, and fully connected layers. CNNs alternate between the convolutional and pooling layers and the output is a fully-connected layer with a nonlinear classifier, e.g., softmax classifier, thus estimating the conditional probability of each class. To introduce nonlinearity in the CNNs, a rectified linear unit (ReLU) is typically used as a nonlinear activation function. In addition, among the different optimization algorithms, gradient descent algorithms are mainly used to train CNNs. The basic components of CNNs are described in the following sub-sections. A schematic of a CNN architecture for image recognition is presented in Fig. 6, where the network consists of three convolutional layers, three pooling layers, and three fully connected layers. For all layers in the network, ReLU is used as the activation function. Further, a softmax loss layer is appended to the fully connected layers for each classification task.

5. Applications

5.1. Pattern recognition

During the last decade, there has been a growing interest in the application of pattern recognition (PR) to structural engineering for purposes such as structural health monitoring (SHM)/damage detection, earthquake engineering and seismic design, structural reliability, structural identification, and performance evaluation. This activity is illustrated in Fig. 7 and a listing of works is summarized in chronological order (i.e., date of publication) in Table 1. The applications are classified with respect to the domain/problem type, the case structure,

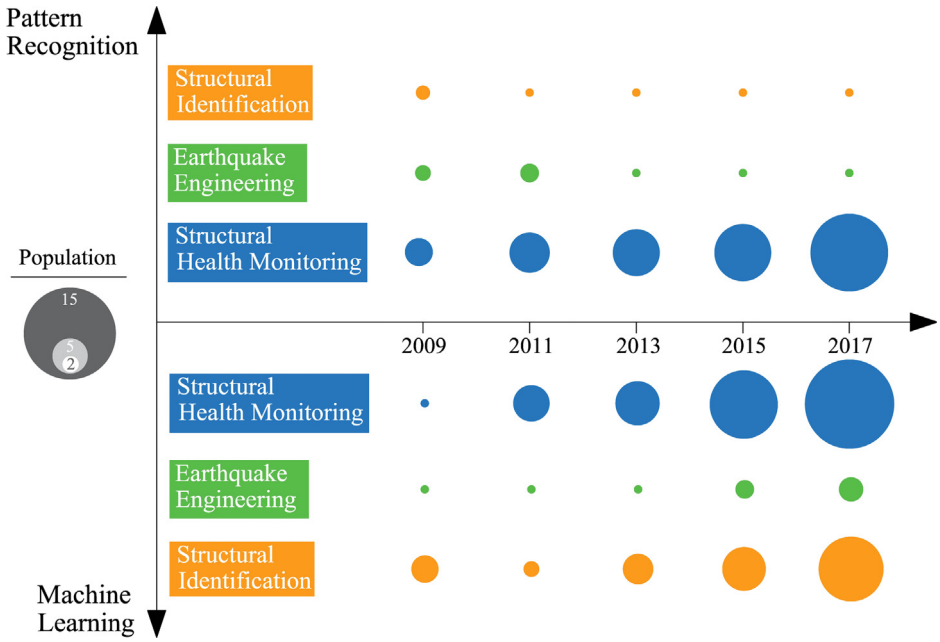

Fig. 7. Research publications on the use of machine learning and pattern recognition.

and the AI method/algorithm used for PR. The classification reveals that the most common use of PR in structural engineering has been for SHM and damage identification.

Two main approaches are commonly considered for damage detection: the inverse approach, known as system identification, and the forward approach, which relies on extracting information from the monitored structure. The computational complexity of the inverse approach, along with the physical importance of model updating, have motivated researchers to investigate methods from the second type of approach (forward) [71]. Therefore, PR is being most frequently utilized in the context of a forward approach for damage detection and SHM.

According to Sohn et al. [72], sensors measuring strain and vibration of a structure produce signals responding to the variation of environmental and operational conditions. Each group of signals can be considered as a pattern having a relationship with structural and ambient environments. The change in physical properties, mainly stiffness, is then reflected on the processed signals or patterns. Thus, the interpretation of signals/patterns can be performed by PR. The idea of using statistical PR for SHM was introduced by Farrar et al. [73,74]. Statistical PR can be described as collecting and processing data from sensors mounted on the structure to remove/filter environmental effects. In this context, statistical pattern comparison and statistical model development methods have been used to evaluate structural condition [75,76]. Most of the studies that focus on the application of statistical PR on SHM are based on the combination of time series modeling with a statistical detection method, such as outlier detection. As a result of using such methodologies only data from the undamaged structure is required in the training/calibration phase [77]. Sohn et al. [75,78] casted SHM within the context of statistical PR. For this purpose, they adopted autoregressive models and outlier analysis with the Mahalanobis distance measure to extract features and construct a reliable statistical model to assess structural conditions of the boat. Farrar and Sohn [79] studied the applicability of statistical PR for vibration-based SHM and described the relevant steps for such process. Worden et al. [80] adopted the methods of outlier analysis to the problem of damage detection, for which they used the Mahalanobis distance in order to detect damage. Further, Manson and Worden [81–83] studied the effectiveness of statistical PR using auto-associative neural networks, outlier analysis, and density estimation through numerical and experimental tests for SHM of an aircraft wing panel. They proved the applicability of the proposed statistical PR damage detection approach through these tests. In addition, Nair and Kiremidjian [84] introduced a time series algorithm based on an autoregressive moving average model for damage assessment of a benchmark structure, where they showed that the algorithm was able to identify and localize small to severe levels of damage. The authors also used a Gaussian Mixture Model to model the feature vectors and incorporated it with a time series-based damage detection algorithm for SHM [85]. They concluded that the proposed framework is useful, especially when several measurements can be used for robust damage identification. Cheung et al. [86] also studied the applicability of statistical PR for SHM of real-life structures, namely a bridge, for which they used autoregressive models. These studies have shown that by using statistical methods a single vibration signal can be analyzed separately from all other signals accumulated in the structure, thus allowing damage detection algorithms to be embedded at the sensor level. This results in significant savings in power and computational time, which are essential for the implementation of a wireless sensor network.

An SHM procedure cast within a statistical PR context is implemented in four phases [75]: (i) operational evaluation, (ii) data acquisition and networking, (iv) feature selection and extraction, and (v) statistical model development and discrimination. According to the recent literature, several studies concerning applications of PR in SHM have addressed all of these four phases. Regarding the operation evaluation phase, numerous techniques have been studied that are either based on linear or non-linear regression models among actions and effects [87], or based on latent variable techniques. Posenato et al. [88] proposed methodologies for model-free data analysis using moving principal component analysis (PCA) and robust regression analysis to identify and localize anomalous behavior in civil structures. Zhou et al. [89] introduced an approach to reconstruct input to back-propagation neural networks used for modeling the temperature-caused modal variability with long-term monitoring data. In addition, a technique based on symbolic data analysis for classifying the structural behavior of railway bridges was developed by Cury et al. [90]. The method was shown to be efficient to discriminate structural modifications based on vibration data. Further, a data-driven strategy integrating PCA, symbolic data, and cluster analysis was proposed by Santos et al. [91], where the method was demonstrated to be effective for early-damage

Table 1
Applications of pattern recognition (PR) in structural engineering.

Reference	Domain	Case structures	AI method used for PR
[125]	SHM	Flexible risers	Statistical PR based on time series analysis
[86,100]	SHM	Bridge structure	Autoregressive models
[117]	Damage detection	Bookshelf structure	Autoregressive models with principal component analysis (PCA)
[126]	Failure mechanism	Fiber-reinforced polymer (FRP) structures	Self-organizing map
[127]	Seismic damage detection	Frame structure	Artificial neural networks (ANN)
[118,119]	Structural identification	Five-story structure resting on shaking table	Support vector regression and autoregressive time series model
[102,103]	SHM	Four-story steel frame	Bayesian method incorporated with ANN
[128,129]	Damage detection	Four-story steel frame	Artificial immune PR method
[77]	SHM	Steel grid structure and simply supported steel beam	Autoregressive model with Mahalanobis distance-based outlier detection
[120]	SHM	Reinforced concrete frames	ANN
[130]	SHM	Railroad steel structure	Outlier analysis with Mahalanobis squared distance
[131,132]	Damage detection	Three-story steel frame and a bookshelf structure	Nearest neighbor classifier and learning vector quantization
[90]	Structural modification assessment	Bridge structure	Clustering techniques (unsupervised PR)
[89]	Modeling temperature-caused modal variability	Bridge structure	Back-propagation neural networks
[133,134]	Damage detection	Prestressed reinforced concrete beams	Statistical PR based on the Mahalanobis and Euclidean distance decision functions
[135]	Seismic performance	Reinforced concrete water tanks	Statistical PR
[88]	SHM	Beam structure	Principal component analysis and robust regression analysis
[93]	Damage detection	Three-story steel frame and a bookshelf structure	Artificial neural networks
[136]	SHM	Simply supported steel beam	Statistical PR based on an autoregressive model
[101]	Damage detection	Bridge slab and space truss	Statistical PR based on an autoregressive models
[137]	Earthquake engineering	Earthquake risk evaluation	Feed-forward multi-layer neural network
[96]	Damage detection	ASCE benchmark structure	PCA
[138]	Damage detection	Three-story steel structure	Statistical PR
[139]	Damage detection	Cantilever plate	Feed-forward multi-layer neural network
[76]	SHM	Bridge structure	Statistical PR based on a pattern comparison approach
[140]	Failure detection	Posttensioned concrete beam	Statistical PR based on a multivariate outlier analysis
[98]	SHM	PSC box girder bridge	Symbolic clustering method
[141]	SHM	Bridge structure and simply supported beam	Support vector machines (SVM) and neural networks
[142]	SHM	Bridge structure	Sparse representation and fourier discriminant method
[91]	Damage detection	Bridge structure	Principal component analysis (PCA) and symbolic data clustering
[143–145]	Damage detection	Bridge structure	Supervised statistical PR
[146]	Performance evaluation	Pretensioned prestressed concrete members	Feed-forward neural regression
[147]	SHM	Cable-stayed bridge structure	PCA and Mahalanobis squared distance
[148]	SHM	Aluminum beams	Bayesian approach
[121]	SHM	Suspension bridge structure	Artificial neural networks, support vector regression, random forest, regression tree
[106]	Damage detection	Plate structures	Multi-layer neural network and PCA
[149]	Damage detection	Three-story prototype building structure	Unsupervised PR based on an outlier analysis
[150]	SHM	Steel reinforced concrete structure	Statistical PR with autoregressive models
[107]	Damage detection	Two-story frame structure	Artificial neural network (ANN) with PCA
[151]	Performance evaluation	Steel beam structure	Statistical PR
[108]	Non-destructive evaluation	Concrete structure	Bayesian fusion model
[104]	Damage detection	Building structures	ANN and SVM
[105]	Structural modification assessment	Simply supported steel beam	Bayesian decision trees, neural network, and SVM
[94,152]	SHM	Four-story steel frame	Statistical PR based on a Mahalanobis squared distance
[122]	Damage detection	Three-story building structure	ANN
[153]	Damage detection	Steel beams	ANN
[110]	SHM	Bridge gusset plate	Probabilistic neural networks and Bayesian approach
[71,154]	Damage detection	Cable-stayed bridge structure	Statistical PR based on a Mahalanobis squared distance
[124]	Seismic damage detection	Concrete structures	Fuzzy PR
[112–114]	SHM	Plate-like structures	Bayesian method, nearest neighbor, two-dimensional principal component analysis (2DPCA), and two-dimensional linear discriminant analysis (2DLDA)
[155]	Risk-based management	Bridge structures	Statistical PR
[156]	Damage detection	Cable-stayed bridge structure	Multi-layer perceptron neural network
[157]	SHM	Plate-like structures	K-nearest neighbor method
[158]	Damage detection	Steel grid structure	Artificial neural network (ANN) and self-organizing maps (SOM)
[111]	Damage detection	Steel tower structures	Principal component analysis (PCA)
[123]	Damage detection	Aircraft skin panel	PCA
[159]	SHM	Composite cantilever beam	Neural network with back propagation based learning mechanism
[160]	SHM	Truss bridge and two-story frame structure	PCA and frequency response function
[109]	Damage detection	Wind turbine blades	Hierarchical nonlinear principal component analysis
[115]	SHM	Stadium structure	Autoregressive models with principal component analysis
[161]	Damage detection	Bridge structure	Statistical PR
[116]	Damage detection	Three-story frame structure	Cosine similarity measure
[162]	SHM	Steel beam	Principal component analysis

detection. To take into account the effect of environmental conditions, e.g., temperature, humidity, dead load redistribution effects, etc., for damage detection of bridge structures, Hsu et al. [92] performed nonlinear PCA using an auto-associative neural network. They showed that the approach is capable of dealing with both non-increasing features (stiffness) and non-decreasing features (damage index).

Methods having the ability to extract and fuse information from data in a sensor network are mainly based on autoregressive models, time frequency analysis, modal analysis, or PCA. Lautour et al. [93] presented a damage classification approach using time series analysis and PR, in which artificial neural networks (ANN) were used to determine the coefficients of the autoregressive models. Results suggest that ANN and autoregressive models are efficient tools for damage estimation. Additionally, an SHM strategy employing cepstral features as damage sensitive parameters was proposed by Balsamo et al. [94] for which the squared Mahalanobis distance was used. A decentralized damage detection approach using signal analysis (wavelet transform) based on wireless sensor data was developed by Yun et al. [95], while Kesavan et al. [96] proposed a wavelet-based damage diagnosis algorithm based on the combination of PCA and wavelet transform. Results revealed that both approaches were able to consistently detect and quantify damage. Further, most works related to statistical model development report the use of a statistical process control [97,98]. However, some of these methods are based on learning algorithms, i.e., support vector machines, neural networks, decision trees, and clustering algorithms [91,99].

Numerous algorithms, including autoregressive models, artificial neural networks (ANNs), support vector machine (SVM), etc., have been adopted and used for PR in structural engineering discipline. Autoregressive models have been extensively considered for feature extraction in numerous studies concerning the use of PR in structural engineering. Kiremidjian et al. [86,100] used autoregressive models for SHM of bridge structures. They demonstrated that damage detection algorithms based on PR methods can effectively detect structural damage. Gul et al. [77] and Yao et al. [101] utilized autoregressive models with a Mahalanobis distance-based outlier detection algorithm for damage detection in civil structures. These studies showed the superior performance of the proposed algorithms in terms of identifying damage with high-dimensional data sets. In addition, ANNs have been widely adopted for structural engineering applications, e.g., SHM and damage detection. Ng et al. [102,103] incorporated an ANN with a Bayesian method for health assessment of a four-story steel frame structure. ANNs have also been integrated with SVM and PCA, a method for dimensionality reduction, to develop PR-based damage detection techniques in civil structures. As a further example on the application of such PR methods in structural engineering, Radhika et al. [104] proposed a wavelet-based change detection method in which damage buildings are recognized using wavelet-extracted statistical feature and classification using ANN and SVM. They proved that the proposed damage classification method was accurate compared to methods employing conventional feature extraction. Further, they showed that SVM outperformed ANN in terms of damage classification accuracy. SVM has also been integrated with ANN for supervised learning classification [105] in structural modification assessment using vibration data from a bridge structure, and the method was found to be effective for continuous monitoring. As previously noted, PCA has been utilized and adapted for damage detection based on PR. An approach for damage detection in plate structures using a multi-layer perceptron network, in which PCA was utilized to retain the principal features, has been proposed [106]. Also, Bandara et al. [107] introduced a frequency response based damage detection method using a combination of PR and PCA. Ramos et al. [108] presented a methodology employing a Bayesian data fusion technique for non-destructive and destructive structural damage detection. They showed that the proposed method, within the context of PR, is able to decrease uncertainties for structural parameter estimation.

Recently, Perez et al. [109] introduced a hierarchical nonlinear PCA method for damage diagnosis in wind turbine blades. The authors demonstrated the effectiveness of the methodology based on strain measurements and PR for SHM. Further, Alavi et al. [110] proposed a damage assessment approach based on probabilistic neural networks and Bayesian decision theory, where they proved that the supervised classification method can be utilized for SHM purposes. In addition, Loh et al. [111] proposed an SHM methodology for damage identification and localization based on PCA, and investigated the applicability of the proposed PR method on a steel tower structure. Salehi et al. [112–114] presented an image-based PR approach based on integrating anomaly detection and a Bayesian method. They also utilized a nearest neighbor classifier, along with a two-dimensional principal component analysis and a two-dimensional linear discriminant analysis (well-established feature extraction techniques), for SHM in plate-like structures. Additionally, Datteo et al. [115] proposed a statistical PR approach integrating autoregressive models and principal component analysis, and explored the applicability of such approach for long-time health monitoring of large-scale structures. Zhou et al. [116] also introduced a damage detection technique using a cosine similarity measure. The authors demonstrated that the presented PR-based method can be effectively used in the context of SHM.

The research studies noted above indicate the significance of PR in structural engineering. Nevertheless, an in-depth analysis of some of the highest cited publications was performed to further investigate their contributions and limitations. Lautour et al. [117] proposed a damage assessment method using autoregressive (AR) models in which the computational burden of the approach was lessened by a dimensionality reduction technique (i.e., PCA). The authors showed that the AR coefficients form separable clusters by increasing the number of principal components, leading to good classification accuracy. Zhang et al. [118,119] introduced a structural identification method employing PR and support vector regression (SVR). SVR was integrated with autoregressive time series analysis for linear and nonlinear structural parameter identification (for damage detection) with vibration data of a five-floor structure shaking table test. Lautour et al. [120] presented an approach using ANN to predict seismic-induced damage on 2D reinforced concrete frames. Relations between parameters that describe the structure, ground motion, and damage were modeled using ANN. Laory et al. [121] developed a methodology to predict natural frequency responses of a suspension bridge with measurements of temperature, wind, and traffic loading, within the context of vibration-based SHM. Multiple linear regression, ANN, SVR, regression tree, and random forest were used to distinguish changes in natural frequency due to structural damage and environmental variations, and the method's prediction accuracy was compared. Bandara et al. [107,122] proposed a damage detection method using frequency response functions in which ANN, PCA, and frequency response functions were combined to detect various levels of nonlinearity using identified patterns. The authors applied the algorithm to a three-story structure and demonstrated the method's applicability for large amounts of data. Tibaduiza et al. [123] developed an SHM method in which PR, feature extraction, and sensor data fusion were examined with different damage indices. Performance of the proposed approach using PCA was tested for an aircraft skin panel and turbine blade. The effectiveness of the approach was validated; yet, the effect of environmental and operational conditions on the damage identification method was not considered. As a final example, Elwood et al. [124] proposed an approach based on fuzzy PR for seismic damage detection in concrete structures. The input to the fuzzy classifier was post-earthquake building damage data to determine the existence of building damage patterns. It follows that the noted studies highlight the emerging applications of PR in structural engineering.

Table 2
Applications of machine learning (ML) in structural engineering.

Reference	Domain	Case structures	AI method used for ML
[207]	Damage detection	Concrete slabs	Support vector machine (SVM)
[175]	SHM	Cable-stayed bridge structure	SVM
[199]	Modelling of concrete strength	Concrete beam	SVM
[208]	Earthquake engineering	Seismic evaluation	Bayesian method
[196]	Modelling of concrete strength	Concrete beam	SVM
[209]	Structural reliability analysis	Truss structures	SVM-based radial basis function (RBF) network
[210]	Seismic damage detection	Buildings with steel moment-frame structure	Neural network
[211]	Structural identification	Concrete bridge	Neural network
[212]	Structural identification	Concrete dam	Neural network
[197]	Prediction of concrete properties	Concrete block with fly ash	Support vector regression
[213]	SHM	Metallic structures	Adaboost machine learning
[214,215]	Performance evaluation	Self-compacting concrete	Artificial neural network (ANN)
[216]	Performance evaluation	Concrete dam	ANN and linear regression
[172]	SHM	Three-story frame structure	Singular value decomposition, Mahalanobis distance, auto-associative neural network, and factor analysis
[217]	Damage detection	Long-span arch bridge structure	SVM
[218]	Damage detection	Transmission tower	SVM and RBF neural network
[219]	Damage detection	Bridge structure	Neural network, SVM, and SOM
[220]	Performance evaluation	Steel beams	Linear genetic programming
[221]	Performance evaluation	Concrete dam	Artificial neural network (ANN)
[222]	Structural identification	Steel-box girder bridge	Principal component analysis (PCA)
[223]	Modeling concrete strength	Concrete cube	SVM
[224]	SHM	Cantilever beam	Dynamic Bayesian networks
[225]	SHM	Concrete structural components	SVM
[226,227]	Prediction of concrete strength	Concrete with construction and demolishing waste	ANN
[168]	Damage detection	Beams on ocean platform	Neural network
[228]	SHM	Steel pipes	SVM and adaptive boosting
[194]	Prediction of concrete properties	Self-compacting concrete block	SVM
[229]	SHM	Cantilever concrete beam	SVM
[201]	Prediction of concrete strength	Cylinder concrete	SVM
[230]	Damage detection	Steel structures	Multi-objective genetic algorithm
[191]	Concrete strength simulations	High performance concrete	ANN,SVM, Classification and regression tree, linear regression
[231]	Damage detection	Steel frame structure	SVM with Gaussian kernel
[232]	Performance evaluation	Concrete dam	Support vector regression
[195]	Prediction of concrete strength	Self-compacting concrete	Least square support vector machine
[233]	Prediction of concrete properties	Corroded reinforced concrete	SVM
[174]	SHM	Mesh-reinforced concrete structure	ANN
[234]	Earthquake engineering	Two-story building	Gaussian process regression
[206]	Prediction of shear strength	Fiber reinforced polymer concrete	ANN
[235]	Seismic damage identification	Reinforced concrete slab column frames	Multiclass support vector machine and multi-layer perceptron neural network
[177]	Damage detection	Bridge structure	Kernel regression method and principal component analysis (PCA)
[236]	Modelling concrete shear strength	Reinforced and unreinforced concrete joints	Multivariate adaptive regression splines and symbolic regression
[237]	Structural identification	Bridge structure	Gaussian process model
[238,239]	Structural reliability	Truss structure	Gaussian process machine learning
[239]	Predicting concrete compressive strength	Concrete specimen	Support vector regression and adaptive neuro-fuzzy inference
[240]	Damage detection	Bridge structure	SVM, regression, random forest
[241]	SHM	Truss structure	Least square support vector machine with a mixed kernel
[169]	SHM	Three-story steel frame structure	SVM
[176]	Seismic damage detection	Seismic performance	SVM, K-nearest neighbor method (K-NN), and random forest
[179]	SHM	Bridge structure	K-NN and k-means clustering
[181]	Damage detection	Bridge structure	Gaussian mixture models and genetic algorithm
[189]	Bridge design optimization	Post-tensioned concrete road bridge structure	Artificial neural network (ANN) and harmony search algorithm
[188]	Reliability-based optimization	Post-tensioned box-girder bridge structure	Modified harmony search algorithm
[190]	Damage detection	Reinforced concrete buildings	Neural network and genetic algorithm
[155]	Risk-based management	Coastal bridge structure	Optimization algorithm
[242]	Tensile strength prediction	Steel plates	ANN
[243]	Seismic performance	Six-story reinforced concrete frame structure	Support vector regression
[180]	Damage detection	Bridge structure	Bayesian inference and Markov Chain Monte Carlo simulation
[182]	SHM	Bridge structure	ANN
[157]	SHM	Plat-like structures	K-NN
[244]	Earthquake engineering	Seismic performance	SVM and neural networks
[245]	Shear capacity estimation	Fiber-reinforced polymer concrete slabs	Least square support vector machine
[246]	Reliability assessment	Steel-box girder bridge	Support vector regression
[247,248]	SHM	Movable bridge structures	Moving principal component analysis and robust regression analysis
[249]	Crack categorization	Reinforced concrete columns	Fuzzy logic
[250]	Performance evaluation	Steel-concrete composite beams	Extreme learning machine models, ANN, and genetic programming
[251]	Predicting concrete compressive strength	Concrete structures	SVM, Gaussian processes regression, and ANN
[252]	SHM	Wind turbine systems	Affinity propagation clustering
[170]	SHM	Aircraft wing structure	Low-rank matrix decomposition and K-NN
[253]	Structural parameter identification	Three story structure and three-span continuous beam	Particle swarm optimization

(*continued on next page*)

Table 2 (*continued*)

Reference	Domain	Case structures	AI method used for ML
[186]	SHM	Structural tower and cable-stayed bridge	l_1 minimization sparse recovery
[254]	Structural parameter identification	Three-story steel frames	Independent component analysis
[178]	Structural reliability assessment	Five-story structures, truss string structures, and cylindrical shell roof	SVM-based neural network
[255,256]	SHM	Steel plate	SVM
[171]	SHM	Reinforced concrete beams	Low-rank matrix decomposition
[257]	SHM	Cable stayed bridge	Compressed sensing based random encoding
[185]	Damage detection	Plate structure	Low-rank matrix decomposition
[258]	SHM	Aircraft wing structure	Low-rank matrix decomposition, K-NN, SVM, and ANN

5.2. Machine learning

Machine learning (ML) methods have been increasingly adopted over the last decade for modelling real-world problems concerning structural engineering (see Fig. 2). This is because of their enormous capacity to capture relations among input and output data that are nonlinear or complicated to formulate mathematically. The first uses of ML techniques in structural engineering have dealt with problems such as the development of management tools for structural safety [163], and information acquisition for the design of steel members [164]. In general, ML methods have been used for SHM and damage identification, optimization, performance evaluation, structural reliability and reliability assessment, and structural parameter identification (e.g., modeling material properties of concrete). Among these, SHM and concrete property modeling are the uses to attain most attention during the last decade. This can be seen in Fig. 7 and a listing works organized by year of publication is provided in Table 2.

5.2.1. Structural health monitoring and optimization

SHM involves monitoring of a structure through data collected from sensors, extracting damage sensitive features, and interpreting the extracted features for condition assessment of the structure. Significant progress has been made over the past two decades in the development of SHM models for different kinds of structures. The numerous studies carried out in this field can be categorized as model-driven and data-driven approaches [165–167]. A model-driven approach uses a numerical model of the structure, e.g., based on the finite element (FE) method, that correlates inconsistencies between the measured and model-generated data for damage detection. Although numerous studies have been conducted to develop model-driven approaches, these methods suffer from several shortcomings. First, the approach is computationally inefficient because it requires an iterative analysis of a computer simulation model. Second, results obtained from the simulation might not be accurate enough for precise evaluation of the structure. By contrast, in a data-driven approach the model is created through the learning gained from measured/sensed data. Damage can thus be detected by conducting a comparison among the measured data and a model. In fact, a data-driven model uses information from previously collected sensor data (i.e., training data). It is worth pointing out that data-driven approaches are beneficial if: (i) large volumes of data exist, (ii) the physical characteristics of the structure are unknown or complicated to model, and (iii) the aim is to decrease the computational effort.

A data-driven approach commonly adopts techniques from pattern recognition (PR) and machine learning (ML). ML in the context of SHM is expressed as creating knowledge from previous experiences, learning the model parameters, and then focusing on predicting new input data. Different learning schemes, such as supervised and unsupervised learning, have been used in SHM applications. Algorithms including artificial neural networks (ANNs) [168], support vector machine (SVM) [169], *k*-nearest neighbor method (*k*-NN) [170], principal component analysis (PCA) [123], and low-rank matrix decomposition [171] are attractive for structural damage identification within the context of ML due to their effectiveness and robustness while dealing with insufficient information, noise, and uncertainty. As mentioned before, there has been a growing interest in the use of ML for SHM models during the last decade. As an example, Figueiredo et al. [172] investigated ANNs, Mahalanobis distance, singular value decomposition techniques, and factor analysis to study environmental variability and its effect on damage detection in civil structures. They used a three-story frame structure as a case study to obtain time-series data from accelerometers, and the data was fed into different ML algorithms. They showed that the Mahalanobis distance provided the best classification accuracy. Dervilis et al. [173] investigated the SHM of wind turbine blades using neural networks. Yan et al. [168] reported on the use of a back-propagation neural network and SVM for damage assessment in beams mounted on ocean platforms. Butcher et al. [174] examined the use of ANNs and extreme learning machine methods for SHM in mesh-reinforced concrete structures. The study revealed that these algorithms can outperform traditional ANN methods. Liu et al. [175] studied SVM for damage detection of a long span cable-stayed bridge and demonstrated that SVM is more accurate compared to a back-propagation neural network. Gui et al. [169] presented a data-driven SVM approach using optimization algorithms, i.e., grid-search and particle swarm optimization, for damage diagnosis of a three-story frame structure. They proved that a genetic algorithm-based SVM yields a better prediction than other methods. Gong et al. [176] also evaluated the applicability of SVM, random forest, and *k*-NN methods for earthquake-induced damage identification in buildings employing images. Results showed that the proposed approach was capable of differentiating collapsed and standing buildings. Lederman et al. [177] used PCA along with a kernel regression method, within the context of signal processing and ML, for damage quantification and localization in bridges. Results suggested that PCA can be effectively used to decrease the dimensionality of the signal, while a kernel regression can be employed to map the signals to the bridge condition. A wavelet SVM-based neural network metamodel for reliability analysis was proposed by Dai et al. [178] to expand the application of wavelet neural network to higher dimensions. The authors used a set of wavelet SVM with various resolution as the activation function of wavelet neural network, where they tested the applicability of the proposed method on five-story structures, truss string structures, and cylindrical shell roof. Further, Diez et al. [179] presented a clustering-based approach incorporated *k*-NN, *k*-means, and Fourier transform for vibration signal processing to detect damage and abnormal behavior in bridge joints. The clustering approach helped to group joints with similar behavior, increasing the SHM performance. Zheng et al. [180] introduced a probabilistic classification framework using vibration measurements to assess the probability of barge collision damage on bridge piers, where Bayesian inference combined with Markov Chain Monte Carlo simulations and PCA were used to extract the feature vectors from variations in modal properties due to damage. Results revealed that the approach can be effectively used to determine the probability of structural damage locations. Santos et al. [181] proposed a hybrid approach based on Gaussian mixture models (GMM) to discover the normal state of a bridge, in which the GMM parameters were estimated through a hybrid

method based on an expectation–maximization algorithm. Results confirmed that the proposed algorithm was more stable than other genetic algorithms in terms of damage detection performance. A model-free damage assessment method based on ANN was presented by Neves et al. [182] for SHM of bridges. The ANN was trained with an unsupervised learning algorithm using accelerations from a bridge, the prediction errors were characterized using a Gaussian process, and damage indices were compared with a threshold to identify damage. The noted studies highlight the importance of ML for data-driven SHM and damage assessment techniques.

Recently, a new class of ML methods, namely low-rank matrix decomposition and singular value decomposition, having the ability of dealing with sparse and incomplete data have been adopted by the SHM community. Structural response measurements from mounted sensors can be represented as a data matrix. These measurements possess a low-rank structure and sparsity nature, which can be processed by emerging mathematical tools such as sparse representation and low-rank matrix decomposition. Salehi et al. [170] presented a machine learning framework for health monitoring of an aircraft stabilizer based on the integration of low-rank matrix decomposition and *k*-NN techniques. They validated the proposed approach through the interpretation of self-powered wireless sensor data generated from a network communication protocol using energy-efficient pulse switching technology [183]. The authors further employed low-rank matrix decomposition and statistical methods for health monitoring and localized damage identification in plate-like structures, and used a data fusion concept to combine the information obtained from a network of self-powered sensors [184]. Nagarajaiah et al. [171] presented a new paradigm for damage detection based on modelling and harnessing sparse and low-rank data structures. They demonstrated that the proposed method is able to effectively address structural dynamics, identification, monitoring, data sensing and management problems. Yang et al. [185,186] also utilized low-rank matrix decomposition along with nuclear-norm-minimization methods for recovering structural vibration responses from a steel tower and a cable-stayed bridge. The authors developed a global computational approach to analyze sparse sets of 2D strain measurements for damage localization. The proposed data-driven approach increased the effectiveness of SHM when limited numbers of strain sensors were deployed. The studies discussed in this paragraph show the use of numerous types of ML algorithms for assessing structural health; and that under specific circumstances these methods can outperform model-driven approaches while being satisfactorily accurate.

Within the context of optimization, ML has been used for infrastructure maintenance and durability assessment. Yepes et al. [187] proposed a cognitive method for selecting an optimal solution for the multi-objective optimization of high-strength reinforced concrete beams, where different Minkowsky metrics were used for the optimization task. Garcia-Segura et al. [188] presented a reliability-based method employing a modified harmonic search algorithm to optimize the design of post-tensioned concrete box-girder bridges under corrosion attack. The authors demonstrated that lower life-cycle cost is correlated to designs with longer corrosion initiation time. The same research group further used multi-objective harmony search integrated with ANN to decrease computational demand for the finite element analysis of post-tensioned box-girder bridges [189]. Mondoro et al. [155] proposed an approach for optimal risk-based management strategies for bridges in which they considered the uncertainties associated with hazards, economic, social, and environmental outcomes of failure under traffic loads and hurricanes. Chatterjee et al. [190] employed a multi-objective genetic algorithm for calibration of a neural network model to minimize the root mean squared error and maximum error of the network. Results of structural failure classification for reinforced concrete buildings indicated that the proposed optimization algorithm outperformed a multi-layer perceptron feed-forward network. The mentioned studies indicate the wide applicability of ML for structural optimization.

5.2.2. Mechanical properties of concrete

The design of concrete structures requires considering several key mechanical properties of the material, such as compressive strength, splitting tensile strength, shear strength, and elastic modulus. Linear or nonlinear regression models to these material parameters have been proposed to save time and costs associated with material testing [191,192]. However, the mechanical properties of concrete are known to have strong nonlinear relations between the constituents and the macroscale material characteristics [167,193]. Therefore, the development of reliable models is of interest to explore material mechanical properties in a way that optimizes cost and time. The potential of ML algorithms has been harnessed to model such properties and address the noted issues.

Several ML algorithms, such as neural networks, genetic programming, fuzzy logic, and support vector machines (SVM) have been used to develop accurate models to forecast the mechanical properties of concrete. Most significantly, ML algorithms have been used for modeling the properties of self-compacting concrete [194,195] (e.g., strength, elastic modulus), as well as modeling the tensile and compressive strength of normal concrete [196,197]. As an example, Yeh et al. [192] proposed a genetic operation tree composed of an operation tree and a genetic algorithm to generate formulas that predict the compressive strength of high-performance concrete. Cheng et al. [198] used a genetic weighted pyramid operation tree to construct a model for determining the compressive strength of high-performance concrete. The obtained model gave better results, using benchmark tests, in comparison to ANN, SVM, and evolutionary support vector inference models. Xu et al. [199] established an SVM-based model to assess the relation between the strength and mechanical properties of concrete obtained from non-destructive testing. They showed that the proposed method is less computationally demanding, while also providing high accuracy in its predictions compared to other numerical methods. Yan and Shi [200] investigated the applicability of SVM for predicting the elastic modulus of normal and high strength concrete. They discovered that SVM has superior performance compared to ANN models. Yan et al. [201] developed an SVM model with experimental data from the literature and compared the results with empirical design equations. They showed that an SVM model is capable of accurately estimating the splitting tensile strength from compressive strength. Parsad et al. [202] used a neural network to predict the compressive strength of self-compacting and high performance concrete. An artificial intelligence system based on combination of fuzzy logic, weighted SVM, and fast messy genetic algorithms was developed by Cheng et al. [203] to predict high-performance concrete compressive strength, where results showed that the method achieved higher performance compared to SVM. Saridemir [204] used gene expression programming to determine the splitting tensile strength concrete from its compressive strength. Results showed that the proposed formulations led to the best accuracy and were able to predict splitting tensile strength similar to experimental results. Nedushan [205] introduced an adaptive network-based fuzzy inference system (ANFIS) model and an SVM for predicting the elastic modulus of normal and high strength concrete, and found that the ANFIS model outperformed nonlinear regression models and the predictive models in the literature. Lee et al. [206] presented a theoretical model using ANNs to predict the shear strength of slender fiber reinforced polymer reinforced concrete beams, which was shown to perform better than other existing equations. All these studies concluded that ML methods are influential tools for evaluating the mechanical properties of concrete without being affected by data complexity and incoherence.

5.3. Deep learning

During the last few years, there has been a growing interest in the

use of deep learning, e.g., convolutional neural networks (CNNs) for structural engineering applications, mainly in structural health monitoring (SHM). The application of CNNs is very new in the field of SHM and damage detection. CNNs within the context of SHM are defined as learning and extracting optimal features and classification using learned features. As previously discussed, CNNs are primarily designed for two-dimensional signals (e.g., images, video frames, etc.), thus leading to an efficient image recognition method. Therefore, CNNs are categorized and used as vision-based SHM techniques in which dataset are images captured at various states of the structure being monitored.

The first use of CNNs in structural engineering was conducted by Sarkar et al. [259] for characterizing crack damage on composite materials. Further, Abdeljaber et al. [260,261] introduced a vibration-based structural damage detection approach using one-dimensional CNNs. They proved that the method was capable of learning directly from the measured acceleration data, yielding an accurate approach for health monitoring of civil structures. However, the proposed system, especially for large civil structures, suffered from the fact that a large number of measurement sessions was required to generate the training data. To overcome this drawback, they proposed a nonparametric damage identification method using CNNs that required two measurement sessions to generate the training data [262]. They showed that the SHM system was effective in estimating the actual amount of damage. Cha et al. [263] presented a deep learning network to detect concrete cracks in the tunnels without the need for computing defect features. They also conducted a comparative study to show how the proposed deep learning-based damage assessment approach was able to detect concrete cracks in a robust manner compared to traditional image detection methods. Gulgec et al. [264] proposed a structural damage identification method using CNNs to discover the unknown relation between the measurements and patterns representing damage. Lee et al. [265] also investigated the applicability of deep learning and CNNs for structural analysis in a ten bar planar truss and proved that such techniques are more efficient compared to conventional neural networks. All these studies suggest that deep learning/CNNs architectures are effective tools for monitoring structural health, and that these frameworks are establishing themselves as viable methods for a new generation of vision-based SHM systems.

6. Discussion and future directions

This study reviewed papers published during the last decade concerning the applications of emerging AI methods, namely, pattern recognition (PR), machine learning (ML), and deep learning (DL), in structural engineering. The papers were thoroughly reviewed to identify the nature of the problem, the AI algorithms adopted and used, and to assess the methods' applicability for the given problem. The survey showed that PR and ML are being widely used by the structural engineering community for applications, such as SHM, structural identification, earthquake engineering, etc. Yet, the most common use for PR and ML has been for SHM. The review further indicated that DL architectures have also been utilized for SHM and damage identification. It is to be expected that the use of AI in structural engineering will increase as their potential is better understood and as new methods are developed.

Current and emerging applications of ML, PR and DL in structural engineering are shown in Fig. 8. The following sub-sections discuss future directions for AI-based methods, including emerging applications and issues for improving their efficiency and robustness.

6.1. Data-driven SHM systems with self-powered sensing technology

Performance of the noted AI methods for SHM applications strongly depends on the amount of data collected through the monitoring system. Wireless sensor networks (WSNs) have emerged to overcome the drawbacks of wires in dense sensor arrays, and have increasingly become an alternative to traditional SHM systems. Durability monitoring using WSNs transforms the way of inspecting structure s to an automated, rapid, and objective manner. Additionally, continuous remote monitoring using WSNs for long periods of time is more economical than conducting periodic field experiments or inspections. Recently, self-powered sensors have evolved to be able to harvest the needed power (for computational, storage and transmission requirements) from the signal being sensed as well as form ambient vibrations, thus providing a promising alternative to traditional sensor systems. PR, ML, and DL methods can then be integrated with self-powered wireless sensor networks to present the new type of data-driven SHM systems that are energy-lean.

Data-driven approaches are nowadays combined with empirical models to monitor the state of a structure. Although these approaches enhance performance prediction, they still depend on empirical formulas, which have the previously discussed limitations. However, data-driven approaches for SHM solutions are expected to rely on data collected from embedded/mounted sensors along with artificial intelligence techniques. ML and PR are powerful tools to extract information and develop predictive models from large data. Furthermore, the increased use of these intelligent methods in structural engineering clearly indicates that these methods are becoming predominant approaches for SHM. The incorporation of WSNs and the noted AI methods for structural engineering purposes could result in the efficient inspection and assessment of civil structures, as the evaluation can be performed remotely through sensors with wireless data transmission capabilities and by interpreting data using PR and ML techniques. Furthermore, ML algorithms are able to learn the complex interrelation among influencing factors, thus performing predictions without the need for empirical models, while also being able to improve on their predictive capability. Advancements in self-powered sensors have also promoted the development of energy-efficient network technologies, such as the pulse switching protocol [183,266], which can be coupled with ML algorithms for SHM and damage identification [170,184,258,114]. As a result of using such an intelligent system, the constraint of a communication power budget for an SHM sensor network can be addressed, thus leading to a reliable and efficient SHM system.

6.2. Vision-based SHM systems and computational mechanics

Deep learning methods emerged to interpret big data in order to identify implicit features from it, and to classify the learned features. Deep learning-based damage detection techniques have been found to be computationally efficient. Unlike conventional ML techniques that use hand-crafted features that result in high computational complexity, DL and CNNs use optimal features learned by the network, thus increasing the classification accuracy significantly. Further, the structure of the DL architecture, specifically one-dimensional CNNs, make their mobile and low-cost hardware implementation quite feasible. Therefore, it is expected that DL will play important role in the future generation of vision-based SHM systems, i.e., those based on computer vision techniques [263,267,268]. Another interesting potential application of ML and DL is in the computational mechanics domain [269]. In computational mechanics, problem solving rules strongly depends on an expert's insight. Such rules are valid when certain assumptions hold, thus indicating a limitation of the expert's ability. To cope with this difficulty, ML and DL can be used to automatically discover the rules required to solve computational mechanics problems such as those using the finite element method (FEM). DL methods are able to generate implicit rules and discover mapping relations among the input-output data. For instance, optimizing numerical quadrature is an essential problem to the FEM that requires great amount of computation. However, DL can be used as a tool to address such problem. A framework of computational mechanics methods enriched by DL/CNNs can be developed and applied to optimize numerical quadrature in order to

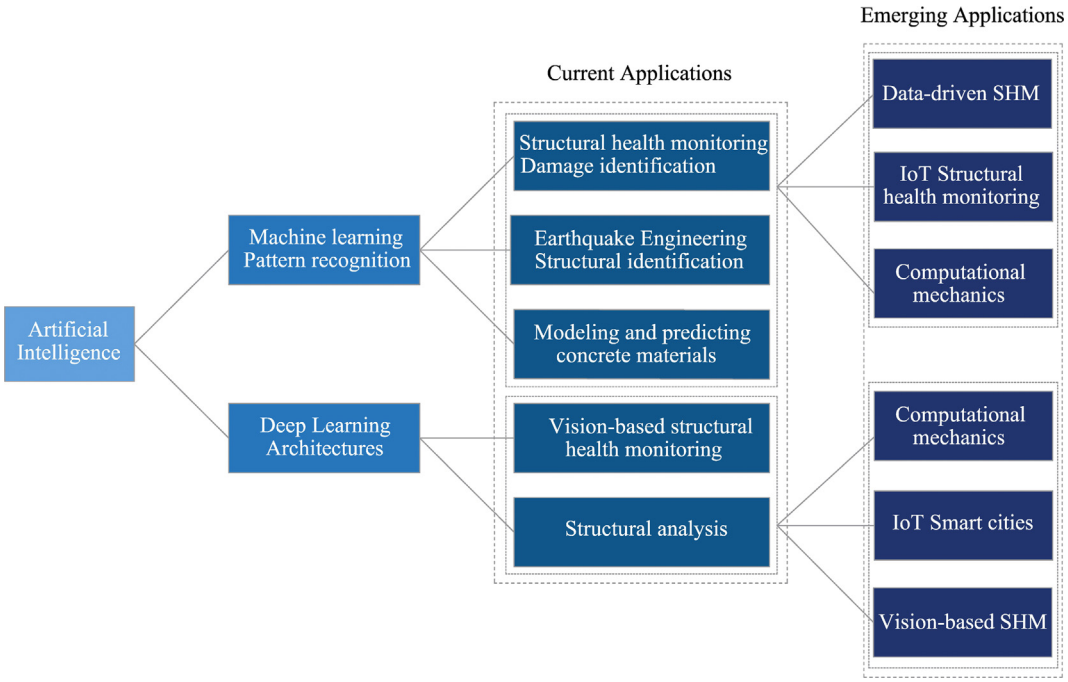

Fig. 8. Applications of ML, PR, and DL in structural engineering.

compute the FEM element matrices. That is, the number of integration points in the numerical quadrature of the element stiffness matrix can be minimized for the prescribed range of error predicted thru DL. The DL architecture can also estimate the most accurate result by optimizing the numerical quadrature parameters.

6.3. SHM systems with IoT

The durability of civil infrastructures has nowadays become a big issue given the number of structures that need to be repaired, and concerns on the efficiency of traditional techniques used to manage maintenance and repair actions. This situation is creating a paradigm shift toward cutting-edge technologies such as the Internet of Things (Iot) [270]. The IoT refers to a system in which WSNs mounted with intelligent software and local computing power could be effectively used for the monitoring of structures. IoT aims to increase machine-to-machine communication thru wireless integrated sensors with the goal of monitoring devices remotely and efficiently. In this new paradigm, smart devices collect data, transmit information, and process information collaboratively using cloud computing techniques. Software is also needed to extract useful information from the large amount of data that is generated. On this basis, ML could be integrated with IoT for SHM purposes [271–273]. ML can thus become an essential tool that can be applied to expand the boundaries of IoT. On the other hand, the important issue regarding the SHM of structures, such as bridges, is to constantly monitor the installed sensors and to compare the new data with previous readings. It is, however, a challenging task to visit all monitored bridges given the fact that they are typically geographically distant from each other. Thus, a technology that links all sensors on the bridges to a common recording device is needed. Further, it is essential to link collected information to a centralized monitoring station that could receive all the data from the sensors through the internet. The IoT and noted artificial intelligence methods could be used to effectively address the noted difficulties. Accordingly, the IoT will enable engineers to collect data from several bridges for further analysis. ML can then be used for data analysis and interpretation. Structural health assessment employing IoT could provide a promising solution for rapid, accurate, and low-cost SHM systems. The integration of SHM, IoT, and cloud computing can lead to powerful processing of the sensed data compared to traditional SHM systems. In fact, cloud platforms can enable an SHM system to store and use data from smart monitoring devices. The structure's health status can then be sent to an Internet server, and data stored on the server can then be monitored remotely from a mobile device and interpreted using ML.

6.4. Smart cities with IoT

The concept of smart cities has been recently gaining attention in diverse engineering communities, and the application of the IoT paradigm to smart cities is generating research interest [274–277]. The main aim of a smart city is to make better use of public services and to reduce operational costs. In other words, the goal of a smart city is to make infrastructure smarter in order to use resources efficiently. The achievement of this goal depends on a data provided by the wireless sensor networks deployed in cities. The IoT for a smart city can provide distributed data of structural integrity measurements of monitored structures using data collected by sensors, where DL architectures, e.g., CNNs, can be used as tools to interpret data and classification [278,279]. The data collated from a city varies so much in format and quality that it is difficult for one given system to effectively process all such data. The fact that every city is unique and has a different set of problems yields the need for smart data interpretation techniques. Thus, robust layers for data collection, communication protocols, data storage, etc. need to be built. DL can then be used as a viable tool for interpreting such large amounts of data. DL can be utilized to train systems to recognize patterns for large numbers of real-time networks and provide early recognition of developing network performance issues. On the other hand, the big challenge for the smart cities concept is how to deal with the large amount of time series data, a particular form of sequential data, received from connected sensors. DL architectures (e.g., CNNs) are very efficient in the analysis of sequential data. DL platforms can thus enable a system to solve optimization problems relating to smart cities and structures.

The notion of a smart city is to use sensors within the city's infrastructures to ensure sustainability, safety, and efficiency. Recent progress in nanotechnology have led to the emergence of a new class of sensors, e.g., self-sensing materials that can provide smart cities with methods to assess and monitor the condition of the infrastructure.

Smart concrete, having the ability of enabling any concrete structure with self-sensing capabilities, is one of the most promising technologies [280–282]. Such functional property is achieved by correlating the variation on internal strain with the variation of appropriate material properties, e.g., electrical resistance. Sensors fabricated using a cementitious matrix with nanoinclusions of carbon nanotubes can be used for condition assessment of concrete structures and traffic monitoring in smart cities. Consequently, AI methods can be effective in the interpretation of sensor data. Other examples include new developing approaches to detect the first stages of corrosion in concrete structures. The aim is to monitor the state of concrete during the curing period, leading to concrete structures with increased lifetime and safety. To accurately monitor the strength and temperature of concrete during curing, sensors are embedded in the concrete at the time of placement and measurements are communicated to smartphones through IoT. AI methods such as ML and DL can then be used to interpret the collected data for structural assessment.

6.5. Improving the performance of AI methods in structural engineering

The findings that make AI methods such valuable tools have been particularly highlighted. However, it is well known that all methods and models have limitations. Table 3 summarizes some general advantages and disadvantages of PR, ML, and DL for structural engineering applications. Further, there are aspects of the implementation of the noted AI methods that could help enhance their performance. First, it is clear that use of AI methods for solving structural engineering problems is no longer at the initial phase. Therefore, it becomes important to shift from exploratory uses to well targeted and rational implementation of the diverse algorithmic options, since different AI methods can lead to various levels of performance and accuracy depending on the application. It is thus important that future studies present a clear rationale for the chosen AI method(s). Another important issue is computational efficiency. Commonly, the performance of an AI method can be defined in terms of accuracy and computational efficiency (i.e., less simulation/computational time). It should be noted that some of the publications studied in this review indicated the good performance of AI method being used, even though the method was found to be computationally expensive. Hence, it is of importance that future studies consider this issue such that the AI methods being used result in good accuracy while also being computationally efficient.

Measurement noise, modeling errors, environmental effects, etc., are unavoidable factors that could significantly affect data availability. It is thus essential to use AI methods that can effectively interpret incomplete and noisy data, and to assess their performance under these influences. Uncertainty analyses could be used for this purpose. The selection of optimal parameters/hyper-parameters can also significantly affect the performance of AI methods. Thus, future studies implementing AI techniques should take into account the noted issue such that optimum algorithmic parameters are chosen. Finally, clear presentation of the process by which the dataset is prepared and preprocessed (i.e., training, validation, and testing) is essential to properly assess the performance of the implemented AI-based methodology.

7. Conclusions

This review paper presented the significance of emerging AI methods for structural engineering applications during the last decade. The survey indicated that among the numerous AI methods, pattern recognition (PR), machine learning (ML), and deep learning (DL) have been increasingly adapted and used for SHM and damage identification, optimization, modeling concrete properties, structural identification, earthquake engineering, etc. Yet, the common use of the noted methods has been for interpreting sensor data in SHM. The survey revealed that ML, PR, and DL algorithmic techniques have the ability to learn complicated interrelations among the contributing parameters, and thus allow solving a diversity of problems that are difficult, or not possible, to solve with traditional methods.

Based on the literature survey, potential research avenues for employing PR, ML, and DL were also presented. Considering the emerging use of wireless sensor networks (e.g., self-powered sensor networks), ML- and PR-based models could become the next generation approaches to conduct non-destructive structural and material evaluation in SHM. This review showed that ML methods are able to discover hidden information about the structure's performance by learning the influence of various damage or degrading mechanisms and the data collected from sensors, leading to reliable and efficient SHM frameworks. The literature further suggests that ML and DL techniques could also be applied to the computational mechanics domain, such as to optimize processes in the finite element method to enhance computational efficiency. These methods can also be used to solve complex problems through the novel concept of the Internet of Things (IoT). On this basis, ML and DL architectures (e.g., convolutional neural networks) within the context of IoT can be used to analyze and interpret complex and big data. Further, the integration of ML and IoT can result in the creation of novel SHM systems employing diverse and noisy sensor data. DL architectures can also be incorporated with IoT to develop unique frameworks for use in smart cities. Data interpretation systems, which are part of the noted frameworks in smart cities, can thus be optimized using such intelligent architectures.

Finally, the review was also used to identify general challenges and limitations on the use of AI techniques. Among those limitations is the lack of rational selection of the AI method, disregarding the effect of missing/incomplete and noisy data, discarding considerations for computational efficiency, reporting classification accuracy without exploring alternative solutions to increase performance, and insufficiency

Table 3
Comparison of different AI methods for structural engineering applications.

	AI methods		
	Pattern recognition	Machine learning	Deep learning
Advantages	Applicable for traditional and data-driven SHM systems Do not necessarily need vast amount of data Can be effectively used for classification and recognition problems	Applicable for traditional and data-driven SHM systems Can be integrated with IoT for smart applications Applicable for optimization problems Do not necessarily need vast amount of data Computationally efficient	Applicable for vision-based SHM systems Effective while dealing with large amount of dataset Applicable for interpretation of Big data in smart cities Can be integrated with IoT for smart applications Computationally efficient
Disadvantages	Cannot be directly integrated with Iot for smart and intelligent applications It does not imply learning	Cannot be used for new vision-based SHM systems based on images	Cannot be effectively used for traditional SHM systems Need vast amount of data for efficient performance

presentation of the process to select optimal parameters for the AI technique. However, it was concluded that by addressing the noted issues/limitations in future studies, ML, PR, and DL could represent pioneering methods to increase the efficiency of many current structural engineering applications as well as for the creation of innovative uses.

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