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Advancing Bridge Structural Health Monitoring: Insights into Knowledge-Driven and Data-Driven Approaches

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Abstract: Structural health monitoring (SHM) is increasingly being used in the field of bridge engineering, and the technology for monitoring bridges has undergone a radical change. It has evolved from the initial local monitoring and assessment, which relied mainly on manual work, to the current all-round and full-time intelligent assessment provided by intelligent monitoring systems. This paper reviews the development of SHM technology in the civil engineering field and examines two current artificial intelligence (AI) methods in bridge SHM, namely knowledge-driven and data-driven approaches. The advantages and disadvantages of these two AI methods are analyzed, and future development trends are also discussed. The overview results reveal that knowledge-driven methods have the advantages of interpretability and stability. However, their current application is limited, and significant technical bottlenecks remain. On the other hand, the data-driven approach demonstrates higher efficiency and accuracy. Nevertheless, it is characterized by instability and insecurity due to its "black-box" nature, which hinders its ability to explain the internal operation mechanism. Given these findings, the hybrid knowledge-data-driven approach emerges as a potential solution. This approach can effectively integrate the advantages of both knowledge-driven and data-driven methods while avoiding their respective disadvantages. Consequently, the hybrid approach proves to be more stable, safe, and efficient in practical applications.

Keywords: deep learning, machine learning, structural damage, crack detection

1. Introduction

Bridge monitoring technology has undergone a fast transformation from the initial local monitoring and assessment, which mainly relied on manual work, to the present-day intelligent monitoring systems that provide all-round and full-time intelligent assessments.

Large bridges are crucial structural projects in the transportation system, playing a pivotal role in the local traffic conditions. As the service life of bridges increases, the deterioration of the service environment gradually reveals structural health problems. These issues arise from daily operational loads during long-term use, as well as unpredictable contingencies such as earthquakes, traffic accidents, and typhoons, which can cause varying degrees of damage to bridge structures, posing safety hazards [1]. Consequently, bridge structural health monitoring (SHM) has become a prominent research topic for scholars worldwide, aiming to prevent health hazards and property damage caused by bridge structural accidents.

From the moment a bridge is constructed, its SHM becomes indispensable. Traditional methods for monitoring structural health mainly involve direct manual observation and manual monitoring combined with simple instrumentation. However, these approaches have significant limitations, relying heavily on manual involvement and suffering from drawbacks like being time-consuming, laborious, subjective, and difficult to quantify, lacking comprehensiveness and systematization. The practice of SHM for bridges started in the 1950s when technology and methods were relatively primitive, resulting in simple and inadequate monitoring approaches with poor systematization and integrity. In the 1980s, Britain installed the first automatic bridge data acquisition system and monitoring instruments for the new bridge Foyle in Northern Ireland. Subsequently, more countries, including China, began researching SHM systems for large bridges. During the 1990s, a period marked by significant infrastructure development in China, the proposal to establish a structural monitoring system for large bridges was put forth. Although manual monitoring is still prevalent for most large bridges in China, equipping each of them with a suitable structural monitoring system is becoming an evident future trend.

Artificial intelligence (AI) was first introduced in 1956 and has since garnered considerable attention from experts and scholars globally across various fields. AI, integrated into computer systems, provides new problem-solving approaches in different disciplines, demonstrating more advanced and efficient capabilities compared to traditional research methods. Presently, AI methods combined with bridge structure monitoring systems primarily address two types of problems: visualization problems based on damage morphology identification, such as structural damage morphology identification, and non-visualization problems based on vibration response, such as bridge structure damage identification and prediction using vibration monitoring data [2].

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During the period from 1956 to the 1980s, two competing schools of thought dominated AI: the symbolism school and the connectionist school. Influenced by these schools, AI approaches applied to bridge SHM systems can be categorized into two main groups: knowledge-driven approaches based on knowledge-based reasoning [3] and data-driven approaches reliant on vast amounts of labeled data [4]. Both knowledge-driven and data-driven perspectives have notable limitations, as they only simulate specific aspects of human thinking, falling short of true human intelligence [5]. To achieve genuine human intelligence, it is necessary to overcome these shortcomings and establish a knowledge–data hybrid-driven research approach. The knowledge–data hybrid-driven method is built on the foundation of both approaches, providing a more secure, reliable, explanatory, and robust AI technique, and it represents a significant future direction in the development of bridge SHM.

In this paper, the first part provides an introduction to the definition, origin, and development of SHM, as well as the monitoring content and the application of AI in SHM system. The second and third parts present the relevant principles of knowledge-driven and data-driven approaches, respectively, along with a summary of research cases focused on knowledge-driven and data-driven methods for intelligent structural monitoring of bridges both domestically and internationally. The fourth part conducts a comparative analysis of the advantages and disadvantages of the two research methods, leading to the proposal that a hybrid knowledge–data-driven research method is necessary to truly approach human intelligence. Furthermore, it explores potential future applications of this hybrid approach in bridge SHM. Lastly, the fifth part serves as the conclusion, outlining the development trend of intelligent health monitoring technology for bridge structures and emphasizing the importance of knowledge–data hybrid-driven methods in bridge structure health monitoring. The conclusion also suggests future research directions in this field.

2. Structural Health Monitoring

SHM aims to collect extensive monitoring information using various measurement techniques and algorithms to evaluate the condition of a structure during its service life. This process is crucial in maintaining the structure throughout its life cycle [6, 7]. SHM of bridges is a comprehensive and intricate system project that encompasses multiple fields such as image technology, laser technology, fiber optic sensing technology, ultrasonic technology, thermal imaging technology, electromagnetic sensing technology, and more. It provides a comprehensive assessment of the structural health condition of bridges.

2.1. Origin and development of SHM of bridges

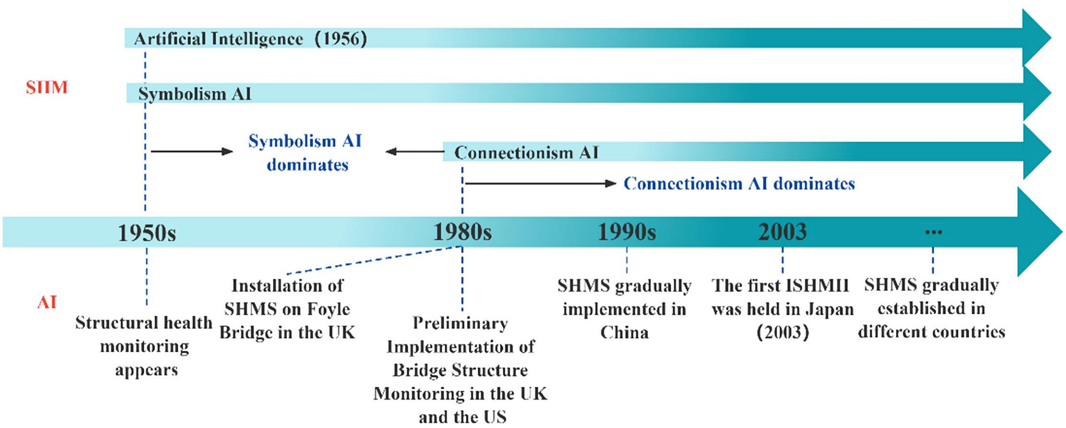
The SHM of bridges started in the 1980s in the United Kingdom and the United States. With the development of materials technology and circuit technology, the United States first proposed the combination of "intelligent materials and intelligent structural systems," which have certain perception and self-regulation capabilities. In the 1990s, the US Science Foundation promoted the research of sensor technology and proposed the idea of combining sensor systems and civil engineering structures, while at the same time, the UK first attempted to install an automatic bridge data acquisition system and monitoring instruments on the new 522 m-long Foyle Bridge in Northern Ireland, mainly to monitor and study the effects of vehicle loads and wind and temperature environmental loads on the bridge's dynamic response. This was an early prototype of a SHM system for bridges.

Research on SHM in China started in the 1990s, when China was in a period of rapid progress in infrastructure construction, with the construction of several representative large-scale bridge projects such as the Sutong Yangtze River Bridge, the Nansha Bridge, the Lupu Bridge, and the Hong Kong-Zhuhai-Macau Bridge. Compared with other countries, China's bridge construction is characterized by a large number of bridges and a large scale. During this period, China successively set up SHM systems of different scales on large bridges such as Shanghai Xu Pu Bridge, Jiangyin Yangtze River Bridge, Runyang Yangtze River Bridge, and Sutong Bridge. Figure 1 illustrates the evolution of SHM and AI, with nodes showing milestone events.

2.2. Content of SHM of bridges

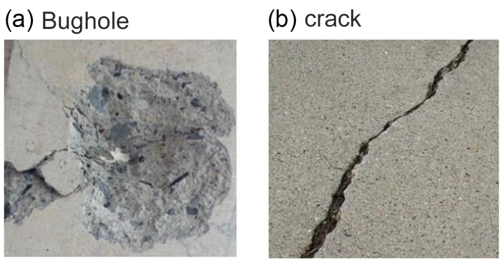
SHM is a complex and comprehensive system project. In general, the overall approach is to measure and collect data characterizing the bridge structure, such as structural deformation, vibration data, and appearance images, through the use of sensors and other instrumentation and then analyze the measured data to assess the structural health of the bridge (flow chart).

Figure 1
Origin and development of structural health monitoring of bridges



The problems of structural health of bridges mainly include structural degradation caused by environmental factors (such as temperature, humidity, acid rain, and freeze-thaw cycles); initial defects of structures caused by improper design or construction, structural fatigue damage caused by long-term operation; and damage to structures caused by unexpected loads such as earthquakes, impacts, and wind vibration. For SHM of large-span bridges, the sources of monitoring data are mainly in three major aspects: environment, load, and structural response, and the specific monitoring contents and tools used are shown in Figures 2 and 3.

Figure 2
Two common surface damage on structure



Generally speaking, the damage types of bridge structures include visualized morphological damage and non-visualized internal damage. Morphological changes refer to the damage that can be recognized by machines or the naked eye, such as cracks, rust, and peeling, which are shown in Figure 4; non-morphological damage refers to the damage that is hidden inside the structure, such as the deterioration of parts. This type of damage also includes morphological changes such as cracks and fractures, but it is hidden inside the structure and therefore difficult to be recognized visually [1].

2.3. Application of AI in bridge SHM system

SHM system generally consists of sensor subsystem, data acquisition and transmission subsystem, data processing and management subsystem, data analysis system, and structural early warning and assessment subsystem. These subsystems are closely and logically related to each other, and each of them plays an irreplaceable and indispensable important function in the daily monitoring operation.

With the continuous development of information technology, AI has gradually replaced some traditional research methods due to its excellent performance effect. In the bridge structure health monitoring system, AI is mainly applied to the data analysis system, which demonstrates more efficient and high-precision prediction effect compared with the traditional research methods. Especially in image recognition and data analysis, the advantages of AI over traditional research methods are very obvious.

Since AI was first proposed in 1956, there have been two competing schools of thought, namely symbolism and connectionism. While SHM also came into prominence in the 1850s, influenced by the two schools of thought, AI approaches applied to SHM can be further classified into mechanism-based knowledge-driven approaches and experience-based data-driven approaches, which coincide with the symbolism and connectionism in AI. Figure 5 shows the subsystems of the structural health inspection system and their main functions

3. Knowledge-Driven Structural Health Based Monitoring

Knowledge-driven is a general term for a class of research methods based on the idea of symbolic AI. In a broad sense, the traditional manual measurement-based bridge technology monitoring techniques belong to the knowledge-driven category, because the manual monitoring methods are ultimately based on various rules and principles or working experience, from the whole monitoring plan to each step of the monitoring behavior, which is “justified”. Traditional SHM methods have the general advantages of knowledge-driven approaches, i.e., they are interpretable and easy to understand, but they have obvious shortcomings. Among them are: (1) simple monitoring techniques, which make it difficult to accurately identify and detect hidden structural damage or hidden internal hazards.

Figure 3
Flow chart for assessing the health of bridge structures

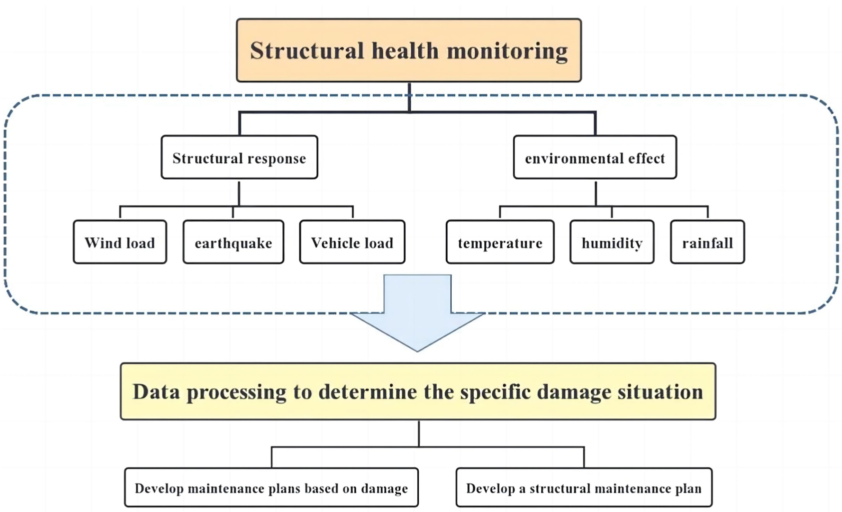


Figure 4
Type of bridge structural health monitoring

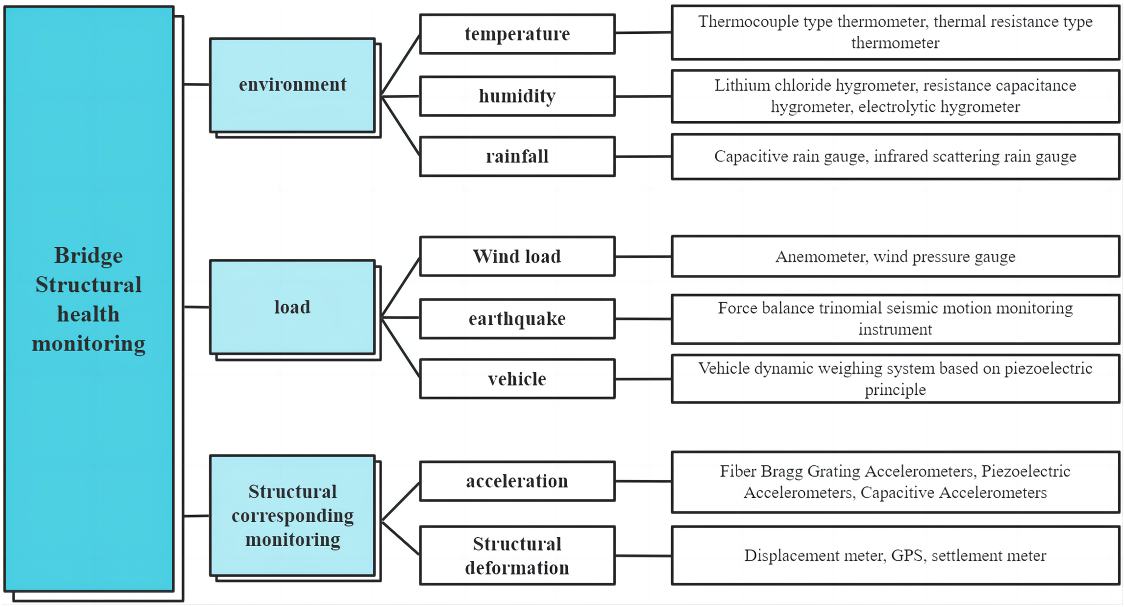
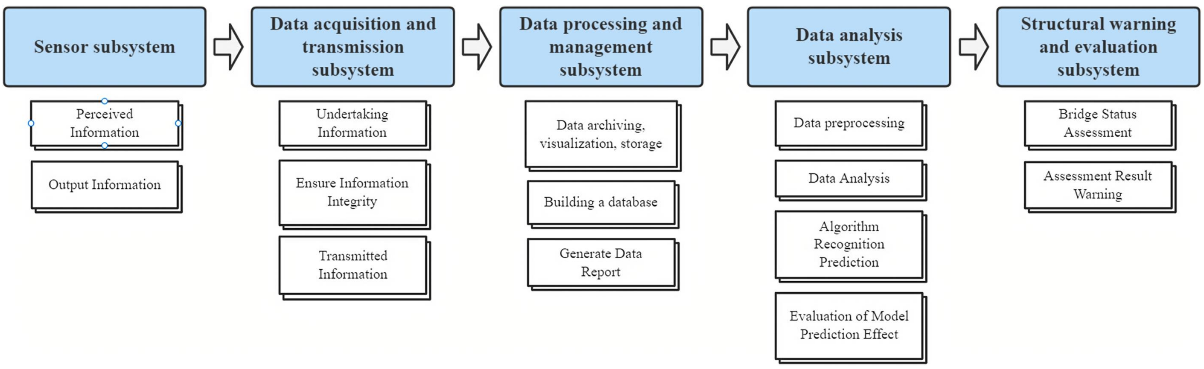


Figure 5
Subsystems and their main functions in structural health inspection systems



(2) Manual subjectivity is too strong, due to the high degree of human involvement, the inspection results are often highly dependent on the experience of technical personnel, with a large error. (3) Poor wholeness and systematicity, for such large projects as large span bridges, it is difficult to systematically inspect and rank the global structural health condition. (4) Low inspection efficiency and traffic impact, usually when a bridge is surveyed and inspected, the traffic of that section will receive a large impact. The early bridge structure health monitoring is very single due to limited technical means, mainly for the bridge structure structural deformation, settlement displacement, and other geometric forms for measurement and monitoring. Its work efficiency is low, the monitoring degree is superficial, some difficult to find structural damage, or internal hidden problems are difficult to identify and detect; therefore, the early SHM is incomplete and superficial, and it is difficult to achieve effective and all-round assessment of the state of the structure.

With the continuous development of information technology, the application of AI in SHM of bridges is becoming more and more widespread, which has led to new developments and innovations in knowledge-driven approaches. According to the symbolist scholars, “a large part of human thinking is composed of new operations on words according to rules of reasoning and conjecture,” they believe that AI should be a “model of reasoning based on knowledge and experience” that imitates the human way of thinking.” However, it is impossible for models to know the relevant knowledge and experience by nature, so it is necessary for humans to transfer the relevant knowledge and experience to the models so that they can “understand” and have some reasoning ability to achieve the ability to solve practical problems.

3.1. Knowledge-driven AI-based approach

Knowledge-driven approaches based on symbolic AI have many advantages, in addition to interpretability and comprehensibility, but have significant shortcomings. The premise of knowledge-driven is based on a fully informative and structured environment, which can only solve deterministic problems (toward third generation AI).

How to convey the knowledge and experience expressed by natural language to a model? That is, how to explore a form of representation that computers can understand is a hot and difficult research area for scholars of the symbolism school. Some methods of just representation have been explored such as generative rules [8] and logic programs [9], but they can only express simple knowledge and experience, and it is difficult to describe more complex and uncertain knowledge. Some scholars are currently researching and exploring complexknowledge representation methods in also, and the methods thathave been proposed are knowledge mapping [10], probabilistic reasoning [11], etc.

3.1.1. Generative rules

Generative representation is the most common type of knowledge representation in AI systems, and the majority of expert systems [12] use generative rules for their knowledge representation. The principle of generative rules is very similar to conditional statements in programming languages, and its basic form can be summarized as IF P THEN Q, where P is a premise and condition and Q is some kind of conclusion or behavior. The meaning of generative rules is that Q is performed when the precondition P is satisfied, i.e., some conclusion is introduced or some behavior is performed. In bridge structure monitoring systems, the function of generative rules is to conditionally transform the mechanisms, knowledge, expert experience, and common sense used in the monitoring process so that they can be imported into the machine model and recognized and understood by the algorithm.

3.1.2. Expert system

Knowledge mapping is an emerging form of knowledge representation that extracts valuable information from large-scale data using inference techniques and builds a framework of knowledge structures, which has received much attention in natural language processing (NLP) [13]. In bridge SHM, due to the many types and complex forms of damage, it is usually necessary to rely on traditional knowledge for damage identification, which makes it less efficient and more subjective in judgment. Therefore, it is necessary to establish a knowledge map through massive data analysis, thus improving the efficiency and accuracy of structural monitoring.

3.1.3. Probabilistic reasoning

Machine reading comprehension is a fundamental task in NLP, which requires a model to understand text and answer a set of questions based on the text content [14], and probabilistic inference (logical reasoning) is a processing model that extracts the corresponding logical relations (e.g., intersection $\wedge$, concatenation $\vee$, non$\neg$) of a text through its semantics [15].

3.2. Knowledge-driven SHM research

From the current state of research at home and abroad, knowledge-driven research cases are obviously much less compared to data-driven ones, which has a considerable relationship with the history of AI development. From the birth of AI in 1956 to the 1980s, symbolism dominated the development of AI, and only in the 1990s did connectionism gradually emerge, culminating in the 21st century, and even replacing symbolism [5]. Second, knowledge-driven research methods currently have many limitations, as they can only reason and analyze in a fully structured and informationalized space, and there is still a great challenge to truly reach human cognitive and analytical reasoning capabilities. Data-driven approaches, on the other hand, have unprecedentedly broader and more flexible applications, due to the fact that data-driven analysis and prediction are based entirely on data and do not require any knowledge or experience.

Luo et al. [16] constructed a knowledge graph and a complex question and answer corpus for bridge monitoring and proposed a naming method of "member name_(center pile number)" to distinguish the same members of different bridges. Then, given the unique tree structure of the bridge monitoring knowledge graph, we creatively propose a three-level relational knowledge graph construction method and annotate a dataset containing five complex question and answer types. Finally, we use our corpus to experiment with mainstream complex question and answer models and further demonstrate the effectiveness of the domain-specific knowledge graph construction method.

4. Data-Driven Structural Health-Based Monitoring

The data-driven approach, as the name implies, is based on a large amount of experimental data to analyze and assess the health of bridge structures. Unlike the knowledge-driven approach, the data-driven approach does not require any a priori knowledge and experience, but rather allows the "model" to learn knowledge and experience through the training data on its own, and finally allows the trained model to predict the new monitoring data to achieve the prediction purpose. Data-driven is simpler and more convenient than knowledge-driven, but it has obvious uncertainty and instability, mainly in two aspects: first, it is not known whether the trained algorithmic model has really learned the universal laws hidden in the data, and second, even if the algorithmic model has really mastered the hidden logic laws in the data, it is not possible to know the laws through machine learning algorithmic model due to the black-box nature of the algorithmic model. The black-box nature of the algorithmic models means that the patterns are not yet known through the machine learning algorithmic models [17], so the machine learning algorithms are not interpretable, although they sometimes have good prediction results. Therefore, how to learn the hidden logic and patterns in training data from machine learning algorithms is a hot and difficult area of research in data-driven methods.

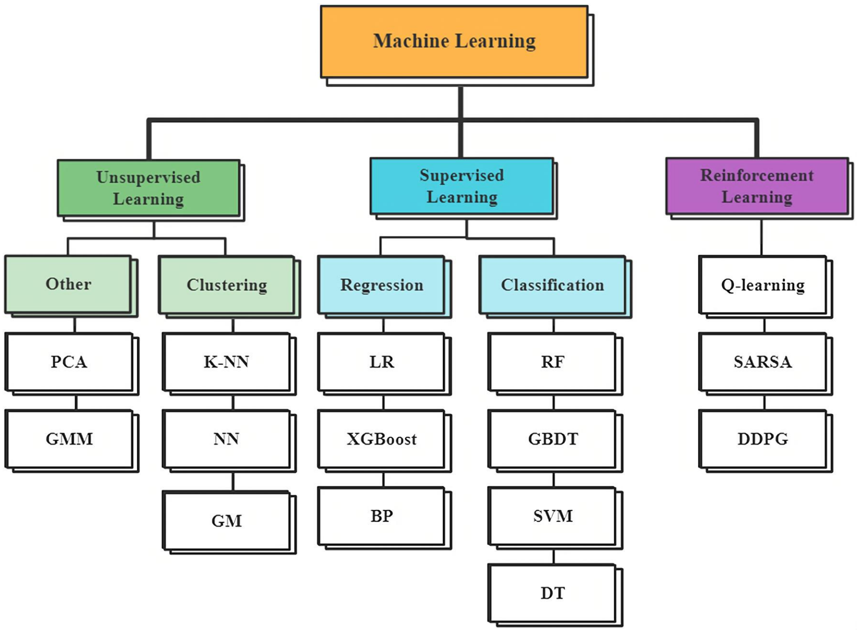
4.1. Data-driven algorithm model

4.1.1. Machine learning

Machine learning is actually a way for machines to imitate human learning behavior to learn knowledge and experience from data and to use their learned knowledge and skills to continuously optimize and improve their own performance. Machine learning mainly contains three learning modes: supervised learning, unsupervised learning, and reinforcement learning, and sometimes it is not so clearly distinguished and is called semi-supervised learning, which is shown in Figure 6.

In supervised learning, data are labeled with specific tags, and algorithmic models learn large amounts of labeled data so that they can make predictions about new data in the future. Supervised learning addresses both regression and classification problems, which correspond to continuous and discrete variables, respectively [1, 18]. Common supervised learning algorithms are decision trees, random forests, support vector machines, linear regression, etc.

Figure 6
Common types of machine learning algorithms



4.1.2. Deep learning

Deep learning actually belongs to machine learning, a smaller branch in the field of AI. The relationship between AI, machine learning, and deep learning and common algorithms in different fields are realistic in Figure 7. The reason why deep learning is separated into a separate section is that the neural network-like algorithms in deep learning perform better than the traditional algorithms of machine learning in bridge structure monitoring, and specific research cases will be elaborated in Section 3.3. The concept of deep learning originally originated from artificial neural networks (ANNs), which mimic the structure of the human nervous system in appearance and mainly contain three parts: input layer, hidden layer, and output layer, with several neurons in different layers, and they are connected together by means of wires, which represent different weights [19].

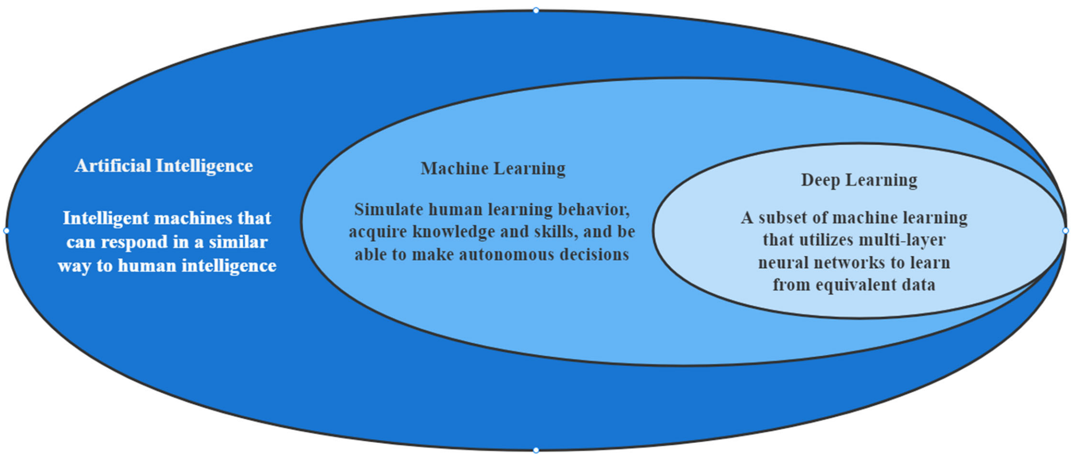
As related research continues, more and more new models are proposed. Common neural network models include feedforward neural networks, convolutional neural networks, generative adversarial networks, recurrent neural networks, Bayesian neural networks, fuzzy neural networks, and other deep learning algorithms.

4.2. Data-driven SHM research based on data driven

4.2.1. Visual damage monitoring

Visual SHM is mainly applied to damage identification with significant morphological changes in bridge engineering, mainly monitoring cracks, crazing, fractures, wormholes, shedding, corrosion, etc. The algorithmic models that are good at visual damage identification are mainly ANNs, convolutional neural networks, and other deep learning algorithms. Silva and Lucena [20] developed a

Figure 7
The relationship between artificial intelligence, machine learning, and deep learning



system for the identification of concrete surface cracks through a convolutional neural network classification algorithm, which is also able to simultaneously take into account the smoothness of the concrete surface, humidity, and objective conditions such as light, and its best prediction accuracy reached 92.27%. Wei et al. [21] proposed a Mask R-CNN-based method for instance-level identification and quantification of concrete surface pores, and the Mask R-CNN framework was modified, improved, trained, and validated using 2198 images, and the results indicated that the average accuracy of bounding box and mask reached 90% and 90.8%, with accuracy of 92.2% and 92.6%, respectively, and good recognition results were realized. Dung et al. [22] monitored fatigue cracks in welded joints of steel bridge nodal plates and developed three monitoring approaches using a combination of migration learning and convolutional neural network. Xu et al. [23] investigated a deep fusion convolutional neural network based on consumer-grade camera images to identify fatigue cracks on the surface of bridge steel box girders. An improved fused convolutional neural network structure is proposed with a regular convolutional neural network as the baseline. More researches about visual damage monitoring could be found in Table 1. The results show that the improved fused convolutional neural network can automatically monitor the cracks in the images, and its seeking training error is smaller than that of the regular convolutional neural network.

4.2.2. Non-visual damage monitoring

Non-visualized damage mainly includes a general term for various types of damage hidden inside the bridge structure, such as hard-to-detect cracks, stiffness degradation, and component deterioration inside the bridge. This type of damage is usually identified by vibration response-oriented methods, and common structural vibration response measurement characteristics include acceleration, velocity, stress, strain, and displacement. In addition, in addition to vibration response, acoustic sensors and electromagnetic devices are commonly used to measure features. Acoustically oriented features can be used to monitor mechanical waves in cracks for damage identification. Electromagnetic response-oriented feature data can be used to measure corrosion of concrete. Gui et al. [40] used a machine learning conventional algorithm support vector machine for health monitoring and damage monitoring of civil engineering structures. And three optimization methods of grid search, particle swarm optimization, and genetic algorithm were used to improve the model, and the final results showed that the optimized model performed better compared

Table 1
Machine learning to solve visualization structure defects

Reference	Model	Type of structural damage	Result
Malekjafarian et al. [24]	ANN, Gaussian process	Bridge damage detection using responses measured by passing vehicles	Better detection results but unstable, easily affected by the environment
Lydon et al. [25]	Pixels conversion, SURF algorithm	Displacement under changing boundary conditions	The method is applicable to medium and large span bridges
Gao and Mosalam [26]	DCNN (deep convolutional neural network)	Cover spalling detection	Accuracy is 80%, TPR is 82%, TNR is 77%
Akintunde et al. [27]	SVD and independent component analysis (ICA)	Crash-induced damage to the concrete barrier	Robust damage detection is better
Cha et al. [28]	CNNs	Concrete cracks	The algorithm can be used in real crack detection
Tang et al. [29]	U-net	Concrete crack	Pixel accuracy of 0.995
Atha and Jahanshahi [30]	CNNs	Corrosion on surface	Improves the computational time and performance
Dung and Anh [31]	DCNN (deep convolutional neural network)	Concrete crack	90% in average precision
Dung and Anh [31]	Mask R-CNN	Concrete surface bughole	The minimum error rates are 0.23%
Wu et al. [32]	ANN	Concrete crack	Improved cracking accuracy and reduced algorithm time
Montaggioli et al. [33]	An algorithm to automatically detect damages	Sub-surface defects	Can be used for large span structure crack detection
Ali and Cha [34]	Deep inception neural network (DINN)	Subsurface damage of steel	Accuracy of 96%
Hoskere et al. [35]	CNNs	Post-earthquake structural inspections	Be evaluated in terms of pixel accuracy
Jiang et al. [36]	Hybrid dilated convolutional block (HDCB)	Concrete crack	The whole detection process takes only 0.64 s to handle a single image
Tran-Ngoc et al. [37]	ANN-CS	Damage localization and quantification	ANN-CS is accurate and requires a lower time
Wang et al. [38]	A multi-layer genetic algorithm (GA) approach	Damage localization	Efficient and feasible for complicated truss bridge
Butcher et al. [39]	Detecting defects in reinforced concrete	Extreme learning machines (ELMs)	The ELM approach offers a significant improvement in performance

Table 2
Machine learning to solve non-visualization structure defects

Reference	Model	Type of structural damage	Result
Tran-Ngoc et al. [37]	Cuckoo search	Stiffness	Improved algorithm accuracy and reduced algorithm time
Pan et al. [43]	Data-intensive machine learning	Vibration	Enhancing the effectiveness and accuracy
Pathirage et al. [44]	ANN	Vibration	More accurate and effective
Wang and Cha [45]	Deep learning	Acceleration response	Accuracy up to 99%
Wang and Cha [46]	CNN	Raw acceleration signals	Performs very well in damage localization
Tran-Ngoc et al. [37]	Multivariate cointegration analysis	Inclined cable force	The damage intensities that can be detected
Tran-Ngoc et al. [37]	Cuckoo search	Stiffness	Be competent for structural damage detection under the exposed environment
Pan et al. [43]	Data-intensive machine learning	Vibration	Learn features from the frequency data
Pathirage et al. [44]	ANN	Vibration	Sensor faults or system malfunctions
Pan et al. [43]	Data-intensive machine learning	Vibration	High accuracy

with the traditional model, and the support vector machine based on genetic algorithm among the three optimization methods had better prediction results. Rageh et al. [41] proposed an automatic damage detection framework. The proposed method relies on appropriate orthogonal decomposition and ANNs to identify the location and strength of damage under non-stationary and unknown train loads. The results indicate that under the uncertainty conditions studied, the detection accuracy of damage location and damage intensity is relatively high, while the detection accuracy decreases with the increase of modeling uncertainty MU. Rafiei and Adeli [42] described a method to assess the global and local health of a structural system using structural vibration response data collected by sensors. The model uses a probability density function for creating a structural health index. This index can be used to assess the health of the structure. More researches about visual damage monitoring could be found in Table 2. To complement this approach and to investigate the damage mechanisms, acoustic emission due to internal damage was also analyzed and used to track microcracks in reinforced concrete beams.

Ma et al. [47] carried out fatigue and static load tests on modular bridge expansion joint (MBEJ). A theoretical evaluation method for fatigue performance of MBEJs based on nominal stress method and linear Miner damage accumulation law was introduced. The theoretical predictions are in good agreement with the experimental observations.

5. Hybrid Knowledge–Data-Driven Approach

Both symbolism and connectionism imitate the human mind from one side and have their own one-sidedness. A single knowledge-driven approach or a data-driven approach can hardly achieve the real human intelligence and show insurmountable limitations in practical applications. In the future, bridge SHM needs to integrate the two approaches with each other, i.e., to establish a hybrid knowledge–data-driven research approach, which is the only way to create a more comprehensive, safe, and reliable algorithmic model and to get closer to the real human intelligence.

5.1. Characteristics of knowledge-driven and data-driven approaches

Knowledge-driven approaches based on symbolism have the advantages of interpretability and security, but they often fail when applied to other problems because of the need to solve problems "on the fly" in an environment where information is fully conditioned and structured.

Data-driven approaches based on connectionism are mainly manifested in machine learning algorithms, which depict and imitate the human mind from the other side. Compared with knowledge-driven methods, data-driven methods do not require a tedious process of knowledge and experience collection, and therefore they do not require any prior knowledge and experience of humans. The data-driven approach can be understood as a "black box of information", people can only change the parameter settings and appearance of the black box from the outside, but cannot analyze the internal operation mechanism of the black box, which means that although the machine learning algorithms can show good prediction results in many cases, but the deep logic and laws hidden inside are difficult to be discovered. This means that although machine learning algorithms can perform well in prediction in many cases, the deep logic and laws hidden inside are difficult to be discovered.

5.2. Construction of hybrid knowledge–data-driven material health monitoring approach

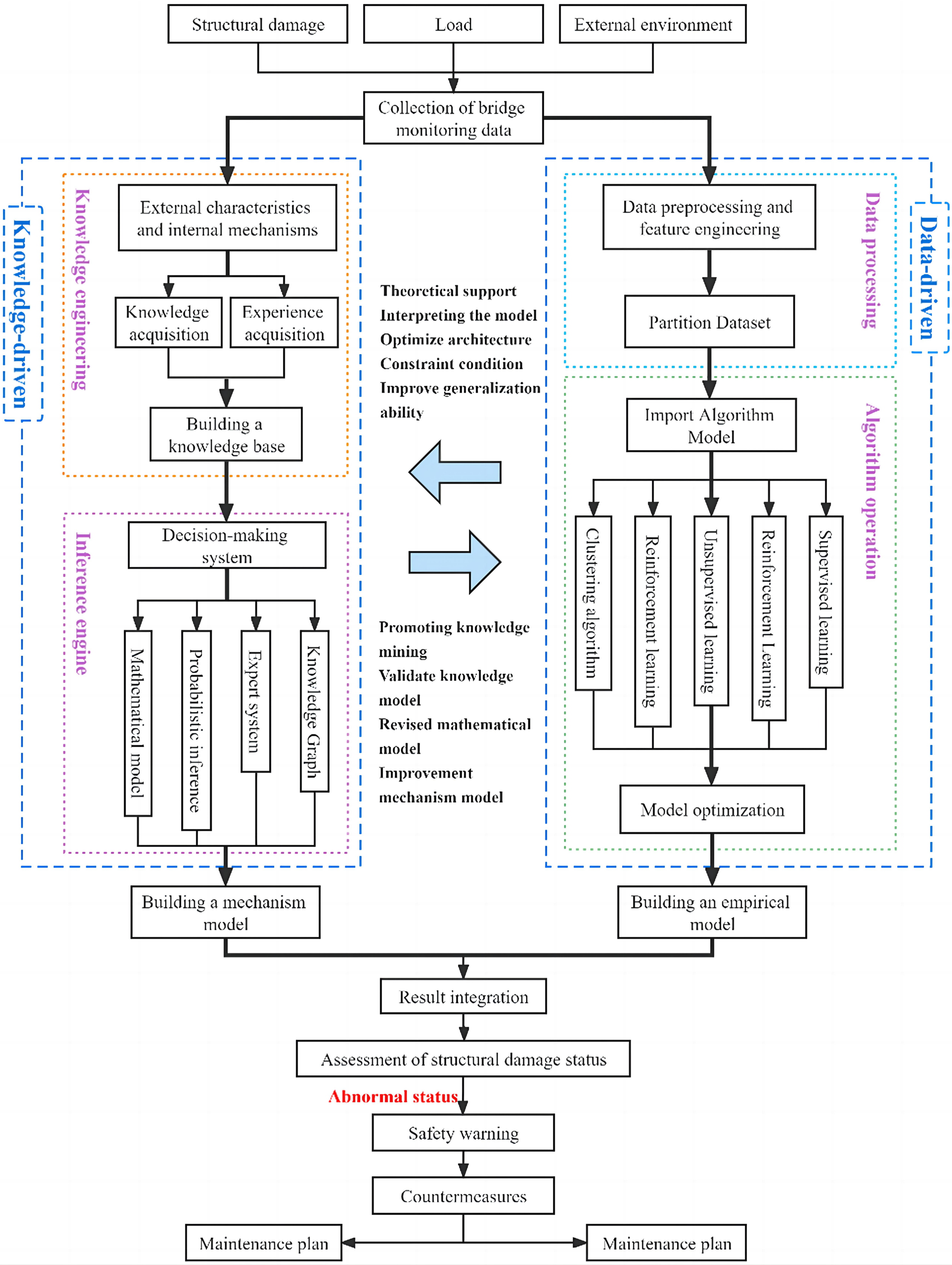
Both knowledge-driven and data-driven have their own advantages and disadvantages, which are the embodiment of human intelligence, and these disadvantages mainly originate from the one-sidedness of the two approaches. To truly achieve human intelligence, AI must consider the integration of the two approaches, i.e., develop a new research idea of knowledge–data hybrid drive. Combining the four elements of knowledge, data, algorithms, and arithmetic power to build a more powerful AI intelligence.

From the current research situation, many experts and scholars have tried to use interpretable AI methods in SHM of bridges. These methods have diversity, and knowledge-driven and data-driven methods can be combined in various forms to improve the interpretability and predictive performance of algorithm models to varying degrees.

Mariani et al. [48] proposed a causal expansion convolutional neural network based on ultrasonic signals. This algorithm does not require operators to perform any feature engineering and can automatically acquire features with strong correlation, which is more accurate and stable than traditional neural networks. Flynn and Todd [49] introduced a new Bayesian-based method for the optimal placement of SHM sensors. Bayesian algorithm is an interpretable algorithm model that explains the optimal placement of sensors from a probabilistic perspective. Yuan et al. [50] applied the guided wave hidden Markov model initialized by k-means clustering method to fatigue crack growth assessment and proposed a new guided wave hidden Markov model based on uniformly initialized Gaussian mixture model, which provides a stable and reliable structure for the guided wave hidden Markov model.

Figure 8 shows a typical solution of knowledge data hybrid driving method in bridge SHM. In this scheme, both

Figure 8
Process of hybrid knowledge–data-driven approach in structural health monitoring of bridges



knowledge-driven and data-driven methods are parallel and can obtain their own prediction results. Finally, the final prediction result is obtained by integrating the prediction results of the two methods. Firstly, measurement data are obtained from three directions: structure, load, and external environment of the monitored bridge, and then run under the dual knowledge–data drive.

5.2.1. Knowledge-driven processes

1) Knowledge engineering

In bridge SHM, the application of the hybrid knowledge–data-driven method can realize the complementary advantages and build a more secure, reliable, and stable monitoring model with more reliable results. The knowledge-driven approach requires researchers to first analyze the external characteristics and internal mechanisms of the research object and summarize various knowledge, experience, and common sense as comprehensively as possible, so as to build a rich knowledge base.

2) Inference engine

The reasoning machine is the core part of the knowledge-driven building block, which is like an expert's brain, matching the rules of knowledge and experience in the knowledge base repeatedly against the known information in the current problem, and then obtaining multiple possible answers, and finally filtering to obtain the answer with the highest confidence among all answers as the final decision.

5.2.2. Data-driven processes

1) Data processing

Data-driven is mainly based on various types of algorithms in machine learning and deep learning. Firstly, the collected data need to be pre-processed, including the process of filling vacant values, outliers, error values, etc. Also, the feature data need to be processed in certain ways according to the requirements of the algorithms, including type transformation, normalization, dimensionless transformation, data upsizing, data downsizing, etc. Next, the data need to be divided. Usually, it is necessary to divide the feature values and prediction labels, and for supervised learning, it is also necessary to divide the test set and validation set.

2) Algorithm operation

The processed experimental data are imported into the algorithmic model run, and different types of algorithmic models are used selectively for different types of problems. In this process, the optimization of the algorithm plays a crucial role, which allows our model to maximize the adaptation to the experimental data and achieve the best prediction results.

5.2.3. Model fusion

The knowledge-driven approach enhances the overall interpretability of the dual model, provides theoretical support, a priori conditions for data-driven, and also allows further optimization of the algorithm structure. The data-driven approach is good at handling huge and complex experimental data, facilitating new knowledge mining, and also optimizing and improving the intrinsic structure model to verify the correctness of the results of the knowledge-driven approach.

The knowledge-driven approach eventually builds the mechanistic model, and the data-driven approach eventually builds the empirical model. The final prediction result is obtained by integrating the prediction results of both knowledge-driven and data-driven methods. This result integrates the advantages of both forecasting methods and is closer to the real value of the forecasting result.

6. Conclusion

This paper introduces two commonly used methods in the field of AI for bridge SHM: knowledge-driven methods and data-driven methods. It analyzes the advantages and disadvantages of these two methods through research cases and emphasizes the importance of developing hybrid knowledge–data-driven methods in bridge SHM. It argues that the hybrid knowledge–data-driven research approach can achieve complementary advantages and represents a necessary path for AI to approach human intelligence, becoming the future development trend of AI in SHM.

Since the inception of AI, two paradigms of thinking have existed, namely symbolism and connectionism, which correspond to knowledge-driven and data-driven research methods, respectively. With the continuous development of information technology, AI's application in bridge SHM is becoming more widespread. It is primarily divided into knowledge-driven and data-driven approaches, addressing two main problem categories: visualization problems based on damage morphology identification, such as bridge appearance damage identification, and studies of non-morphological change type damage, such as vibration-oriented structural damage studies.

The knowledge-driven approach has significant advantages, including interpretability, security, and stability. However, it also has significant shortcomings, mainly its limited ability to solve "matter-of-fact" problems and its requirement to operate in a fully informed environment. On the other hand, data-driven methods are more straightforward to implement, offering efficiency, high accuracy, and flexibility without requiring specific domain-related knowledge or experience. However, data-driven methods are uninterpretable due to their black-box nature, and in many cases, even though the algorithmic model performs well, the internal logic and underlying laws remain unknown. Additionally, data-driven methods are highly susceptible to attacks that may produce unexpected and erroneous results, making them less secure.

Both knowledge-driven and data-driven approaches attempt to mimic aspects of the human brain's thinking process, yet they are incapable of fully replicating true human intelligence. To further approach human intelligence, the two approaches need to be integrated through a knowledge-data hybrid drive. The hybrid knowledge–data-driven approach overcomes the limitations of both methods and achieves complementary advantages in practical problem-solving. Knowledge-driven methods provide interpretability, security, and stability, guiding the architectural design of data-driven models, constraining their a priori conditions, and offering theoretical support. In return, data-driven methods enable rapid prediction and validation of knowledge-driven experiences, thanks to their efficiency and speed, allowing for the revision and improvement of knowledge experiences, as well as the discovery of new knowledge.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

References

[1] Zhang, Y., & Yuen, K. V. (2022). Review of artificial intelligence-based bridge damage detection. *Advances in Mechanical Engineering*, *14*(9). https://doi.org/10.1177/16878132221122770
[2] Baduge, S. K., Thilakarathna, S., Perera, J. S., Arashpour, M., Sharafi, P., Teodosio, B., . . . , & Mendis, P. (2022). Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Automation in Construction*, *141*, 104440. https://doi.org/10.1016/j.autcon.2022.104440
[3] Todorovski, L., & Džeroski, S. (2006). Integrating knowledge-driven and data-driven approaches to modeling. *Ecological Modelling*, *194*(1–3), 3–13. https://doi.org/10.1016/j.ecolmodel.2005.10.001
[4] Nguyen, K. T., Medjaher, K., & Tran, D. T. (2023). A review of artificial intelligence methods for engineering prognostics and health management with implementation guidelines. *Artificial Intelligence Review*, *56*(4), 3659–3709. https://doi.org/10.1007/s10462-022-10260-y
[5] Zhang, B., Zhu, J., & Su, H. (2023). Toward the third generation artificial intelligence. *Science China Information Sciences*, *66*(2), 121101. https://doi.org/10.1007/s11432-021-3449-x
[6] Cremona, C., & Santos, J. (2018). Structural health monitoring as a big-data problem. *Structural Engineering International*, *28*(3), 243–254. https://doi.org/10.1080/10168664.2018.1461536
[7] Zinno, R., Haghshenas, S. S., Guido, G., Rashvand, K., Vitale, A., & Sarhadi, A. (2023). The state of the art of artificial intelligence approaches and new technologies in structural health monitoring of bridges. *Applied Sciences*, *13*(1), 97. https://doi.org/10.3390/app13010097
[8] Katelman, M., Keller, S., & Meseguer, J. (2012). Rewriting semantics of production rule sets. *The Journal of Logic and Algebraic Programming*, *81*(7–8), 929–956. https://doi.org/10.1016/j.jlap.2012.06.002
[9] Riguzzi, F., Bellodi, E., & Zese, R. (2014). A history of probabilistic inductive logic programming. *Frontiers in Robotics and AI*, *1*, 6. https://doi.org/10.3389/frobt.2014.00006
[10] Ehrlinger, L., & Wöß, W. (2016). Towards a definition of knowledge graphs. In *Joint Proceedings of the Posters and Demos Track of 12th International Conference on Semantic Systems - SEMANTiCS2016 and 1st International Workshop on Semantic Change & Evolving Semantics*.
[11] Russell, S. J., Norvig, P., & Davis, E. (2009). *Artificial intelligence: A modern approach*. USA: Prentice Hall.
[12] Ng, C. B. R., Bil, C., Sardina, S., & O'bree, T. (2022). Designing an expert system to support aviation occurrence investigations. *Expert Systems with Applications*, *207*, 117994. https://doi.org/10.1016/j.eswa.2022.117994
[13] Ding, Y., Ma, J., & Luo, X. (2022). Applications of natural language processing in construction. *Automation in Construction*, *136*, 104169. https://doi.org/10.1016/j.autcon.2022.104169
[14] Ren, H., & Leskovec, J. (2020). Beta embeddings for multi-hop logical reasoning in knowledge graphs. In *34th Conference on Neural Information Processing Systems*, *33*, 19716–19726.
[15] Yu, W., Jiang, Z., Dong, Y., & Feng, J. (2020). ReClor: A reading comprehension dataset requiring logical reasoning. *arXiv Preprint: 2002.04326*.
[16] Luo, M., Yang, X., Zhang, H., Zhang, Y., Ji, L., & Li, R. (2022). Construction and application of knowledge graph for bridge inspection. In *IEEE 10th Joint International Information Technology and Artificial Intelligence Conference*, 2565–2569. https://doi.org/10.1109/ITAIC54216.2022.9836776
[17] Chen, Z., Xiao, F., Guo, F., & Yan, J. (2023). Interpretable machine learning for building energy management: A state-of-the-art review. *Advances in Applied Energy*, *9*, 100123. https://doi.org/10.1016/j.adapen.2023.100123
[18] Topuz, B., & Alp, N. Ç. (2023). Machine learning in architecture. *Automation in Construction*, *154*, 105012. https://doi.org/10.1016/j.autcon.2023.105012
[19] You, K., Zhou, C., & Ding, L. (2023). Deep learning technology for construction machinery and robotics. *Automation in Construction*, *150*, 104852. https://doi.org/10.1016/j.autcon.2023.104852
[20] Silva, W. R. L. d., & Lucena, D. S. d. (2018). Concrete cracks detection based on deep learning image classification. In *Proceedings of the 18th International Conference on Experimental Mechanics, 2*(8), 489. https://doi.org/10.3390/ICEM18-05387
[21] Wei, F., Yao, G., Yang, Y., & Sun, Y. (2019). Instance-level recognition and quantification for concrete surface bughole based on deep learning. *Automation in Construction*, *107*, 102920. https://doi.org/10.1016/j.autcon.2019.102920
[22] Dung, C. V., Sekiya, H., Hirano, S., Okatani, T., & Miki, C. (2019). A vision-based method for crack detection in gusset plate welded joints of steel bridges using deep convolutional neural networks. *Automation in Construction*, *102*, 217–229. https://doi.org/10.1016/j.autcon.2019.02.013
[23] Xu, Y., Bao, Y., Chen, J., Zuo, W., & Li, H. (2019). Surface fatigue crack identification in steel box girder of bridges by a deep fusion convolutional neural network based on consumer-grade camera images. *Structural Health Monitoring*, *18*(3), 653–674. https://doi.org/10.1177/1475921718764873
[24] Malekjafarian, A., Golpayegani, F., Moloney, C., & Clarke, S. (2019). A machine learning approach to bridge-damage detection using responses measured on a passing vehicle. *Sensors*, *19*(18), 4035. https://doi.org/10.3390/s19184035
[25] Lydon, D., Lydon, M., Kromanis, R., Dong, C. Z., Catbas, N., & Taylor, S. (2021). Bridge damage detection approach using a roving camera technique. *Sensors*, *21*(4), 1246. https://doi.org/10.3390/s21041246
[26] Gao, Y., & Mosalam, K. M. (2022). Deep learning visual interpretation of structural damage images. *Journal of Building Engineering*, *60*, 105144. https://doi.org/10.1016/j.jobe.2022.105144
[27] Akintunde, E., Azam, S. E., Rageh, A., & Linzell, D. G. (2021). Unsupervised machine learning for robust bridge damage detection: Full-scale experimental validation. *Engineering Structures*, *249*, 113250. https://doi.org/10.1016/j.engstruct.2021.113250

[28] Cha, Y. J., Choi, W., & Büyüköztürk, O. (2017). Deep learning-based crack damage detection using convolutional neural networks. *Computer-Aided Civil and Infrastructure Engineering*, *32*(5), 361–378. https://doi.org/10.1111/mice.12263

[29] Tang, Y., Huang, Z., Chen, Z., Chen, M., Zhou, H., Zhang, H., & Sun, J. (2023). Novel visual crack width measurement based on backbone double-scale features for improved detection automation. *Engineering Structures*, *274*, 115158. https://doi.org/10.1016/j.engstruct.2022.115158

[30] Atha, D. J., & Jahanshahi, M. R. (2018). Evaluation of deep learning approaches based on convolutional neural networks for corrosion detection. *Structural Health Monitoring*, *17*(5), 1110–1128. https://doi.org/10.1177/1475921717737051

[31] Dung, C. V., & Anh, L. D. (2019). Autonomous concrete crack detection using deep fully convolutional neural network. *Automation in Construction*, *99*, 52–58. https://doi.org/10.1016/j.autcon.2018.11.028

[32] Wu, L., Mokhtari, S., Nazef, A., Nam, B., & Yun, H. B. (2016). Improvement of crack-detection accuracy using a novel crack defragmentation technique in image-based road assessment. *Journal of Computing in Civil Engineering*, *30*(1), 04014118. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000451

[33] Montaggioli, G., Puliti, M., & Sabato, A. (2021). Automated damage detection of bridge's sub-surface defects from infrared images using machine learning. In *Paper Presented at the Health Monitoring of Structural and Biological Systems XV*, 115932A. https://doi.org/10.1117/12.2581783

[34] Ali, R., & Cha, Y. J. (2019). Subsurface damage detection of a steel bridge using deep learning and uncooled micro-bolometer. *Construction and Building Materials*, *226*, 376–387. https://doi.org/10.1016/j.conbuildmat.2019.07.293

[35] Hoskere, V., Narazaki, Y., Hoang, T., & Spencer Jr, B. (2018). Vision-based structural inspection using multiscale deep convolutional neural networks. *arXiv Preprint: 1805.01055*.

[36] Jiang, W., Liu, M., Peng, Y., Wu, L., & Wang, Y. (2021). HDCB-Net: A neural network with the hybrid dilated convolution for pixel-level crack detection on concrete bridges. *IEEE Transactions on Industrial Informatics*, *17*(8), 5485–5494. https://doi.org/10.1109/TII.2020.3033170

[37] Tran-Ngoc, H., Khatir, S., de Roeck, G., Bui-Tien, T., & Wahab, M. A. (2019). An efficient artificial neural network for damage detection in bridges and beam-like structures by improving training parameters using cuckoo search algorithm. *Engineering Structures*, *199*, 109637. https://doi.org/10.1016/j.engstruct.2019.109637

[38] Wang, F. L., Chan, T. H., Thambiratnam, D. P., Tan, A. C., & Cowled, C. J. (2012). Correlation-based damage detection for complicated truss bridges using multi-layer genetic algorithm. *Advances in Structural Engineering*, *15*(5), 693–706. https://doi.org/10.1260/1369-4332.15.5.693

[39] Butcher, J. B., Day, C., Austin, J., Haycock, P., Verstraeten, D., & Schrauwen, B. (2014). Defect detection in reinforced concrete using random neural architectures. *Computer-Aided Civil and Infrastructure Engineering*, *29*(3), 191–207. https://doi.org/10.1111/mice.12039

[40] Gui, G., Pan, H., Lin, Z., Li, Y., & Yuan, Z. (2017). Data-driven support vector machine with optimization techniques for structural health monitoring and damage detection. *KSCE Journal of Civil Engineering*, *21*(2), 523–534. https://doi.org/10.1007/s12205-017-1518-5

[41] Rageh, A., Azam, S. E., & Linzell, D. G. (2020). Steel railway bridge fatigue damage detection using numerical models and machine learning: Mitigating influence of modeling uncertainty. *International Journal of Fatigue*, *134*, 105458. https://doi.org/10.1016/j.ijfatigue.2019.105458

[42] Rafiei, M. H., & Adeli, H. (2018). A novel unsupervised deep learning model for global and local health condition assessment of structures. *Engineering Structures*, *156*, 598–607. https://doi.org/10.1016/j.engstruct.2017.10.070

[43] Pan, H., Azimi, M., Yan, F., & Lin, Z. (2018). Time-frequency-based data-driven structural diagnosis and damage detection for cable-stayed bridges. *Journal of Bridge Engineering*, *23*(6), 04018033. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001199

[44] Pathirage, C. S. N., Li, J., Li, L., Hao, H., Liu, W., & Ni, P. (2018). Structural damage identification based on autoencoder neural networks and deep learning. *Engineering Structures*, *172*, 13–28. https://doi.org/10.1016/j.engstruct.2018.05.109

[45] Wang, Z., & Cha, Y. J. (2021). Unsupervised deep learning approach using a deep auto-encoder with a one-class support vector machine to detect damage. *Structural Health Monitoring*, *20*(1), 406–425. https://doi.org/10.1177/1475921720934051

[46] Wang, Z., & Cha, Y. J. (2018). Automated damage-sensitive feature extraction using unsupervised convolutional neural networks. In *Proceedings of Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems, 10598*, 105981J. https://doi.org/10.1117/12.2295966

[47] Ma, Y., Peng, A., Wang, L., Zhang, C., Li, J., & Zhang, J. (2020). Fatigue performance of an innovative shallow-buried modular bridge expansion joint. *Engineering Structures*, *221*, 111107. https://doi.org/10.1016/j.engstruct.2020.111107

[48] Mariani, S., Rendu, Q., Urbani, M., & Sbarufatti, C. (2021). Causal dilated convolutional neural networks for automatic inspection of ultrasonic signals in non-destructive evaluation and structural health monitoring. *Mechanical Systems and Signal Processing*, *157*, 107748. https://doi.org/10.1016/j.ymssp.2021.107748

[49] Flynn, E. B., & Todd, M. D. (2010). A Bayesian approach to optimal sensor placement for structural health monitoring with application to active sensing. *Mechanical Systems and Signal Processing*, *24*(4), 891–903. https://doi.org/10.1016/j.ymssp.2009.09.003

[50] Yuan, S., Zhang, J., Chen, J., Qiu, L., & Yang, W. (2019). A uniform initialization Gaussian mixture model–based guided wave–hidden Markov model with stable damage evaluation performance. *Structural Health Monitoring*, *18*(3), 853–868. https://doi.org/10.1177/1475921718783652

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