Noncontact Sensing Techniques for AI-Aided Structural Health Monitoring: A Systematic Review

Alessandro Sabato, *Member, IEEE*, Shweta Dabetwar, Nitin Nagesh Kulkarni, and Giancarlo Fortino, *Fellow, IEEE*

***Abstract*—Engineering structures and infrastructure continue to be used despite approaching or having reached their design lifetime. While contact-based measurement techniques are challenging to implement at a large scale and provide information at discrete locations only, noncontact methods are more user-friendly and offer accurate, robust, and continuous spatial information to quantify the structural conditions of the targeted systems. Advancements in optical sensors and image-processing algorithms increased the applicability of image-based noncontact techniques, such as photogrammetry, infrared thermography, and laser imaging for structural health monitoring (SHM). In addition, with the incorporation of artificial intelligence (AI) algorithms, the assessment process is expedited and made more efficient. This article summarizes the efforts made in the last five years to leverage AI-aided noncontact sensing techniques for applications in SHM with an emphasis on image-based methods. Future directions to advance AI-aided image-based sensing techniques for SHM of engineering structures are also discussed.**

***Index Terms*— Artificial intelligence (AI), infrared thermography (IRT), laser imaging, photogrammetry, unmanned aerial vehicles (UAVs).**

I. Introduction

ENGINEERING structures continue to be used despite approaching or having reached their design lifetime. For this reason, growth in structural health monitoring (SHM) and nondestructive testing and evaluation (NDT&E) techniques has been observed in the last two decades. SHM includes a number of condition-based methods that allow early detection of incipient problems and failures (i.e., prevention) and provide insights for preventing damages in the targeted engineering systems (i.e., maintenance) [1]. Traditionally, SHM and NDT&E rely on contact-based measurement methods, such as strain gauges and accelerometers to collect data and extract information [2]. While recent trends leverage the use of Internet-of-Things methodologies for data transmission reducing constraints related to sensors' wiring [3], [4], [5], contact-based methods are still expensive, time-consuming to install, can interfere with the functionality of the targeted structure, and produce results only at the locations where the sensors are attached [6]. As a result, contact-based methods are not well suited for SHM and NDT&E of large-scale engineering systems [7].

Recently developed algorithms to process video, acoustic, and electromagnetic signals have made noncontact sensing techniques viable options for measuring structural changes in engineering systems [8]. Noncontact sensing techniques rely on multispectral images, radar [9], acoustic [10], and ultrasonic [11], or global navigation satellite system's [12] signals to quantify the conditions of a targeted system. While each of those methods has its own advantages and limitations, image-based approaches, such as photogrammetry [13], infrared thermography (IRT) [14], [15], and laser imaging [16], have shown great potential for SHM and NDT&E as they allow achieving denser spatial resolution measurements (e.g., any pixel can be used as a measurement point) and improved ease of use

Manuscript received 18 December 2022; revised 24 January 2023; accepted 24 January 2023. Date of publication 31 January 2023; date of current version 28 February 2023. The associate editor coordinating the review of this article and approving it for publication was Prof. Octavian Postolache. *(Corresponding author: Alessandro Sabato.)*

Alessandro Sabato, Shweta Dabetwar, and Nitin Nagesh Kulkarni are with the Department of Mechanical Engineering, University of Massachusetts Lowell, Lowell, MA 01852 USA (e-mail: Alessandro_Sabato@uml.edu; Shweta_Dabetwar@uml.edu; Nitin_Kulkarni@student.uml.edu).

Giancarlo Fortino is with the Department of Informatics, Modeling, Electronics and Systems (DIMES), University of Calabria, 87036 Rende, Italy (e-mail: giancarlo.fortino@unical.it).

Digital Object Identifier 10.1109/JSEN.2023.3240092

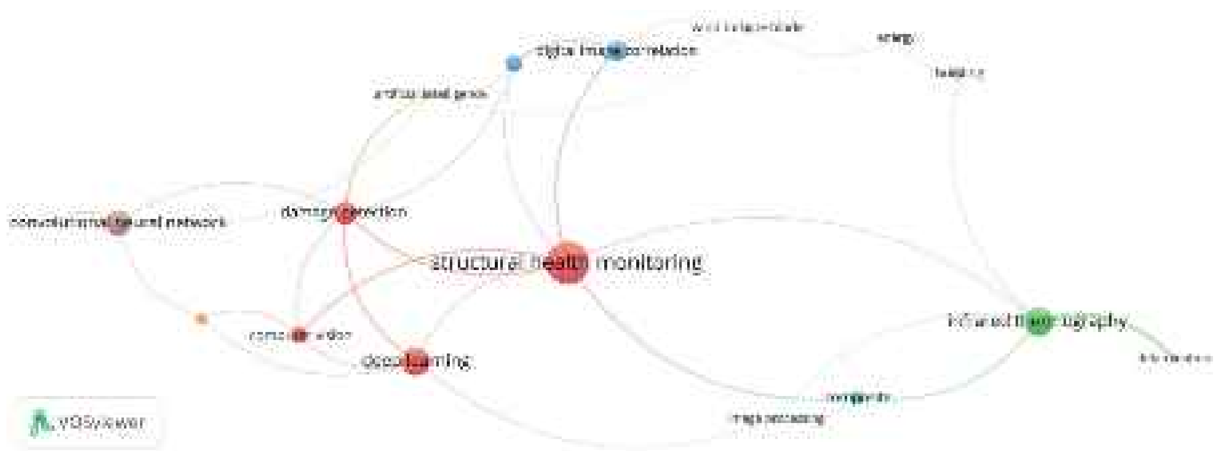

Fig. 1. Neural network of double-occurrence keywords in the reviewed scientific literature.

compared to other noncontact techniques. Considering the large amount of data generated when image-based noncontact sensing techniques are used, artificial intelligence (AI) plays a key role in providing a cost-effective data analytics tool [17]. Therefore, a significant amount of work has been performed in the area of AI-aided SHM using image-based sensing techniques. Moreover, AI models also allow predicting future conditions of the system and provide information for damage prognostics [18]. For these reasons, AI can be an asset for all the steps of the SHM processes that include sensing, data analytics, prevention, maintenance, and prognostic. Because a systematic effort to organize this knowledge is missing, this work provides a summary of previous research and future directions in the area of image-based noncontact sensing by addressing the following research questions (RQs):

1) *RQ1:* What are the advantages and challenges of image-based noncontact sensing techniques used for SHM?
2) *RQ2:* What are the applications of AI-aided, image-based, noncontact sensing techniques used for SHM?

A systematic review process was undertaken by conducting a literature survey on IEEE Xplore, Google Scholar, Science Direct, Scopus, MDPI, and Web of Science using the following three queries:

1) (“photogrammetry” OR “computer vision” OR “laser” OR “infrared” OR “thermography” OR “point cloud” OR “3DDIC”) AND “structural health monitoring” OR “non-destructive evaluation” OR “non-destructive techniques” OR “NDT-E”);
2) (“photogrammetry” OR “computer vision” OR “laser” OR “infrared” OR “thermography” OR “point cloud” OR “3DDIC”) AND (“artificial intelligence” OR “machine learning” OR “deep learning” OR “neural networks”) AND (“structural health monitoring” OR “non-destructive evaluation” OR “non-destructive techniques” OR “NDT-E”);
3) (“photogrammetry” OR “computer vision” OR “laser” OR “infrared” OR “thermography” OR “point cloud” OR “3DDIC”) AND (“unmanned aerial vehicle” OR “uncooled microbolometer”).

The review includes: 1) articles published between 2018 and 2022; 2) literature surveys/reviews; and 3) peer-reviewed research journals only. The review excludes articles: 1) written in a language other than English; 2) published as books, book chapters, dissertations, or conference proceedings; and 3) not related to the SHM/NDT&E domains (e.g., forest engineering). As a result, 135 papers were collected. It is interesting to observe that, while civil engineering and mechanical engineering are among the most targeted domains with 57 and 47 papers surveyed, respectively, building (18 papers), energy (9), and aerospace (4) engineering also showed applications of AI-aided image-based monitoring. In particular, the most targeted systems for the SHM approaches are bridges (38 papers) given the economic importance of those structures and the availability of funds to conduct research in that area. Other targeted structures include beams (20), composites (16), concrete (16), railroads and pavements (12), wind turbines (10), and dynamic systems (5).

To verify that the literature review was comprehensive and covered all the aspects of image-based noncontact sensing techniques for AI-aided SHM, a keyword recurrence analysis with the bibliometric software *VOSviewer* has been performed. In this analysis, the keywords with a double occurrence found in the surveyed papers were processed to obtain the neural network shown in Fig. 1. The neural network map indicates the areas where the literature is concentrated and reveals three central clusters: 1) SHM; 2) deep learning (DL); and 3) convolutional neural network (CNN). SHM serves as the main cluster with all the other ones, including the different sensing techniques, AI, damage detection, and unmanned aerial vehicles (UAVs) connected to it. This review is organized as follows. Section II presents an overview of recent applications of image-based noncontact sensing techniques in the civil, mechanical, building, and energy engineering domains with a discussion of advantages and disadvantages. Section III summarizes recent integrations of AI methods with image-based noncontact sensing techniques for SHM. Future directions and conclusions are drawn in Sections IV and V, respectively.

II. Applications of Image-Based Noncontact Sensing Techniques for SHM

In this section, an overview of the image-based noncontact sensing techniques outcome of RQ1 is provided with an

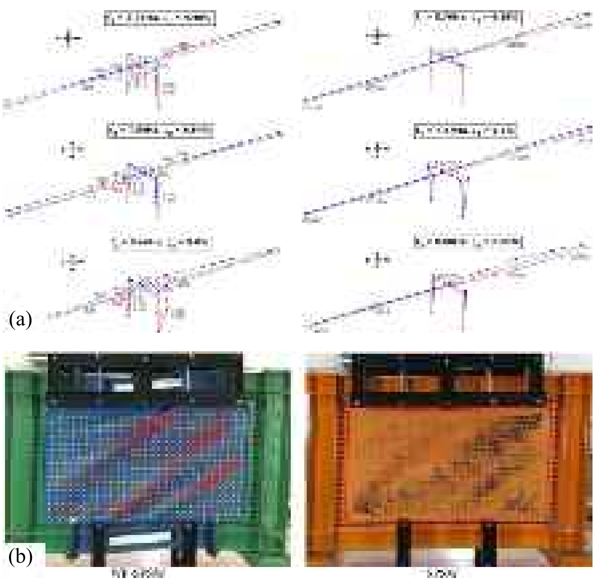

Fig. 2. Examples of 3-D-DIC applications for SHM of bridges' substructures: (a) mode shapes, natural frequencies, and damping ratio of a bridge deck extracted using 3DPT [25] and (b) strain measurement on a metal joint subject to cyclic loading [27].

emphasis on the advantages and disadvantages of each method for its deployment in real-world scenarios.

A. Photogrammetry-Based Methods

Photogrammetry and stereophotogrammetry methods, such as 3-D digital image correlation (3-D-DIC) and 3-D point tracking (3DPT), have been used for long- and short-term monitoring of various critical infrastructures, such as wind turbine blades [19] and bridges [20]. For the wind turbine certification process, 3-D-DIC has been used to stitch together multiple fields of view (FOVs) and obtain full line-of-sight strain and displacement over larger areas of the blades during static and dynamic tests [21]. 3DPT has been proven effective in measuring vibrations during modal tests and extracting natural frequencies, operating deflection shapes, and damping coefficients with accuracy comparable to accelerometers [22], [23]. For bridge inspection, studies have focused on monitoring the displacement of hairline cracks using optical methods and comparing the results with those measured using contact-based techniques. One of the studies successfully demonstrated the use of 3-D-DIC with a UAV to perform bridge monitoring [24]. Other studies proposed to use of advanced video measurement to monitor the seismic response and deformation of bridges' substructures [25], [26], [27]. Some notable examples of 3-D-DIC and 3DPT for bridge monitoring are shown in Fig. 2. In particular, Fig. 2(a) shows the results of a test performed on a portion of a bridge's column-deck structure placed on a shanking table that used 3DPT to extract dynamics parameters [25]. Fig. 2(b) shows how a multipoint tracking measurement performed on a steel plate subjected to cyclic loading was able to capture strain fields and in-plane deformations with an accuracy of 0.2 mm [27].

3-D-DIC and 3DPT have shown great potential to measure displacement and strain with submillimeter accuracy without providing any mass-loading effect and interfering with the dynamics of the systems [28], [29]. However, a speckle pattern must be applied to the targeted structure in order to extract the spatial and temporal characteristics of the system using 3-D-DIC. Applying a speckle pattern on real-world structures is a nontrivial operation that limits the use of this technique. Another challenge in performing 3-D-DIC and 3DPT on large-scale systems is the requirement for the calibrated stereo camera before performing a measurement. Calibration is done by taking pictures of a calibration object with known geometry and dimensions comparable to the size of the object being tested [28]. For this reason, research is now focusing on developing alternative methods to streamline the calibration process [30], [31], [32].

Photogrammetry methods, such as Structure from Motion (SfM), which rely on point cloud generation, are now constantly used to inspect a variety of civil engineering structures. SfM is used in conjunction with UAVs to generate a photorealistic rendering of bridges [33] and heritage sites [34], as well as with IR photographs, to perform an energy audit and identify subsurface damages on residential buildings [35], [36]. By taking advantage of correct camera oblique angles and image overlaps, SfM can reconstruct the targeted system with accuracy on the order of centimeters in a relatively smaller amount of time [37], [38]. Similarly, combining IRT with simultaneous localization and mapping (SLAM)-based algorithms made it possible to generate 3-D models of large-scale industrial systems and 3-D thermograms to determine the heat loss and temperature profiles on the surface of an injection molding machine [39]. The possibility of reconstructing multiple point clouds of the targeted structure over time allows for comparing the different clouds to track any deterioration. However, because lighting and external environmental conditions significantly affect the reconstruction accuracy, the comparison between different clouds is not as accurate as for other photogrammetry techniques. Furthermore, while SfM has shown great potential, there are still restrictions that must be considered, such as constraints over UAV flights (e.g., time of the day, location) and the tradeoff between high-resolution small area mapping and low-resolution large area mapping.

B. Infrared-Based Methods

IRT has traditionally been used for energy audits and material characterization [40], [41]. Because of advancements in postprocessing algorithms and IR cameras, the use of IRT for SHM and NDT&E has increased significantly in recent years. IRT finds its main application in detecting subsurface defects within the targeted structure, which cannot be located with the naked eye. Concrete bridges have been among the most common applications of IRT in the civil engineering domain. In particular, the use of this technique for detecting air voids in concrete bridge decks that reduce the mechanical properties of the structure has been investigated extensively [42], [43], [44], [45]. Fig. 3 shows some examples of IRT for the inspection of bridges' decks and abutment walls. In particular, Fig. 3(a) shows that IRT can be used to detect the level of severity of damages in a concrete deck, while Fig. 3(b) is an

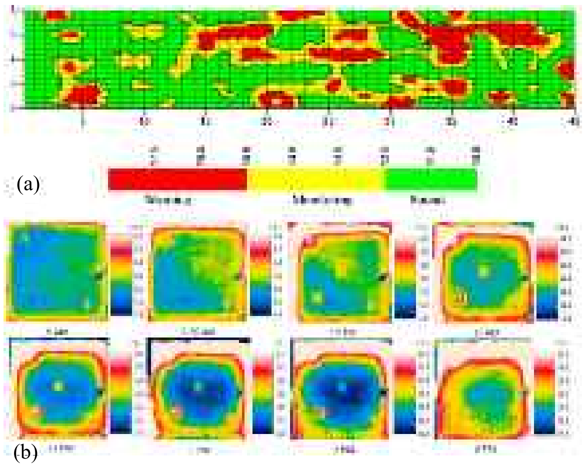

Fig. 3. Examples of IRT applications for SHM of bridges: (a) identification and classification of defects on a bridge deck [44] and (b) defect characterization as a function of the time of the day at which the IR data are collected [45].

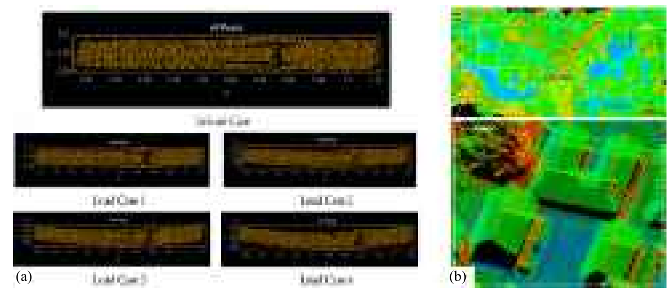

Fig. 4. Examples of LiDAR applications for SHM of large-scale structures: (a) measurement of displacement of a bridge deck under variable loading conditions [57] and (b) 3-D point cloud reconstruction using UAV-borne LiDAR [58].

example of the sensitivity of IRT as a function of the time of the day when the inspection is performed [45].

Besides concrete bridge SHM, IRT has been used to monitor damage propagation in crack-patched composite materials [46], as well as delamination and corrosion defects in railroad tracks and steel bridges [47], [48], [49]. IR imaging also found application for vibration analysis in harsh environments, showing accuracy ranging from 99.4% to 96.16% in measuring the natural frequency of a laboratory-scale acrylic frame when results are compared to accelerometer measurements [50]. Furthermore, due to the possibility of integrating IRT with drones, UAV-borne IRT has been used to inspect areas such as roadways and culverts to evaluate subpavement defects without interfering with road traffic [51], [52].

IRT requires thermal excitation, either active or passive, to distinguish between damaged and undamaged parts. The main drawback of IRT is the limited resolution of the camera, which is restricted by the size of the microbolometers used to measure the thermal radiation. The lower resolution requires significant thermal differences between the structural parts or a thermal excitation that is not always available in real-world settings to detect any damage. In addition, the cost of a thermal camera is higher compared to traditional visible-spectrum sensors limiting the use of this technique for SHM of large-scale structures [53].

C. Laser-Based Methods

Numerous studies have used laser imaging techniques, such as light detection and ranging (LiDAR) for strain measurement, damage detection in buildings, and bridge monitoring [54], [55], [56], [57]. Some of the results of those studies are shown in Fig. 4. In particular, an example of displacement of a bridge deck under variable loading conditions (see Fig. 4(a) [57]) and the 3-D point cloud obtained using UAV-borne LiDAR for cultural heritage site monitoring is shown (see Fig. 4(b) [58]). LiDAR can generate a 3-D reconstruction of the targeted structure with very limited geometric distortion because of the wavelength of the signal used [59]. For example, errors in the order ± 1 mm were observed when measuring the deflection of a beam [60]. In addition, LiDAR measurements are robust irrespective of the presence of sunlight, contributing to the wide applicability of this technique. Because LiDAR relies on a laser beam to map the surface contours, health concerns for interaction with the human eye must be considered when planning acquisition with this technique.

Furthermore, LiDAR accuracy depends on atmospheric conditions, which might cause deviation in the mapped surface, if not corrected [54]. LiDAR also has limited spatial information due to the fluctuation and multiple path effects. As a result, it is challenging to obtain calibrated measurements that have the accuracy necessary for SHM, even with high-resolution models [61]. An additional advancement in LiDAR technology included the use of multispectral cameras to increase geometric accuracy. However, this approach requires a dual-band to collect the data simultaneously, which increases not only the cost of the system but also the complexity of the analysis. Table I summarizes the advantages and disadvantages of the image-based techniques described in this section.

III. AI Methods for Automated Analysis of Remote Sensing Measurements

Advancements in AI, machine learning (ML), and DL algorithms made remote sensing techniques significantly appealing for SHM when large amounts of data need to be analyzed and classified. Despite some limitations and errors associated with new algorithms being developed, AI algorithms provide accurate assessment for damage detection and localization in complex systems. The applications, advantages, and challenges posed by AI algorithms are discussed in this section.

A. Features of AI Algorithms for SHM Applications

Based on the reviewed literature, current research trends mainly concentrate on: 1) damage localization; 2) damage classification; and 3) detection of the damage type and size. The general steps of AI implementation for SHM and NDT&E are summarized in Fig. 5. These steps are common for damage detection, localization, and classification procedures. Initially, the collected data are preprocessed to reduce the noise and enhance the information contained. Then, the dataset is divided

TABLE I
ADVANTAGES AND DISADVANTAGES OF THE REVIEWED IMAGE-BASED NONCONTACT SENSING TECHNIQUES FOR SHM

Method	Advantages	Limitations
3D-DIC/3DPT	• Full line-of-sight displacement and strain • High accuracy • Reduced interference with the structure	• Need for speckle patterns or optical target • Restriction of the FOV • Calibration takes a long time for larger objects
SfM	• Scan very large areas • High detailed reconstruction • Results easy to be imported into the BIM environment	• Scan size limited by flight constraints • Cannot perform under poor lighting conditions • Limited accuracy compared to other techniques
IRT	• Subsurface damage detection (e.g., voids, cracks) • It can be used for energy and heat loss audit	• High instrument cost • Limited Resolution • External heat excitation is required
LiDAR	• No geometry distortion • Can be used during the day and night • Data can be visualized as high accuracy map	• Hazardous for human iteration • Not reliable in presence of water • Not suitable for measuring dynamic events and mechanical properties

Fig. 5. General flowchart for application of AI algorithms to SHM and NDT&E.

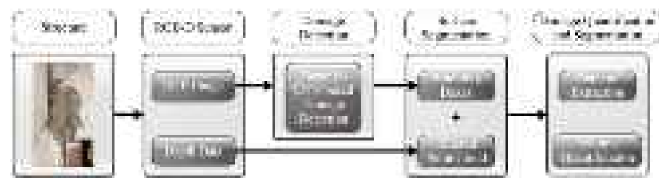
Fig. 6. Workflow of visible spectrum images used to create a point cloud for the detection and segmentation of the concrete spalling [67].

into two categories: 1) training (i.e., 100 – n) to train the algorithm and 2) validation (i.e., n) to evaluate the performance of the algorithm. Generally, this division can be in the range of 70%–80% for training and 30%–20% for validation depending on the specific application.

The steps presented in Fig. 5 are explained in detail in the following with reference to specific examples related to image-based noncontact sensing techniques for SHM and NDT&E of engineering structures.

1) Data Collection: The majority of AI algorithms are data-driven; thus, creating a large and reliable dataset is of utmost importance. Over the years, data collected from various noncontact sensing methods have been utilized successfully to train AI models and achieve desired results. By far, visible spectrum images and videos (e.g., RGB) have been the most popular methods for collecting data. For example, visible spectrum images of a wind turbine were used to create a point cloud of the structure and used as input for a support vector machine (SVM) algorithm to determine the size of the defects on the blades [62]. Visible spectrum images have also been used to classify the damaged and undamaged states of steel wire ropes [63] but especially "*crack*" and "*no-crack*" states of lab-scale concrete [64] and masonry [65] structures, given the texture of those elements. Multiclass damage classification of bridges' components has also been proven possible for damages such as rebar exposure, delamination, cracks, and undamaged regions [66]. Besides damage classification, visible spectrum images were also used to quantify the severity of concrete spalling using point clouds, as shown in Fig. 6 [67].

In another study, RGB videos were used to create sample images to segment cracks in concrete structures, which further leads to the evaluation of the grade of concrete, the dimension and percentage of steel, and other descriptors used to characterize the conditions of the system [68]. Similar crack segmentation methods for the analysis of concrete structures were used to evaluate the density of the cracks for systems under cyclic loading [69]. In addition, AI methods have been used to improve the performance of condition monitoring of structures using data collected from 3-D-DIC [70]. The possibility of using UAVs to acquire visible spectrum images has been leveraged to detect damage states of structures. Creating point clouds from visible spectrum images of large structures for the health assessment of the targeted system is one of the most widely used applications of UAVs [71]. UAVs require a global positioning system (GPS) to collect the data, which is a critical limitation of this approach. However, researchers have created methodologies for collecting data using UAVs, even for GPS-denied environments [72]. Other applications of the data collected using UAVs included locating and detecting cracks in steel surfaces [73], developing strategies for condition assessments of bridges such as inspecting steel box girders located at the bottom of long-span bridges that are difficult to access [74], [75]. Another application of visible spectrum images collected using UAVs is focused on classifying damaged and undamaged wind turbine blades using multiple DL methods to find the most suitable algorithm [76]. UAV-borne visible spectrum images were also used to classify roadways' pavement and reduce inspection time [77].

Aside from RGB images, IR images are also being used for structural assessment. IRT recently gained attention for integration with AI methods due to its ability to highlight subsurface defects. One of the most critical applications reported is the possibility of detecting delamination in concrete structures, which otherwise could not be detected using visible spectrum images [78], [79]. Multiple research used IRT for detecting subsurface voids in composite materials. Customized DL algorithms have been developed and used with IRT to detect damages in the matrix of carbon-fiber-reinforced

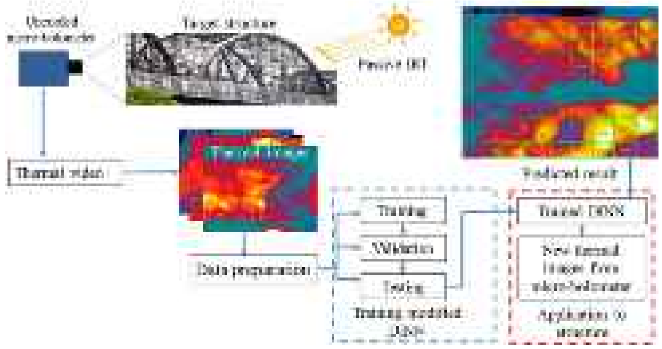

Fig. 7. UAV-borne IRT combined with DL methods: flowchart of a proposed approach for bridge inspection [48].

polymer composites [80], [81]. However, because the resolution of IR images is low and the amount of IR images available is limited, generative adversarial networks (GANs) are used to increase the size of the datasets for complex procedures, such as damage segmentation [82]. Recently, autoencoders have also been employed to enhance IR images and cope with low-resolution issues [83]. IRT has also been implemented with UAVs to collect data from large and relatively inaccessible structures, such as long-span bridges. In fact, the inspection of structural elements of bridges is time-consuming when performed manually. However, UAV-borne IRT can be performed in relatively less time with higher accuracy, as shown in Fig. 7 [48]. Similarly, UAV-borne IRT has been applied for highlighting delamination in the asphalt layers of inspected bridge decks [84].

2) Data Preprocessing: After data are collected, preprocessing methods are used to enhance the information contained in the dataset. Data preprocessing is a crucial step because the quality of the collected data directly affects the quality of the AI analysis. Depending on the specific image-based technique considered, different data preprocessing methods yield better results than others. For RGB images, generally, the images are enhanced by isolating the damaged area and improving the contrast [76]. If not enough images of the targeted structure are available, data augmentation methods are used to increase the size of the dataset artificially. Traditional data augmentation methods include rotating the image in multiple directions, cropping, zooming in, and changing the illumination [77]. Recently, GAN has been successfully used to increase the dataset size.

IRT images are generally preprocessed and normalized by: 1) balancing the temperature scale; 2) modifying the color palette; 3) reducing the noise in the image; and 4) improving the contrast [85], [86], [87], [88]. In the case of the image's background being too complicated and affecting the training of the AI models, masks are applied to remove the background and isolate the targeted structure [89]. In the case of thermographic analyses on bridge decks, heritage buildings, and composite materials, more advanced techniques, such as CNN-based autoencoders [83], [84], [90], Otsu thresholding [65], [76], the second derivative of temperature [79], and principal component analysis [91], [92], have been used for image enhancement.

3) Untrained and Trained AI Algorithms: Once data preprocessing is completed, it is possible to divide the dataset into two categories (i.e., training and validation) that will be fed into the selected AI algorithm. Depending upon the specific task to be developed, multiple AI algorithms can be employed that can be customized based on the end goal of the analysis. From the literature, it is possible to observe that the majority of the research focused on the domains of damage detection, classification, and localization. At the same time, very few works targeted the prognostic aspect of SHM and NDT&E.

For damage classification, traditional ML algorithms, such as k-nearest neighbors (KNNs), decision trees (DTs), and random forest (RF), have been used for a long time. Examples include the classification of defects based on different depths in laboratory-scale steel components using IRT images as input [87], [93], classification of damages in the bearings of induction motors [86], detection of cracks in railway tunnels [94], and classification of thermal defects in the façade of buildings using a mixed approach that combined IR and visible-spectrum images [95]. The variations of these algorithms, such as k-means clustering (KMC), are equally popular and have been proposed for image segmentation. KMC was used for crack rebar detection in bridge decks [96] and subsurface cracks in industrial materials [72].

The introduction of transfer learning (TL) has steered the research community in the direction of DL algorithms, thanks to the improved performance caused by the TL addition. DL algorithms, such as CNNs and modified versions of CNN, gained popularity because of better performance (e.g., computation time and accuracy) compared to traditional damage diagnostics algorithms [48], [85]. For example, TL algorithms are pretrained on many datasets and then trained again on the desired dataset. This double-training process improves the performance of the algorithms. Repositories such as *TensorFlow Hub* make available to researchers several algorithms pretrained on millions of images by Google, which would otherwise take weeks and months to train [97]. The most popular algorithms currently used are ResNet [96], YOLO [73], R-CNN [98], and its variations Faster R-CNN [67], [81] and masked R-CNN [98], [99] that have been used to monitor and detect surface cracks in composite and other structural materials. These algorithms are region-based and, thus, suitable for image segmentation. Most of the literature has been focused on crack segmentation in concrete slabs [68], [69], masonry [65], water-related problems and thermal bridges in civil infrastructure [99], bridges [100], and structural components made of composite materials [101] or stainless-steel [48]. Other TL algorithms, such as VGG16 [65] and inception V2/V3 [81], have also been used for classifying damages in masonry structural components and damage segmentation in composites. One of the most interesting characteristics of those algorithms is their versatility and flexibility in operating with different datasets. Because the algorithms are trained on the specific dataset after being pretrained, they can be used with RGB images, IR images, laser scans, and other signals (e.g., vibration, ultrasonic, and guided waves). A summary of the different AI algorithms used for SHM and the specific

TABLE II
LITERATURE DISTRIBUTION ACCORDING TO THE AI ALGORITHMS AND CORRESPONDING IMAGE-BASED SENSING METHOD

AI algorithm	Sensing technique
Traditional machine learning (i.e., KNN, SVM, DT, RF, KMC)	Photogrammetry: [62], [102] Photogrammetry with UAVs: [76] IRT: [45], [73], [85], [86], [87], [92], [93], [95] Laser: [94]
DL algorithms (i.e., CNN, deep neural network, artificial neural network)	Photogrammetry: [63], [70], [84], [98], [104 – 109] IRT: [83], [84], [85], [89], [90], [110], [111] IRT with UAVs: [48] Laser: [112], [113]
TL algorithms for damage classification (i.e., VGG16, inception V2/V3)	Photogrammetry: [64], [65], [69], [76], [114], [115] IRT: [78], [88], [116]
Region-based algorithms (i.e., R-CNN, faster R-CNN, masked R-CNN, UNet)	Photogrammetry: [67], [117], [118], [119], [120], [121], [122], [123] Photogrammetry with UAVs: [75], [100] IRT: [81], [82], [99], [124], [125]
YOLO, ResNet, AlexNet, DenseNet	Photogrammetry: [65], [66], [101], [115], [126], [127] Photogrammetry with UAVs: [73], [74], [77], [128] IRT: [79] IRT with UAVs: [35] Laser: [129]

image-based noncontact sensing technique to which each method has been applied is shown in Table II.

B. Advantages and Challenges of AI Algorithms for SHM Applications

An increasing number of researchers are investigating the use of AI algorithms for SHM given the terrific advantages that those methods offer compared to traditional human-centered analyses. AI algorithms can be used in the data processing stage to improve the datasets without compromising their quality. This can be done by using AI-based data augmentation tools to increase the size of the dataset [82]. AI algorithms can also be utilized to improve the efficiency of damage detection and localization [94].

In addition, AI algorithms increase the robustness of the selected sensing technique so that the final results remain unaffected by unfavorable experimental conditions. One example is the detection of delamination in concrete slabs where the detectability of the damage is proportional to the depth of the delamination, and the results are not affected by the presence of mortar and water [72]. In the case of 3-D-DIC applications, the performance of the technique gets affected by low light and requires optical targets to track the motion of the pixels' subset. However, with the help of CNN and other background removal tools, 3-D-DIC can be made more resistant to changes in illumination and remove the requirement of having optical targets [130]. Some AI models do not require extensive data preprocessing due to their effectiveness, which is another advantage of these techniques when applied to a domain such as vibration-based SHM for extracting mode shapes and dynamic parameters of a structure of interest [131]. Overall, AI algorithms are highly robust and can detect damages that are very difficult to spot given their small size (e.g., delamination in composite materials that can be confused with the bonding material [81] and hairline cracks in damaged bearings [132]). It should be noted that the performance of AI algorithms can be determined based on parameters such as confusion matrix, accuracy, precision, F-1 score, recall, and rms values [95]. A discussion about those parameters is external to the scope of this review; however, interested readers can refer to [67] and [133].

TABLE III
FUTURE DIRECTIONS FOR THE USE OF IMAGE-BASED SENSING FOR SHM

Technique	Future research directions
3-D-DIC/ 3DPT	• Simplify stereo camera calibration for large areas • Replace speckle pattern with surface features using template matching
SfM	• Verify performance under poor lighting conditions and extreme environments • Verify effect of oblique angles and overlap ratio when used with UAVs and non visible spectrum images.
IRT	• Poor image resolution. • Understand the effect of the type of thermal excitation used and environmental factors on accuracy.
LiDAR	• Optimize 3D reconstruction and non-linear surface mapping when used with UAVs.

While AI algorithms can provide benefits for an expedited analysis of large datasets, data quality and quantity are still one of the main limitations for automated detection and classification. Poor quality data used to train the algorithms can affect the results of the analysis. Hence, the data selection and preprocessing steps are essential when data-driven models are used. Even when the data are of good quality, an insufficient amount of data can affect the results. From the literature, it was clear that there is a requirement for publicly available large datasets. Because most of the available datasets were collected in lab-scale, ad hoc settings (e.g., aluminum beams and concrete slabs), their applicability to real-world scenarios is questionable. As a result, there is a need to create more real-world datasets, which can be used to train new algorithms. While it is possible to limit the effects of insufficient data on the accuracy of the results by incorporating

TABLE IV
CONCLUSIVE REMARKS AND FUTURE DIRECTIONS FOR THE USE OF AI WITH APPLICATION IN SHM

Application	Future research directions	Ref.
Wind turbines	• Improvement in the safety, reliability, and robustness of the use of automation in wind turbine farms. • Develop remote, NDT&E, and wireless techniques for online monitoring of wind turbine blades.	[135], [136], [137]
Bridges	• Weigh-in-motion is a promising technology for bridge maintenance. To use it with AI, high-quality data collection is important as well as uncertainty quantification. • Datasets for multiple damage types (e.g., corrosion, delamination) and dynamic response of the bridge are needed. • Given the currently available data and lack of uncertainty quantification, supervised algorithms have been performing better. However, unsupervised DL methods have untapped potential.	[138], [139], [140], [141], [142]
Crack detection	• Need for developing datasets for cracks. • Designing AI methods that can quantify the depth of a crack.	[143]
Pavements	• Laser scans are very expensive and require further research to optimize the data collection parameters. • Thermal and stereovision imaging needs to be explored more to make them compatible with AI algorithms.	[142], [144]
Structural engineering	• Need for diverse high-quality public datasets to aid the development of AI algorithms. • DL can provide significant improvements for point cloud reconstruction and the building of information models. • Lack of data, including environmental parameters (e.g., noise measurement), modeling errors, and multiple damage types, limits the use of AI in this area.	[71], [145], [146], [147], [148]
Buildings	• Building structural design and performance assessment need to be combined with the AI models. • Advancements in digital twin technology can optimize the building life cycle.	[149], [150], [151]
Automation with human factor	• Including the human factor in the decision-making process making to increase efficiency and reduce the subjectivity of the algorithms. • Considering constraints to keep automation safe for humans and the environment.	[152], [153]
Augmented reality	• Possibility to inspect structures of interest remotely reducing risks and costs for the inspectors. • Further studies for solving occlusion and latency problems and increase acceptance of this approach from the academic and engineering communities. • Improve accuracy of 3D reconstruction from 2D images	[154], [155], [156], [157]
CNN-based SHM	• Requirement for a high-quality dataset. • Improvement in AI frameworks is also needed to increase the accuracy of the models.	[158], [159]

physics in the AI models (i.e., physics-based AI models), the research in this area is still at a very rudimentary stage to be used for SHM. This area offers promising potential because of the incorporation of physics, which will decrease the sole dependence of the results on the training datasets of the AI algorithms. In turn, the resiliency of the AI model for SHM and prognostics will improve [134]. In addition, recent advancements in digital twin technology showed the possibility to bring significant improvements by generating high-quality results for analyses of complex systems, such as wind turbines, road infrastructures, and long-span bridges. Therefore, digital twin technology is considered a very promising research direction toward an effective automated SHM and NDT&E.

IV. FUTURE DIRECTIONS FOR AI-ENHANCED SHM

Image-based noncontact sensing techniques provide several advantages compared to their contact-based counterpart. Stereophotogrammetry techniques, such as 3-D-DIC and 3DPT, can be used for monitoring the targeted structure and full-line-of-sight displacement and strain field measurements. The method can be integrated with UAVs to expedite the image-capturing process and to collect data from areas difficult to access. However, because of problems related to cumbersome calibration, it is challenging to use 3-D-DIC and 3DPT for large-scale systems, such as bridges and wind turbine blades that require larger FOVs. Other photogrammetry methods, such as SfM, have been successfully used with UAVs for highly detailed point cloud reconstruction of various large-scale civil and transportation engineering infrastructures, such as concrete dams and highways. SfM performances under poor lighting conditions and extreme environments are still to be verified. SfM has also been combined with IRT showing the potential to be used at night and detect subsurface defects in residential buildings and facilitate energy audits too. However, studies to address temperature sensitivity, problems related to the different thermal emissivity of different surfaces, the effect of different camera angles on the accuracy of the reconstructed point cloud, and the resolution when large areas are mapped are still very limited in the literature [36]. When used as a stand-alone technique, IRT has proved capable to detect voids, subsurface defects, and delamination with specific postprocessing methods. Still, research is needed to address the poor signal-to-noise ratio of this technique and how to automate the process of emissivity selection in images of structures made of different materials. LiDAR has been used for generating high-resolution models of buildings' roofs, facades, and entire portions of a city. Despite the operational ease, this method cannot still reconstruct models of structures having complex geometry (e.g., curved rooftops) as the model reconstruction is based on a liner piecewise segmentation.

Table III summarizes future research directions needed to increase the applicability of the techniques discussed in this review for SHM of large-scale civil, mechanical, building, and energy engineering structures.

AI improves the quality of the dataset and the accuracy of damage detection. However, the limitations regarding data dependency are still a concern. There is a need to create publicly available large datasets with real-world information to train new emerging AI algorithms. At the same time, introducing physics in the AI models is an important future direction that the SHM community just started to investigate. Table IV summarizes future research directions for advancing AI algorithms as a function of the application domain. Table IV also indicates references for readers interested in gaining a better understanding of current practices for the specific applications discussed.

While this survey focuses on the application of computer vision techniques augmented with AI algorithms in the fields of SHM and NDT&E for condition monitoring, prevention, maintenance, and prognostics of engineering systems, it is worth mentioning that machine vision and ML methods have had a terrific impact also for uses within industry 4.0. Even if external to the scope of this survey, several demonstrations of image-based AI-augmented methods for construction management [145], [160], [161], [162], robotic navigation [163], cybersecurity [164], [165], and medical imaging [166] are available to the interested readers.

V. Conclusion

Monitoring aging engineering structures poses challenges and difficulties to stakeholders and operators. Image-based sensing techniques have proven adequate for SHM and NDT&E applications to simplify data collection and provide more accurate information. Benefits are even more accentuated when those techniques are paired with UAVs to expedite the data collection and with AI algorithms for increased data analytics capabilities. This study provides a systematic review of image-based noncontact techniques used for SHM and NDT&E while summarizing recent advancements in the integration of said approaches with AI methods. One hundred thirty-five papers have been surveyed for this review. SfM has been successfully used with UAVs for highly detailed point cloud reconstruction of various large-scale civil and transportation engineering infrastructures. SfM performances under poor lighting conditions and extreme environments are still to be verified. SfM has also been used in conjunction with IRT. It has shown the potential to be used at night and detect subsurface defects. However, studies to address temperature sensitivity, the effect of different camera angles on the accuracy of the reconstructed point cloud, and the resolution when large areas are mapped are still limited in the literature. Even when LiDAR can generate high-resolution models of buildings' roofs, facades, and entire portions of a city, this technique cannot reconstruct complex geometries. Hence, more advanced postprocessing methods need to be developed. For the AI part of this review, 97 articles were considered, showing how the automated analysis of data collected using image-based sensing techniques represents a promising venue for SHM and NDT&E. AI improves the quality of the dataset and the accuracy of damage detection but requires a significant amount of images due to its data-driven nature. Hence, large datasets need to be created and made publically available. On the other hand, introducing physics in the AI models is an important future direction that can reduce the effects of low-quality data on the final results.

References

[1] N. Ida and N. Meyendorf, *Handbook of Advanced Nondestructive Evaluation*. Cham, Switzerland: Springer, 2019, pp. 235–251.

[2] C. R. Farrar and K. Worden, "An introduction to structural health monitoring," *Philos. Trans. Roy. Soc. London A, Math. Phys. Sci.*, vol. 365, no. 1851, pp. 303–315, 2007.

[3] A. Sabato, M. Q. Feng, Y. Fukuda, D. L. Carní, and G. Fortino, "A novel wireless accelerometer board for measuring low-frequency and low-amplitude structural vibration," *IEEE Sensors J.*, vol. 16, no. 9, pp. 2942–2949, May 2016.

[4] A. Sabato, C. Niezrecki, and G. Fortino, "Wireless MEMS-based accelerometer sensor boards for structural vibration monitoring: A review," *IEEE Sensors J.*, vol. 17, no. 2, pp. 226–235, Jan. 2017.

[5] G. Fortino, C. Savaglio, G. Spezzano, and M. C. Zhou, "Internet of Things as system of systems: A review of methodologies, frameworks, platforms, and tools," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 51, no. 1, pp. 223–236, Jan. 2021.

[6] Y. Yang, Y. Zhang, and X. Tan, "Review on vibration-based structural health monitoring techniques and technical codes," *Symmetry*, vol. 13, no. 11, p. 1998, Oct. 2021.

[7] C. Niezrecki, J. Baqersad, and A. Sabato, "Digital image correlation techniques for non-destructive evaluation and structural health monitoring," in *Handbook of Advanced Non-Destructive Evaluation*. Cham, Switzerland: Springer, 2018, p. 46.

[8] K. Ghaedi, M. Gordan, Z. Ismail, H. Hashim, and M. Talebkhah, "A literature review on the development of remote sensing in damage detection of civil structures," *J. Eng. Res. Rep.*, vol. 20, no. 10, pp. 39–56, Jul. 2021.

[9] Z. Tong, J. Gao, and D. Yuan, "Advances of deep learning applications in ground-penetrating radar: A survey," *Construction Building Mater.*, vol. 258, Oct. 2020, Art. no. 120371.

[10] M. Mitra and S. Gopalakrishnan, "Guided wave based structural health monitoring: A review," *Smart Mater. Struct.*, vol. 25, no. 5, Mar. 2016, Art. no. 053001.

[11] S. Cantero-Chinchilla, P. D. Wilcox, and A. J. Croxford, "Deep learning in automated ultrasonic NDE—Developments, axioms and opportunities," *NDT E Int.*, vol. 131, Oct. 2022, Art. no. 102703.

[12] N. Shen et al., "A review of global navigation satellite system (GNSS)-based dynamic monitoring technologies for structural health monitoring," *Remote Sens.*, vol. 11, no. 9, p. 1001, Apr. 2019.

[13] D. Feng and M. Q. Feng, "Computer vision for SHM of civil infrastructure: From dynamic response measurement to damage detection—A review," *Eng. Struct.*, vol. 156, pp. 105–117, Feb. 2018.

[14] F. López et al., "Thermal stresses applied on helicopter blades useful to retrieve defects by means of infrared thermography and speckle patterns," *Thermal Sci. Eng. Prog.*, vol. 18, Aug. 2020, Art. no. 100511.

[15] W. Minkina, B. B. Lahiri, T. Saravanan, J. Philip, and T. Jayakumar, "Theoretical basics of radiant heat transfer–practical examples of calculation for the infrared (IR) used in infrared thermography measurements," *Quant. Infr. Thermography J.*, vol. 18, no. 4, pp. 269–282, Apr. 2020.

[16] D. Moon, S. Chung, S. Kwon, J. Seo, and J. Shin, "Comparison and utilization of point cloud generated from photogrammetry and laser scanning: 3D world model for smart heavy equipment planning," *Autom. Construction*, vol. 98, pp. 322–331, Feb. 2019.

[17] X. W. Ye, T. Jin, and C. B. Yun, "A review on deep learning-based structural health monitoring of civil infrastructures," *Smart Struct. Syst.*, vol. 24, no. 5, pp. 567–585, 2019.

[18] M. Moradi, A. Broer, J. Chiachío, R. Benedictus, T. H. Loutas, and D. Zarouchas, "Intelligent health indicator construction for prognostics of composite structures utilizing a semi-supervised deep neural network and SHM data," *Eng. Appl. Artif. Intell.*, vol. 117, Jan. 2023, Art. no. 105502.

[19] R. Wu, D. Zhang, Q. Yu, Y. Jiang, and D. Arola, "Health monitoring of wind turbine blades in operation using three-dimensional digital image correlation," *Mech. Syst. Signal Process.*, vol. 130, pp. 470–483, Sep. 2019.

[20] J. Winkler and M. D. Hansen, "Innovative long-term monitoring of the great belt bridge expansion joint using digital image correlation," *Structural Eng. Int.*, vol. 28, no. 3, pp. 347–352, Jul. 2018.

[21] P. Poozesh, A. Sabato, A. Sarrafi, C. Niezrecki, P. Avitabile, and R. Yarala, "Multicamera measurement system to evaluate the dynamic response of utility-scale wind turbine blades," *Wind Energy*, vol. 23, no. 7, pp. 1619–1639, 2020.

[22] A. Khadka, B. Fick, A. Afshar, M. Tavakoli, and J. Baqersad, "Non-contact vibration monitoring of rotating wind turbines using a semi-autonomous UAV," *Mech. Syst. Signal Process.*, vol. 138, Apr. 2020, Art. no. 106446.

[23] R. Janeliukstis and X. Chen, "Review of digital image correlation application to large-scale composite structure testing," *Composite Struct.*, vol. 271, Sep. 2021, Art. no. 114143.

[24] D. Reagan, A. Sabato, and C. Niezrecki, "Feasibility of using digital image correlation for unmanned aerial vehicle structural health monitoring of bridges," *Struct. Health Monitor.*, vol. 17, no. 5, pp. 1056–1072, Sep. 2018.

[25] L. Ngeljaratan and M. A. Moustafa, "Structural health monitoring and seismic response assessment of bridge structures using target-tracking digital image correlation," *Eng. Struct.*, vol. 213, Jun. 2020, Art. no. 110551.

[26] M. S. Dizaji, D. K. Harris, B. Kassner, and J. C. Hill, "Full-field non-destructive image-based diagnostics of a structure using 3D digital image correlation and laser scanner techniques," *J. Civil Struct. Health Monitor.*, vol. 11, no. 5, pp. 1415–1428, Nov. 2021.

[27] S. Khalilzadehtabrizi, A. Seifiasl, and M. H. Asl, "Measurement of deformation patterns in steel plate shear walls subjected to cyclic loading based on multi-target digital image correlation (MT-DIC)," *Structures*, vol. 33, pp. 2611–2627, Oct. 2021.

[28] B. Pan, "Digital image correlation for surface deformation measurement: Historical developments, recent advances and future goals," *Meas. Sci. Technol.*, vol. 29, no. 8, Aug. 2018, Art. no. 082001.

[29] C. B. Gamboa, S. Martín-Béjar, F. J. T. Vilches, G. C. López, and L. S. Hurtado, "2D–3D digital image correlation comparative analysis for indentation process," *Materials*, vol. 12, no. 24, p. 4156, Dec. 2019.

[30] A. Sabato, N. A. Valente, and C. Niezrecki, "Development of a camera localization system for three-dimensional digital image correlation camera triangulation," *IEEE Sensors J.*, vol. 20, no. 19, pp. 11518–11526, Oct. 2020.

[31] D. Kumar, C.-H. Chiang, and Y.-C. Lin, "Experimental vibration analysis of large structures using 3D DIC technique with a novel calibration method," *J. Civil Struct. Health Monitor.*, vol. 12, no. 2, pp. 391–409, Apr. 2022.

[32] Y. Wang, X. Wang, Z. Wan, and J. Zhang, "A method for extrinsic parameter calibration of rotating binocular stereo vision using a single feature point," *Sensors*, vol. 18, no. 11, p. 3666, Oct. 2018.

[33] S. Zollini, M. Alicandro, D. Dominici, R. Quaresima, and M. Giallonardo, "UAV photogrammetry for concrete bridge inspection using object-based image analysis (OBIA)," *Remote Sens.*, vol. 12, no. 19, p. 3180, 2020.

[34] K. Kingsland, "Comparative analysis of digital photogrammetry software for cultural heritage," *Digit. Appl. Archaeology Cultural Heritage*, vol. 18, Sep. 2020, Art. no. e00157.

[35] M. Puliti, G. Montaggioli, and A. Sabato, "Automated subsurface defects' detection using point cloud reconstruction from infrared images," *Autom. Construction*, vol. 129, Sep. 2021, Art. no. 103829.

[36] S. Dabetwar, N. N. Kulkarni, M. Angelosanti, C. Niezrecki, and A. Sabato, "Sensitivity analysis of unmanned aerial vehicle-borne 3D point cloud reconstruction from infrared images," *J. Building Eng.*, vol. 58, Oct. 2022, Art. no. 105070, doi: 10.1016/j.jobe.2022.105070.

[37] J. M. de Luis-Ruiz, J. Sedano-Cibrián, R. Pérez-Álvarez, R. Pereda-García, and B. Malagón-Picón, "Metric contrast of thermal 3D models of large industrial facilities obtained by means of low-cost infrared sensors in UAV platforms," *Int. J. Remote Sens.*, vol. 43, no. 2, pp. 457–483, Jan. 2022.

[38] Y. Hou, M. Chen, R. Volk, and L. Soibelman, "Investigation on performance of RGB point cloud and thermal information data fusion for 3D building thermal map modeling using aerial images under different experimental conditions," *J. Building Eng.*, vol. 45, Jan. 2022, Art. no. 103380.

[39] S. Schramm, P. Osterhold, R. Schmoll, and A. Kroll, "Combining modern 3D reconstruction and thermal imaging: Generation of large-scale 3D thermograms in real-time," *Quant. Infr. Thermography J.*, vol. 19, no. 5, pp. 295–311, Oct. 2021.

[40] M. H. A. Larbi Youcef, V. Feuillet, L. Ibos, and Y. Candau, "In situ quantitative diagnosis of insulated building walls using passive infrared thermography," *Quant. Infr. Thermography J.*, vol. 19, no. 1, pp. 41–69, Aug. 2020.

[41] T. Aujeszky, G. Korres, and M. Eid, "Material classification with laser thermography and machine learning," *Quant. Infr. Thermography J.*, vol. 16, no. 2, pp. 181–202, Dec. 2018.

[42] Z. Wang, G. Tian, M. Meo, and F. Ciampa, "Image processing based quantitative damage evaluation in composites with long pulse thermography," *NDT E Int.*, vol. 99, pp. 93–104, Oct. 2018.

[43] S. Hiasa, R. Birgul, M. Matsumoto, and F. Necati Catbas, "Experimental and numerical studies for suitable infrared thermography implementation on concrete bridge decks," *Measurement*, vol. 121, pp. 144–159, Jun. 2018.

[44] J. H. A. Rocha, C. F. Santos, and Y. V. Póvoas, "Evaluation of the infrared thermography technique for capillarity moisture detection in buildings," *Proc. Structural Integrity*, vol. 11, pp. 107–113, 2018.

[45] T. Omar, M. L. Nehdi, and T. Zayed, "Infrared thermography model for automated detection of delamination in RC bridge decks," *Construction Building Mater.*, vol. 168, pp. 313–327, Apr. 2018.

[46] U. Martens and K.-U. Schröder, "Monitoring multiple damage mechanisms in crack-patched structures using optical infrared thermography," *Fatigue Fract. Eng. Materials Struct.*, vol. 44, no. 3, pp. 705–718, Mar. 2021.

[47] B. Ramzan, M. S. Malik, M. Martarelli, H. T. Ali, M. Yusuf, and S. M. Ahmad, "Pixel frequency based railroad surface flaw detection using active infrared thermography for structural health monitoring," *Case Stud. Thermal Eng.*, vol. 27, Oct. 2021, Art. no. 101234.

[48] R. Ali and Y.-J. Cha, "Subsurface damage detection of a steel bridge using deep learning and uncooled micro-bolometer," *Construction Building Mater.*, vol. 226, pp. 376–387, Nov. 2019.

[49] S. Doshvarpassand, C. Wu, and X. Wang, "An overview of corrosion defect characterization using active infrared thermography," *Infr. Phys. Technol.*, vol. 96, pp. 366–389, Jan. 2019.

[50] J. H. He, D. P. Liu, C. H. Chung, and H. H. Huang, "Infrared thermography measurement for vibration-based structural health monitoring in low-visibility harsh environments," *Sensors*, vol. 20, no. 24, p. 7067, 2020.

[51] N. N. Kulkarni, S. Dabetwar, J. Benoit, T. Yu, and A. Sabato, "Comparative analysis of infrared thermography processing techniques for roadways' sub-pavement voids detection," *NDT E Int.*, vol. 129, Jul. 2022, Art. no. 102652.

[52] J.-G. Sim, "Improved image processing of road pavement defect by infrared thermography," *Sel. Scientific Papers J. Civil Eng.*, vol. 13, no. s1, pp. 61–72, Mar. 2018.

[53] R. A. Osornio-Rios, J. A. Antonino-Daviu, and R. J. Romero-Troncoso, "Recent industrial applications of infrared thermography: A review," *IEEE Trans. Ind. Informat.*, vol. 15, no. 2, pp. 615–625, Feb. 2019.

[54] Soilán, Sánchez-Rodríguez, P. D. Río-Barral, C. Perez-Collazo, P. Arias, and B. Riveiro, "Review of laser scanning technologies and their applications for road and railway infrastructure monitoring," *Infrastructures*, vol. 4, no. 4, p. 58, Sep. 2019.

[55] H. C. Jo, J. Kim, K. Lee, H.-G. Sohn, and Y. M. Lim, "Non-contact strain measurement for laterally loaded steel plate using LiDAR point cloud displacement data," *Sens. Actuator A, Phys.*, vol. 283, pp. 362–374, Nov. 2018.

[56] R. Albano, "Investigation on roof segmentation for 3D building reconstruction from aerial LIDAR point clouds," *Appl. Sci.*, vol. 9, no. 21, p. 4674, Nov. 2019.

[57] G. Cha, S. H. Sim, S. Park, and T. Oh, "LiDAR-based bridge displacement estimation using 3D spatial optimization," *Sensors*, vol. 20, no. 24, pp. 1–19, 2020.

[58] Y. Jo and S. Hong, "Three-dimensional digital documentation of cultural heritage site based on the convergence of terrestrial laser scanning and unmanned aerial vehicle photogrammetry," *ISPRS Int. J. Geo-Inf.*, vol. 8, no. 2, p. 53, Jan. 2019.

[59] R. Wang, J. Peethambaran, and D. Chen, "LiDAR point clouds to 3-D urban models: A review," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 11, no. 2, pp. 606–627, Feb. 2018.

[60] M. B. Maru, D. Lee, G. Cha, and S. Park, "Beam deflection monitoring based on a genetic algorithm using lidar data," *Sensors*, vol. 20, no. 7, p. 2144, 2020.

[61] S. Xia, D. Chen, R. Wang, J. Li, and X. Zhang, "Geometric primitives in LiDAR point clouds: A review," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 13, pp. 685–707, 2020.

[62] Z. Wang and D. Zhu, "An accurate detection method for surface defects of complex components based on support vector machine and spreading algorithm," *Measurement*, vol. 147, Dec. 2019, Art. no. 106886.

[63] X. Huang, Z. Liu, X. Zhang, J. Kang, M. Zhang, and Y. Guo, "Surface damage detection for steel wire ropes using deep learning and computer vision techniques," *Measurement*, vol. 161, Sep. 2020, Art. no. 107843.

[64] J. A. Guzmán-Torres, M. Z. Naser, and F. J. Domínguez-Mota, "Effective medium crack classification on laboratory concrete specimens via competitive machine learning," *Structures*, vol. 37, pp. 858–870, Mar. 2022.

[65] D. Dais, İ. E. Bal, E. Smyrou, and V. Sarhosis, "Automatic crack classification and segmentation on masonry surfaces using convolutional neural networks and transfer learning," *Autom. Construction*, vol. 125, May 2021, Art. no. 103606.

[66] W. Deng et al., "Vision based pixel-level bridge structural damage detection using a link ASPP network," *Autom. Construction*, vol. 110, Feb. 2020, Art. no. 102973.

[67] G. H. Beckman, D. Polyzois, and Y.-J. Cha, "Deep learning-based automatic volumetric damage quantification using depth camera," *Autom. Construction*, vol. 99, pp. 114–124, Dec. 2019.

[68] S. Das, S. Dutta, D. Adak, and S. Majumdar, "On the crack characterization of reinforced concrete structures: Experimental and data-driven numerical study," *Structures*, vol. 30, pp. 134–145, Dec. 2021.

[69] C. V. Dung and L. D. Anh, "Autonomous concrete crack detection using deep fully convolutional neural network," *Autom. Construction*, vol. 99, pp. 52–58, Dec. 2019.

[70] Q. Song, J. Wu, H. Wang, Y. An, and G. Tang, "Computer vision-based illumination-robust and multi-point simultaneous structural displacement measuring method," *Mech. Syst. Signal Process.*, vol. 170, Oct. 2022, Art. no. 108822.

[71] W. Fang et al., "Computer vision applications in construction safety assurance," *Autom. Construction*, vol. 110, Feb. 2020, Art. no. 103013.

[72] A. Risheh, P. Tavakolian, A. Melinkov, and A. Mandelis, "Infrared computer vision in non-destructive imaging: Sharp delineation of subsurface defect boundaries in enhanced truncated correlation photothermal coherence tomography images using K-means clustering," *NDT E Int.*, vol. 125, Jan. 2022, Art. no. 102568.

[73] Q. Han, X. Liu, and J. Xu, "Detection and location of steel structure surface cracks based on unmanned aerial vehicle images," *J. Building Eng.*, vol. 50, Jun. 2022, Art. no. 104098.

[74] B. J. Perry, Y. Guo, R. Atadero, and J. W. van de Lindt, "Streamlined bridge inspection system utilizing unmanned aerial vehicles (UAVs) and machine learning," *Measurement*, vol. 164, Nov. 2020, Art. no. 108048.

[75] D. Wang, Y. Zhang, Y. Pan, B. Peng, H. Liu, and R. Ma, "An automated inspection method for the steel box girder bottom of long-span bridges based on deep learning," *IEEE Access*, vol. 8, pp. 94010–94023, 2020.

[76] X. Yang, Y. Zhang, W. Lv, and D. Wang, "Image recognition of wind turbine blade damage based on a deep learning model with transfer learning and an ensemble learning classifier," *Renew. Energy*, vol. 163, pp. 386–397, Aug. 2021.

[77] J. Zhu, J. Zhong, T. Ma, X. Huang, W. Zhang, and Y. Zhou, "Pavement distress detection using convolutional neural networks with images captured via UAV," *Autom. Construction*, vol. 133, Jan. 2022, Art. no. 103991.

[78] J.-Y. Wu, S. Sfarra, and Y. Yao, "Sparse principal component thermography for subsurface defect detection in composite products," *IEEE Trans. Ind. Informat.*, vol. 14, no. 12, pp. 5594–5600, Dec. 2018.

[79] J.-C. Gu, S. Unjoh, and H. Naito, "Detectability of delamination regions using infrared thermography in concrete members strengthened by CFRP jacketing," *Composite Struct.*, vol. 245, Nov. 2020, Art. no. 112328.

[80] J. Ahmed, B. Gao, and W. Lok Woo, "Wavelet-integrated alternating sparse dictionary matrix decomposition in thermal imaging CFRP defect detection," *IEEE Trans. Ind. Informat.*, vol. 15, no. 7, pp. 4033–4043, Jul. 2019.

[81] H.-T. Bang, S. Park, and H. Jeon, "Defect identification in composite materials via thermography and deep learning techniques," *Composite Struct.*, vol. 246, Aug. 2020, Art. no. 112405.

[82] L. Cheng, Z. Tong, S. Xie, and M. Kersemans, "IRT-GAN: A generative adversarial network with a multi-headed fusion strategy for automated defect detection in composites using infrared thermography," *Composite Struct.*, vol. 290, Jun. 2022, Art. no. 115543.

[83] M. Zheng, K. Liu, N. Li, Y. Yao, and Y. Liu, "Deep autoencoder for non-destructive testing of defects in polymer composites," in *Proc. 8th Int. Conf. Inf., Cybern., Comput. Social Syst. (ICCSS)*, 2022, pp. 91-95.

[84] C. Cheng, Z. Shang, and Z. Shen, "Automatic delamination segmentation for bridge deck based on encoder–decoder deep learning through UAV-based thermography," *NDT E Int.*, vol. 116, Jul. 2020, Art. no. 102341.

[85] Y. Cao, Y. Dong, Y. Cao, J. Yang, and M. Y. Yang, "Two-stream convolutional neural network for non-destructive subsurface defect detection via similarity comparison of lock-in thermography signals," *NDT E Int.*, vol. 112, Jun. 2020, Art. no. 102246.

[86] A. Choudhary, D. Goyal, and S. S. Letha, "Infrared thermography-based fault diagnosis of induction motor bearings using machine learning," *IEEE Sensors J.*, vol. 21, no. 2, pp. 1727–1734, Aug. 2021.

[87] H. Chen, Z. Zhang, W. Yin, C. Zhao, F. Wang, and Y. Li, "A study on depth classification of defects by machine learning based on hyper-parameter search," *Measurement*, vol. 189, Feb. 2022, Art. no. 110660.

[88] J. Gu and S. Unjoh, "Image processing methodology for detecting delaminations using infrared thermography in CFRP-jacketed concrete members by infrared thermography," *Composite Struct.*, vol. 270, Oct. 2021, Art. no. 114040.

[89] G. Montaggioli, M. Puliti, and A. Sabato, "Automated damage detection of bridge's sub-surface defects from infrared images using machine learning," *Proc. SPIE*, vol. 11593, pp. 427–435, Mar. 2021.

[90] K. Kaur, R. Mulaveesala, and P. Mishra, "Constrained autoencoder-based pulse compressed thermal wave imaging for sub-surface defect detection," *IEEE Sensors J.*, vol. 22, no. 18, pp. 17335–17342, Sep. 2021.

[91] X. Li, X. Ying, W. Zhu, W. Liu, B. Hou, and L. Zhou, "Nondestructive detection and analysis based on data enhanced thermography," *Meas. Sci. Technol.*, vol. 33, no. 6, Jun. 2022, Art. no. 064006.

[92] Z. Wang, L. Wan, N. Xiong, J. Zhu, and F. Ciampa, "Variational level set and fuzzy clustering for enhanced thermal image segmentation and damage assessment," *NDT E Int.*, vol. 118, Mar. 2021, Art. no. 102396.

[93] H. Chen et al., "Depth classification of defects based on neural architecture search," *IEEE Access*, vol. 9, pp. 73424–73432, 2021.

[94] A. Sánchez-Rodráguez, B. Riveiro, M. Soilán, and L. M. González-de-Santos, "Automated detection and decomposition of railway tunnels from mobile laser scanning datasets," *Autom. Constr.*, vol. 96, pp. 171–179, Sep. 2018.

[95] C. Kim, G. Park, H. Jang, and E. J. Kim, "Automated classification of thermal defects in the building envelope using thermal and visible images," *Quantum Infr. Thermogr. J.*, pp. 1–25, Jan. 2022, doi: 10.1080/17686733.2022.2033531.

[96] H. Ahmed, H. M. La, and K. Tran, "Rebar detection and localization for bridge deck inspection and evaluation using deep residual networks," *Autom. Construction*, vol. 120, Dec. 2020, Art. no. 103393.

[97] *TensorFlow Hub*. Accessed: May 14, 2022. [Online]. Available: https://tfhub.dev/s

[98] M. Alipour and D. K. Harris, "Increasing the robustness of material-specific deep learning models for crack detection across different materials," *Eng. Struct.*, vol. 206, Mar. 2020, Art. no. 110157.

[99] I. Garrido, S. Lagüela, Q. Fang, and P. Arias, "Introduction of the combination of thermal fundamentals and deep learning for the automatic thermographic inspection of thermal bridges and water-related problems in infrastructures," *Quant. Infr. Thermography J.*, pp. 1–25, Apr. 2022, doi: 10.1080/17686733.2022.2060545.

[100] R. Ali, D. Kang, G. Suh, and Y.-J. Cha, "Real-time multiple damage mapping using autonomous UAV and deep faster region-based neural networks for GPS-denied structures," *Autom. Construction*, vol. 130, Oct. 2021, Art. no. 103831.

[101] S. Fotouhi, F. Pashmforoush, M. Bodaghi, and M. Fotouhi, "Autonomous damage recognition in visual inspection of laminated composite structures using deep learning," *Composite Struct.*, vol. 268, Jul. 2021, Art. no. 113960.

[102] E. Valero, A. Forster, F. Bosché, E. Hyslop, L. Wilson, and A. Turmel, "Automated defect detection and classification in ashlar masonry walls using machine learning," *Autom. Construction*, vol. 106, Oct. 2019, Art. no. 102846.

[103] Y. Duan et al., "Automated defect classification in infrared thermography based on a neural network," *NDT E Int.*, vol. 107, Oct. 2019, Art. no. 102147.

[104] S. Li, C. Wu, and N. Xiong, "Hybrid architecture based on CNN and transformer for strip steel surface defect classification," *Electronics*, vol. 11, no. 8, p. 1200, Apr. 2022.

[105] A. Reddy, V. Indragandhi, L. Ravi, and V. Subramaniyaswamy, "Detection of cracks and damage in wind turbine blades using artificial intelligence-based image analytics," *Measurement*, vol. 147, Dec. 2019, Art. no. 106823.

[106] J. Shan, Y. Liu, X. Cui, H. Wu, C. N. Loong, and Z. Wei, "Multi-level deformation behavior monitoring of flexural structures via vision-based continuous boundary tracking: Proof-of-concept study," *Measurement*, vol. 194, May 2022, Art. no. 111031.

[107] Y. Shao, L. Li, J. Li, S. An, and H. Hao, "Computer vision based target-free 3D vibration displacement measurement of structures," *Eng. Struct.*, vol. 246, Nov. 2021, Art. no. 113040.

[108] Y. Yao, Y. Yang, Y. Wang, and X. Zhao, "Artificial intelligence-based hull structural plate corrosion damage detection and recognition using convolutional neural network," *Appl. Ocean Res.*, vol. 90, Sep. 2019, Art. no. 101823.

[109] D. Zhang, K. Song, J. Xu, H. Dong, and Y. Yan, "An image-level weakly supervised segmentation method for no-service rail surface defect with size prior," *Mech. Syst. Signal Process.*, vol. 165, Feb. 2022, Art. no. 108334.

[110] A. Choudhary, T. Mian, and S. Fatima, "Convolutional neural network based bearing fault diagnosis of rotating machine using thermal images," *Measurement*, vol. 176, May 2021, Art. no. 109196.

[111] B. Kim, N. Yuvaraj, H. W. Park, K. R. S. Preethaa, R. A. Pandian, and D.-E. Lee, "Investigation of steel frame damage based on computer vision and deep learning," *Autom. Construction*, vol. 132, Dec. 2021, Art. no. 103941.

[112] J. Zhu, C. Zhang, Z. Lu, and X. Li, "A multi-resolution deep feature framework for dynamic displacement measurement of bridges using vision-based tracking system," *Measurement*, vol. 183, Jun. 2021, Art. no. 109847.

[113] M. J. Castro-Toscano et al., "Novel sensing approaches for structural deformation monitoring and 3D measurements," *IEEE Sensors J.*, vol. 21, no. 10, pp. 11318–11328, 2021.

[114] E. Karaaslan, U. Bagci, and F. N. Catbas, "Attention-guided analysis of infrastructure damage with semi-supervised deep learning," *Autom. Construction*, vol. 125, May 2021, Art. no. 103634.

[115] W. Ye, S. Deng, J. Ren, X. Xu, K. Zhang, and W. Du, "Deep learning-based fast detection of apparent concrete crack in slab tracks with dilated convolution," *Construction Building Mater.*, vol. 329, Apr. 2022, Art. no. 127157.

[116] G. Park, M. Lee, H. Jang, and C. Kim, "Thermal anomaly detection in walls via CNN-based segmentation," *Autom. Construction*, vol. 125, May 2021, Art. no. 103627.

[117] H. He, D. Yang, S. Wang, S. Wang, and X. Liu, "Road segmentation of cross-modal remote sensing images using deep segmentation network and transfer learning," *Ind. Robot, Int. J. Robot. Res. Appl.*, vol. 46, no. 3, pp. 384–390, May 2019.

[118] D. Kang, S. S. Benipal, D. L. Gopal, and Y.-J. Cha, "Hybrid pixel-level concrete crack segmentation and quantification across complex backgrounds using deep learning," *Autom. Construction*, vol. 118, Oct. 2020, Art. no. 103291.

[119] P. Kumar, A. Sharma, and S. Raju Kota, "Automatic multiclass instance segmentation of concrete damage using deep learning model," *IEEE Access*, vol. 9, pp. 90330–90345, 2021.

[120] Z. Liu, Y. Cao, Y. Wang, and W. Wang, "Computer vision-based concrete crack detection using U-Net fully convolutional networks," *Autom. Construct.*, vol. 104, pp. 129–139, Dec. 2019.

[121] Y. Ren et al., "Image-based concrete crack detection in tunnels using deep fully convolutional networks," *Construction Building Mater.*, vol. 234, Feb. 2020, Art. no. 117367.

[122] W. Wang and C. Su, "Semi-supervised semantic segmentation network for surface crack detection," *Autom. Construction*, vol. 128, Aug. 2021, Art. no. 103786.

[123] J. Tao, H. Gong, F. Wang, X. Luo, X. Qiu, and J. Liu, "Deep learning based automated segmentation of air-void system in hardened concrete surface using three dimensional reconstructed images," *Construction Building Mater.*, vol. 324, Mar. 2022, Art. no. 126717.

[124] Q. Luo, B. Gao, W. L. Woo, and Y. Yang, "Temporal and spatial deep learning network for infrared thermal defect detection," *NDT E Int.*, vol. 108, Dec. 2019, Art. no. 102164.

[125] D. Sadhukhan et al., "Estimating surface temperature from thermal imagery of buildings for accurate thermal transmittance (U-value): A machine learning perspective," *J. Building Eng.*, vol. 32, Nov. 2020, Art. no. 101637.

[126] Y. Li et al., "A deep residual neural network framework with transfer learning for concrete dams patch-level crack classification and weakly-supervised localization," *Measurement*, vol. 188, Jan. 2022, Art. no. 110641.

[127] Z. Yu, Y. Shen, and C. Shen, "A real-time detection approach for bridge cracks based on YOLOv4-FPM," *Autom. Construction*, vol. 122, Feb. 2021, Art. no. 103514.

[128] T. Xia, J. Yang, and L. Chen, "Automated semantic segmentation of bridge point cloud based on local descriptor and machine learning," *Autom. Construction*, vol. 133, Jan. 2022, Art. no. 103992.

[129] S. E. Park, S.-H. Eem, and H. Jeon, "Concrete crack detection and quantification using deep learning and structured light," *Construction Building Mater.*, vol. 252, Aug. 2020, Art. no. 119096.

[130] A. A. Ijjeh and P. Kudela, "Deep learning based segmentation using full wavefield processing for delamination identification: A comparative study," *Mech. Syst. Signal Process.*, vol. 168, Apr. 2022, Art. no. 108671.

[131] J. Guo et al., "Non-contact vibration sensor using deep learning and image processing," *Measurement*, vol. 183, Oct. 2021, Art. no. 109823.

[132] Y. Wang, F. Liu, and A. Zhu, "Bearing fault diagnosis based on a hybrid classifier ensemble approach and the improved dempster-shafer theory," *Sensors*, vol. 19, no. 9, p. 2097, May 2019.

[133] S. Dabetwar, S. Ekwaro-Osire, and J. P. Dias, "Damage classification of composites based on analysis of Lamb wave signals using machine learning," *ASME J. Risk Uncertainty Eng. Syst., B, Mech. Eng.*, vol. 7, no. 1, Mar. 2021, Art. no. 011002.

[134] C. Yüce et al., "Prognostics and health management of wind energy infrastructure systems," *ASME J. Risk Uncertainty Eng. Syst., B, Mech. Eng.*, vol. 8, no. 2, pp. 1–18, Jun. 2022.

[135] Y. Du, S. Zhou, X. Jing, Y. Peng, H. Wu, and N. Kwok, "Damage detection techniques for wind turbine blades: A review," *Mech. Syst. Signal Process.*, vol. 141, Jul. 2020, Art. no. 106445.

[136] F. P. G. Márquez and A. M. P. Chacón, "A review of non-destructive testing on wind turbines blades," *Renew. Energy*, vol. 161, pp. 998–1010, Dec. 2020.

[137] D. Mitchell et al., "Symbiotic system of systems design for safe and resilient autonomous robotics in offshore wind farms," *IEEE Access*, vol. 9, pp. 141421–141452, 2021.

[138] W. Fan et al., "Machine learning applied to the design and inspection of reinforced concrete bridges: Resilient methods and emerging applications," *Structures*, vol. 33, pp. 3954–3963, Oct. 2021.

[139] Z. He, W. Li, H. Salehi, H. Zhang, H. Zhou, and P. Jiao, "Integrated structural health monitoring in bridge engineering," *Autom. Construction*, vol. 136, Apr. 2022, Art. no. 104168.

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

[141] J. Yang et al., "Intelligent bridge management via big data knowledge engineering," *Autom. Construction*, vol. 135, Mar. 2022, Art. no. 104118.

[142] M. Sujon and F. Dai, "Application of weigh-in-motion technologies for pavement and bridge response monitoring: State-of-the-art review," *Autom. Construction*, vol. 130, Oct. 2021, Art. no. 103844.

[143] R. Ali, J. H. Chuah, M. S. A. Talip, N. Mokhtar, and M. A. Shoaib, "Structural crack detection using deep convolutional neural networks," *Autom. Construction*, vol. 133, Jan. 2022, Art. no. 103989.

[144] Z. Du, J. Yuan, F. Xiao, and C. Hettiarachchi, "Application of image technology on pavement distress detection: A review," *Measurement*, vol. 184, Nov. 2021, Art. no. 109900.

[145] R. Khallaf and M. Khallaf, "Classification and analysis of deep learning applications in construction: A systematic literature review," *Autom. Construction*, vol. 129, Sep. 2021, Art. no. 103760.

[146] K. Mostafa and T. Hegazy, "Review of image-based analysis and applications in construction," *Autom. Construction*, vol. 122, Feb. 2021, Art. no. 103516.

[147] B. Zhong et al., "Mapping computer vision research in construction: Developments, knowledge gaps and implications for research," *Autom. Construction*, vol. 107, Nov. 2019, Art. no. 102919.

[148] T. Hong, Z. Wang, X. Luo, and W. Zhang, "State-of-the-art on research and applications of machine learning in the building life cycle," *Energy Buildings*, vol. 212, Apr. 2020, Art. no. 109831.

[149] H. Sun, H. V. Burton, and H. Huang, "Machine learning applications for building structural design and performance assessment: State-of-the-art review," *J. Building Eng.*, vol. 33, Jan. 2021, Art. no. 101816.

[150] H. Salehi and R. Burgueño, "Emerging artificial intelligence methods in structural engineering," *Eng. Struct.*, vol. 171, pp. 170–189, May 2018.

[151] A. Al-Habaibeh, A. Sen, and J. Chilton, "Evaluation tool for the thermal performance of retrofitted buildings using an integrated approach of deep learning artificial neural networks and infrared thermography," *Energy Built Environ.*, vol. 2, no. 4, pp. 345–365, Oct. 2021.

[152] S. Agnisarman, S. Lopes, K. C. Madathil, K. Piratla, and A. Gramopadhye, "A survey of automation-enabled human-in-the-loop systems for infrastructure visual inspection," *Autom. Construction*, vol. 97, pp. 52–76, Jan. 2019.

[153] M. Valero, F. Li, L. Zhao, C. Zhang, J. Garrido, and Z. Han, "Vibration sensing-based human and infrastructure safety/health monitoring: A survey," *Digit. Signal Process.*, vol. 114, Jul. 2021, Art. no. 103037.

[154] R. Napolitano, Z. Liu, C. Sun, and B. Glisic, "Combination of image-based documentation and augmented reality for structural health monitoring and building pathology," *Frontiers Built Environ.*, vol. 5, p. 50, Apr. 2019.

[155] S. Wang, S. A. Zargar, and F.-G. Yuan, "Augmented reality for enhanced visual inspection through knowledge-based deep learning," *Structural Health Monitor.*, vol. 20, no. 1, pp. 426–442, Jan. 2021.

[156] J. Xu and F. Moreu, "A review of augmented reality applications in civil infrastructure during the 4th industrial revolution," *Frontiers Built Environ.*, vol. 7, Jun. 2021, Art. no. 640732.

[157] A. Sadhu, J. E. Peplinski, A. Mohammadkhorasani, and F. Moreu, "A review of data management and visualization techniques for structural health monitoring using BIM and virtual or augmented reality," *J. Structural Eng.*, vol. 149, no. 1, Jan. 2023, Art. no. 03122006.

[158] S. Kiranyaz, O. Avci, O. Abdeljaber, T. Ince, M. Gabbouj, and D. J. Inman, "1D convolutional neural networks and applications: A survey," *Mech. Syst. Signal Process.*, vol. 151, Apr. 2021, Art. no. 107398.

[159] S. Sony, K. Dunphy, A. Sadhu, and M. Capretz, "A systematic review of convolutional neural network-based structural condition assessment techniques," *Eng. Struct.*, vol. 226, Jan. 2021, Art. no. 111347.

[160] M. Wang, C. C. Wang, S. Sepasgozar, and S. Zlatanova, "A systematic review of digital technology adoption in off-site construction: Current status and future direction towards industry 4.0," *Buildings*, vol. 10, no. 11, p. 204, Nov. 2020.

[161] S. O. Abioye et al., "Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges," *J. Building Eng.*, vol. 44, Dec. 2021, Art. no. 103299.

[162] Y. Pan and L. Zhang, "Roles of artificial intelligence in construction engineering and management: A critical review and future trends," *Autom. Construction*, vol. 122, Feb. 2021, Art. no. 103517.

[163] J. Ribeiro, R. Lima, T. Eckhardt, and S. Paiva, "Robotic process automation and artificial intelligence in industry 4.0—A literature review," *Proc. Comput. Sci.*, vol. 181, pp. 51–58, Jan. 2021.

[164] J. Zhao, R. Masood, and S. Seneviratne, "A review of computer vision methods in network security," *IEEE Commun. Surveys Tuts.*, vol. 23, no. 3, pp. 1838–1878, 3rd Quart., 2021.

[165] J.-H. Li, "Cyber security meets artificial intelligence: A survey," *Frontiers Inf. Technol. Electron. Eng.*, vol. 19, no. 12, pp. 1462–1474, Dec. 2018.

[166] D. Dey et al., "Artificial intelligence in cardiovascular imaging: JACC state-of-the-art review," *J. Amer. College Cardiol.*, vol. 73, no. 11, pp. 1317–1335, 2019.

Alessandro Sabato (Member, IEEE) received the B.S. and M.S. degrees in environmental engineering and the Ph.D. degree in mechanical engineering from the University of Calabria, Rende, Italy, in 2006, 2010, and 2014, respectively.

He was a Visiting Ph.D. Student and a Research Associate with the Department of Civil Engineering and Engineering Mechanics, Columbia University, New York, NY, USA. He is currently an Assistant Professor with the Department of Mechanical Engineering, University of Massachusetts Lowell, Lowell, MA, USA. His research and work interests include structural health monitoring, nondestructive evaluations, smart structures, sensors' development, structural dynamics, machine learning, and acoustics. He is the author of numerous publications in these fields.

Dr. Sabato is a member of Society of Photographic Instrumentation Engineers (SPIE) and Society for Experimental Mechanics (SEM). He was a recipient of several grants.

Shweta Dabetwar received the B.E. degree in mechanical engineering from the University of Mumbai, Mumbai, India, in 2014, and the Ph.D. degree in mechanical engineering from Texas Tech University, Lubbock, TX, USA, in 2020.

She is currently a Postdoctoral Research Associate with the Department of Mechanical Engineering, University of Massachusetts Lowell, Lowell, MA, USA, under the supervision of Dr. Alessandro Sabato. Her research interests are structural health monitoring of wind turbines, buildings, and infrastructure; fracture, fatigue, and failure; composite materials; risk and uncertainty; artificial intelligence; machine learning; nondestructive evaluation; and structure from motion.

Dr. Dabetwar is a member of the Early Career Editorial Board of *ASCE-American Society of Mechanical Engineers (ASME) Journal of Risk and Uncertainty in Engineering Systems, Part B*: *Mechanical Engineering*.

Nitin Nagesh Kulkarni received the B.S. degree in mechanical engineering from the University of Mumbai, Mumbai, India, in 2018, and the M.S. degree in mechanical engineering from Texas Tech University, Lubbock, TX, USA, in 2020. He is currently pursuing the Ph.D. degree with the Structural Dynamics and Acoustic Systems Laboratory (SDASL), University of Massachusetts Lowell, Lowell, MA, USA.

His research interests include machine learning, computer vision, and statistical methods for structural health monitoring.

Dr. Kulkarni is also an Active Student Member of American Society of Mechanical Engineers (ASME), Society for Experimental Mechanics (SEM), and Society of Photographic Instrumentation Engineers (SPIE).

Giancarlo Fortino (Fellow, IEEE) received the Ph.D. degree in systems and computer engineering from the University of Calabria (Unical), Rende, Italy, in 2000.

He is a Full Professor of Computer Engineering with the Department of Informatics, Modeling, Electronics, and Systems, Unical. He is a Cofounder and the CEO of SenSysCal S.r.l., Rende, an Unical spinoff focused on innovative Internet-of-Things (IoT) systems, and a cofounder of BigTech S.r.l., Cosenza, Italy, a startup focused on artificial intelligence (AI)-driven systems and big data. He is a Highly Cited Researcher 2002–2022 by Clarivate in Computer Science. He is the author of more than 600 papers in international journals, conferences, and books. His research interests include wearable computing systems, IoT, and cybersecurity.

Dr. Fortino is currently a member of the IEEE Systems, Man, and Cybernetics Society (SMCS) Board of Governors (BoG) and the Co-Chair of the SMCS Technical Committee (TC) on Interactive and Wearable Computing and Devices (IWCD). He is a (Founding) Series Editor of the *IEEE Press Series on Human-Machine Systems* and the *Internet of Things* series (Springer) and an associate editor (AE) of premier IEEE TRANSACTIONS.