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Crack Detection and Monitoring: Review and Comparison of IoT and Image-based Methods

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Introduction

The aging of critical civil infrastructure, such as bridges and buildings, and their vulnerability to damage often requires inspection and predictive maintenance tasks. Physical damage in the structure can represent danger and potentially lead to catastrophic consequences, such as the collapse of the structure. Cracks usually emerge as small fissures in the surface of infrastructure components, making them weak and potentially leading to structural failures. The early detection of such cracks and their continuous monitoring leads to prompt intervention and increases the safety and lifetime of the monitored infrastructure [1]. For this reason, several studies proposed automatic techniques to detect and monitor cracks by analyzing their length, width, depth, and severity [2], [3], [4]. The advent of Machine Learning (ML), Deep Learning (DL), and computer vision techniques created a new breed of image-based methods to detect cracks and monitor them over time [5]. However, ML/DL methods require a preliminary phase of model training, in which a crack image dataset must be collected and labeled. Moreover, risks significantly limit human accessibility for building inspections, particularly in external areas. Therefore, numerous researchers propose the integration of unmanned aerial vehicles (UAVs) to perform autonomous image collection from a target structure [6], [7], [8]. Although image-based methods are widely used for detection purposes [4], [5], they have many limitations. Areas that are always obscured prevent the utilization of those techniques. Further, detecting and monitoring cracks through images is challenging in non-uniform structures, such as masonry and cultural heritage buildings, as well as in large structures due to the extensive surface area needed to analyze. In those scenarios, the joint employment of sensor measurements with image-based techniques has the potential to enhance the accuracy and precision of crack monitoring systems [2]. Crack detection and monitoring have been extensively explored in the literature, and many approaches and tools have been proposed. Each combination is adequate for a set of use cases and presents its own set of requirements, outcomes, and challenges. Due to the diversity of techniques and approaches, it is difficult for new researchers to comprehend this field. To fill this gap, this paper discusses the state of the art and the future direction of autonomous crack detection and monitoring systems, focusing on those based on modern Information Technologies (IT). As a core contribution, in Section II, we propose a taxonomy based on five orthogonal features of crack detection and monitoring systems. Then, we illustrate the processing pipeline of both image-based (Section III) and IoT-based (Section IV) systems and list their advantages and limitations. Finally, in Section V, we explore the potential of integrating both approaches.

Crack detection and monitoring: taxonomy

The proposed taxonomy (Fig. 1), focus in key aspects for effective crack monitoring and detection system. It introduces specific terms, as: crack detection or identification, crack monitoring and quantification and classification. *Crack detection or identification* refers to determining whether a crack is present or not in a specific surface. *Crack quantification or measurement* involves measurements performed on a detected crack (e.g., width, depth, length). When these measurements are performed over time to track changes, the process is termed *crack monitoring*. Crack classification denotes the ability to categorize detected image features (e.g., pixels, radiometric and geometric information) as Crack, Non-Crack, or other defect types. To explore recent advancements, we examined studies focused mainly on the last 5 years. The proposed classification is based on five directions:

- *Functionality*: description and classification of the methods in performing crack detection, monitoring or both.
- *Methods*: description and classification of the methods in image-based and sensor-based approaches.
- *Responsiveness*: methods classification based on the continuous, periodic and autonomous data acquisition capability.
- *Use case*: analysis of those applications that put an emphasis on civil infrastructure or cultural heritage (CH) domain.
- *Testing methodology*: classification of the studies under investigation based on laboratory-only testing, real testbed-only testing or both.

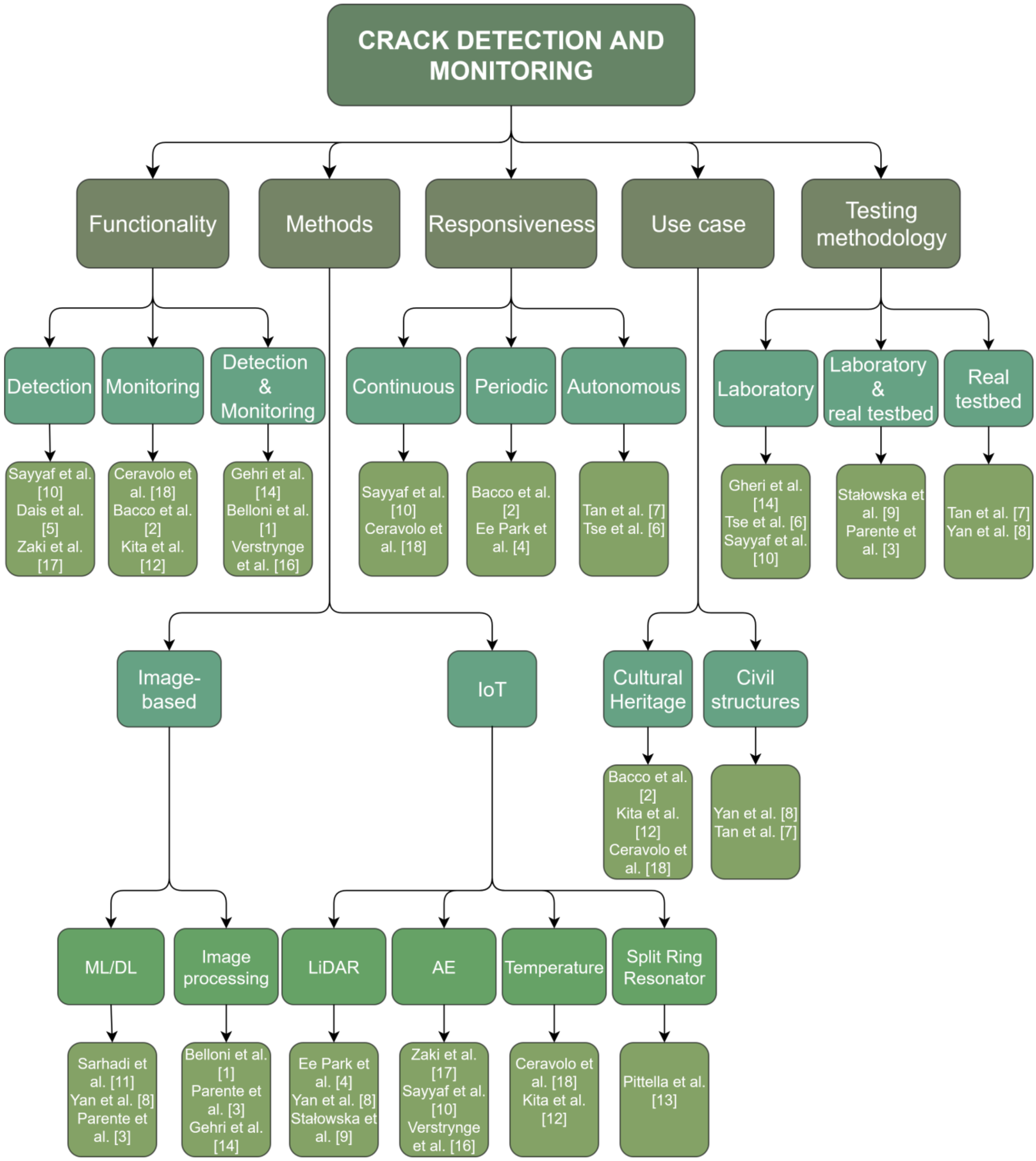


Fig. 1. Proposed taxonomy of crack detection and monitoring systems.

Functionality

The first dimension in the taxonomy (Fig. 1) addresses Functionality, focusing on whether methods are used for crack detection, monitoring, or both. A Venn diagram (Fig. 2) illustrates that most reviewed studies fall under crack detection or a combination of detection and monitoring, while only a few are solely for monitoring. This highlights a trend toward automating the entire crack analysis process, moving away from manual detection by humans. All methods, designed for crack detection, distinguish cracks from various other features such as material patterns, shadows, and other potential interferences. Many of the reviewed articles propose only crack detection; for instance Dais et al. [5] implement a Convolutional Neural Network (CNN)-based binary classification with non-crack and crack cases corresponding to negative and positive class, respectively. Stałowska et al. [9] propose a crack detection based on variation of geometric and radiometric point information in respect of the average value trend. Sayyaf et al. [10] propose a binary crack detection system based on acoustic emission threshold. Sarhadi et al. [11] implement a binary Crack and Non-Crack classification for segmentation using a self-attention mechanism (Swin U-Net). Conversely, methods that offer crack monitoring possess the capability to measure and track variations in crack characteristics over time. Kita et al. [12] propose a monitoring of two existing cracks, providing an evolution in time of amplitudes and temperature. Bacco et al. [2] compute distances between the barycenter of each pair of markers, providing the width in specific crack spots. Pittella et al. [13] propose a method where cracks are detected by analyzing the variation of resonance frequency in the monitored material. In contrast, other studies present both crack detection and monitoring, offering a more comprehensive and automated analysis. Gehri et al. [14] detect cracks with a binary classification of the principal tensile strain field into high strain areas containing the crack locations and low strain areas representing uncracked zones. The features monitored are width, slip, and inclination. Tan et al. [7] propose a crack detection based on a binary classification, while the monitored parameters are area, width, and length. Similarly, Tse et al. [6] implement a crack detection with segmentation based on binary classification and propose a crack size estimation. Ee Park et al. [4] classify image objects in cracks, lasers, and pseudo cracks and monitor the crack width and length. A similar binary classification is proposed by Parente et al. [3] and Belloni et al. [1], while the monitoring features are crack width and length. Yan et al. [8] binarize crack patches based on pixels' grayscale intensity and propose a monitoring application of crack width and length.

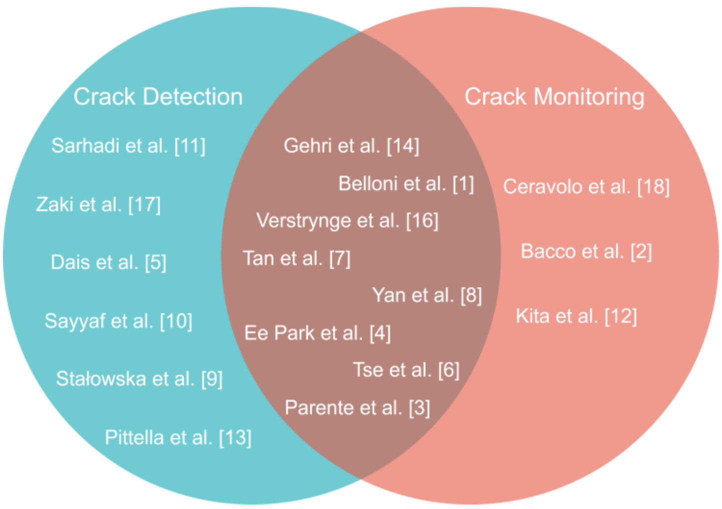


Fig. 2. Functionality based analysis of the reviewed methods.

Methods

To achieve effective crack analysis in specific structures, a range of methods with distinct functionalities, approaches, and hardware systems were evaluated. The reviewed studies are categorized into: image-based methods and Internet of Things (IoT)-based methods. The image-based category is divided into two subcategories: ML/DL techniques and image processing methods. The IoT-based methods are subdivided into four sensor categories: LiDAR, Acoustic Emission (AE) sensors, temperature sensors, and split ring resonator. Some methods such as infrared camera (IR) and Digital Volume Correlation (DVC) are not analyzed in this manuscript because they require a combination with other technologies for defects detection. Since most of the methods rely on image-based techniques, the camera sensor serves as the primary device [6] – [8], [14]. Various ML/DL algorithms have been deployed to support image-based crack detection, such as Support Vector Machine (SVM), Random Forest Classifier (RFC) and CNN. Concerning image-based techniques, Parente et al. [3] present an open-source software, Ilastik, for crack detection, which, after radiometric optimization, performs image segmentation and classification through an RFC algorithm. Yan et al. [8] implement a CNN-based classifier for crack detection, integrating a camera system with a LiDAR sensor mounted on a UAV. Sarhadi et al. [11] introduce an attention-based SWIN U-Net approach that enables the use of different resolution images, eliminating the need for a large amount of data. Diverse image processing and shape context algorithms have been proposed for crack quantification and monitoring. Belloni et al. [1] advocate for a monitoring framework utilizing the Scale-Invariant Feature Transform (SIFT) algorithm. This approach automatically matches corresponding features in images captured at different time points, enabling the estimation of homography transformations that represent the camera movement between reference and deformed images. Parente et al. [3] employ the Ridge Detection method to analyze structural cracks. This method enables the determination of various crack characteristics, including geometry, area, length, and other parameters essential for maintenance decision-making. Other methodologies leverage innovative solutions utilizing indirect image-based crack detection techniques, such as digital image correlation (DIC) integrated with an automated crack detection and measurement (ACDM) algorithm [14]. In contrast, numerous studies have focused on crack detection and monitoring using more traditional, yet still widely adopted, IoT systems. Laser scanning technology (i.e., LiDAR), is widely used in modern applications due to its ability to generate highly accurate 3D models of target objects. This is achieved by emitting laser pulses, which are reflected off the object's surface and detected by an optical sensor, allowing the collection of spatial coordinates for each point. The outcome is a detailed point cloud of the target object, which has proven highly useful in surveying applications [8]. Since laser scanner functions as a sensor, it is extensively applied in monitoring, particularly for tracking movements in large civil structures. For instance, Stałowska et al. [9] presents a TLS-based method to detect cracks using both geometric and radiometric data. Other studies have proposed using laser scanners as supplementary tools for ML/DL approaches. For example, Ee Park et al. [4] suggests a method where crack size is calculated based on the positions of calibrated laser beams projected onto the object surface. Laser beams emitted by a LiDAR-Lite v3 from Garmin mounted on a drone are used to estimate the ratio between pixel and mm dimension in order to quantify the crack width. The formation of cracks is always characterized by the release of energy in the form of elastic waves, and AE signals, which propagate through the material and can be detected by AE sensors [10]. The ability to continuously monitor structures in a quasi-non-invasive manner makes this technique applicable in Structural Health Monitoring (SHM) scenarios [15]. For instance, Sayyaf et al. [10] present a wireless crack detection system for concrete structures, based on AE technologies. Results from this method demonstrated a significant improvement in safety and reliability by detecting cracks at an early stage. Considering a distributed array of sensors, sound picks can be used for passive acoustic localization. The source position is determined by measuring the difference in arrival times. Hence, the sensors have to be synchronized up to a fraction of the expected time differences of arrivals for the system to be able to produce accurate location estimates [15]. Verstrynge et al. [16] develop an integration procedure combining AE and strain sensors, demonstrating both robustness and efficiency in monitoring cracks in historical masonry structures. In their approach, when a crack tip is detected, the AE sensors are able to register the moment of occurrence of crack growth and friction-related AE events and can identify unstable crack propagation in advance. Similarly, in the study by Zaki et al. [17], AE monitoring is utilized to access the crack development and failure modes of large-scale repaired RC beams. The investigation focused on several AE parameters, including the number of hits, cumulative signal strength (CSS), signal amplitude, peak frequency, absolute energy, and b-value analysis. In particular, the b-value, which is the amplitude number of hits, can be used to indicate the level of damage in a structure, while CSS is used to detect early cracking in composite structures subjected to specific loading conditions. On the other hand, signal amplitudes are used to detect debonding in lightweight hybrid concrete beams. Since we do not provide an in-depth technical description of the AE-based methods, more details can be found in [17]. Temperature is another crucial factor to consider in crack detection and monitoring. In SHM applications, temperature must be controlled in static and dynamic signatures, as it can significantly affect the measurements obtained. In many cases, particularly in crack monitoring, temperature variations need to be examined for potential correlations and subsequently filtered out to enhance the reliability of the results [12]. Ceravolo et al. [18] present a decade-long analysis of data collected from the static monitoring system. The seasonal temperature fluctuations imply cycles of crack opening and closing, with cracks reaching their maximum opening during the summer and gradually closing in the winter. A low-cost, mixed static and dynamic long-term SHM system was installed for this purpose. Their analysis shows that the amplitudes of two major cracks in the building exhibited a distinct linear decrease as ambient temperature increase. In the IoT context, SHM applications can be performed considering embedded sensors, fundamental to monitor a structure at an early stage of its construction. This is the case of the system proposed by Pittella et al. [13] where an embedded split resonator network detects cracks in concrete samples. As a result of a variation in the dielectric characteristics of the structure a frequency shift arises pointing out the presence of damage.

Responsiveness

Responsiveness capability is particularly significant in monitoring applications, because it allows us to assess and interpret the damage response of the monitored object. Generally speaking, the responsiveness definition depends on the temporal resolution of the detection method. In particular, three classes are defined: continuous, periodic, and autonomous. Continuous monitoring involves the ongoing acquisition and analysis of data and represents, with rapid data processing, a key element in alarm generation approaches. In contrast, periodic monitoring consists of scheduled inspections, in a manual or autonomous way, designed to enhance knowledge over time [19]. To this aim, autonomous systems are capable of performing human-like inspection without human intervention, often utilizing robotic technologies or drones [7]. Among the monitoring systems analyzed, continuous monitoring is the most used method for crack analysis, in particular within IoT-based frameworks. While crack inspection traditionally falls under static monitoring, continuous monitoring can be particularly beneficial in laboratory tests where damage propagation is forced rapidly, or in real-world applications where quick responses or the comparison with additional parameters is required. For example, Sayyaf et al. [10] propose a sensing layer designed to enable continuous real-time monitoring of the structure. To ensure this capability the layer is able to identify the signal of interest, acquiring and storing signals related to potentially critical events, and synchronizing measurements from various smart objects. These challenges are addressed through the implementation of the logic flat amplifier and trigger (L-FAT) component.

Several UAV-based methods employ periodic inspections for crack monitoring. For instance, Bacco et al. [2] use UAVs for periodic inspections or in response to anomalies detected by an IoT sensor network. Regarding autonomous monitoring, Tan et al. [7] validate a “global-local” approach, wherein a UAV autonomously performs crack inspections on a building by converting Building Information Modelling (BIM) model coordinates into real-world coordinates. Tse et al. [6] propose an autonomous crack detection and quantification based on a path planner achieved with LiDAR and the generated point cloud of the target structure.

Use case

The built environment encompasses a diverse range of structural typologies, each necessitating distinct applications of SHM techniques. In this section, we provide a classification of those methods based on two key use cases: civil structures and CH buildings. These categories exhibit significant differences in terms of applied loads, construction materials, and functional requirements, which underscore the need for customized SHM solutions. The civil structures examined in the reviewed studies are primarily bridges and public buildings. For example, Yan et al. [8] focus on crack detection and quantification of a steel girder bridge. The CH category comprises buildings of architectonic, cultural, and historical relevance. A significant portion of historical and architectural heritage consists of masonry buildings, which pose unique challenges due to uncertainties in both geometry and material properties. When adapting SHM from conventional civil infrastructure to CH structures, certain features and constraints must be considered: for instance, the diverse physical and chemical material properties, often variable within the same structure; the challenging conditions for data collection (with areas difficult to access, or variable environmental conditions); and non-invasive data acquisition and monitoring methods are often essential for CH applications [2], [15]. Kita et al. [12] describe the implementation of a SHM-IoT system for the Consoli Palace in Gubbio, Italy. The palace is characterized by bearing walls of considerable thickness made of calcareous stone masonry, and masonry vaults as the horizontal structure. Similarly, Ceravolo et al. [18] deployed an IoT sensor network at the "Regina Montis Regalis" Basilica in Vicoforte, Italy. Bacco et al. [2] monitor three buildings: Torre Grossa, Voltone, and Mastio di Matilde.

Testing methodology

The proposed taxonomy explores three primary subcategories of testing methodology: laboratory-only testing, laboratory and real testbed, and real testbed-only. The papers selected for this review focus solely on crack monitoring applications in structural elements mainly affected by cracking phenomena, such as concrete and masonry. Studies related to metal specimens are excluded from the scope of this review. The majority of studies propose laboratory testing of concrete samples, where environmental conditions can be easily controlled ensuring faster deployment and testing of the specimen. In this scenario, Gehri et al. [14] apply DIC to a square concrete panel, while Tse et al. [6] propose crack detection and quantification on a double-gate-shaped concrete structure, a common shape encountered in bridge structures. Belloni et al. [1] implement the Crack Monitoring from Motion (CMfM) setup for a concrete beam, and Sayyaf et al. [10] deploy a wireless crack detection system on a concrete structure. Since the laboratory conditions are not representative of the real ones, some researchers test methods in the laboratory and then validate them on real-testbed structures. For example, Stałowska et al. [9] initially test a crack detection method on a white silicate specimen in the laboratory, later applying it to a plastered masonry wall in a residential building. Similarly, Parente et al. [3] perform image-based crack monitoring on a white paper in the laboratory; later, the method was extended to a masonry wall in a residential building. Where the monitoring system does not require physical installation (e.g., drone applications), direct implementation of the methods to existing structures is commonly preferable. In this context, Tan et al. [7] implement a crack inspection method directly at the College of Civil and Transportation Engineering at Shenzhen University. Crack detection and quantification systems of bridges are also reported in [8].

Are image-based techniques sufficient for crack detection and monitoring?

The proposed review highlights that image-based methods constitute a contemporary standard for crack detection and monitoring. However, as revealed in the literature, DL techniques are primarily suited for crack detection and not quantification. Thus, most of the reviewed methods propose image processing integration to achieve crack quantification, defining image-based approaches as the combination of ML/DL and image processing algorithms [2] - [4], [7], [8]. The standard workflow is generally divided into: (i) crack detection, (ii) crack measurement and (iii) crack monitoring. The crack detection process involves building a large dataset of crack images and training algorithm models to automatically identify different types of cracks. Due to the development of computer vision, DL methods have successfully achieved hierarchical feature representation of images. This has led to notable image segmentation results. As a baseline case study, this section outlines a potential application of crack detection. The crack classification process involves two phases: (i) pixel labelling distinguishing the crack from the background and (ii) generation of the mask representing the ground truth. Once the dataset is built, a DL algorithm is then responsible for the classification. An example of the described pipeline is shown in Fig. 3. We present a U-Net model applied to a dataset of images and corresponding segmentation masks with the objective of identifying cracks. The crack images are taken from an existing crack image dataset [5]. The U-Net model employed is based on an encoder-decoder structure, where the downsampling path extracts high-level features while reducing spatial resolution, the bottleneck captures complex representations, and the upsampling path restores spatial resolution while incorporating skip connections from the downsampling path. Finally, a convolution layer produces a binary segmentation mask. The model employs Binary Cross-Entropy Loss (BCE) ensuring a probabilistic interpretation of pixel-wise classifications. As a result of the classification, an example of the prediction is shown in Fig. 4. For the crack measurement, a parameter calculation and data storing of the crack width in pixels is defined as the distance of two intersection pixels with the normal line of the skeleton line and the two edge lines. In crack monitoring, the label of one crack in different images stays the same since the crack appears; hence the long-term monitoring and the crack parameter analysis can be performed. An algorithm of shape matching is introduced and modified to identify whether two cracks in different images are the same. If true, the correspondent relationship between every pixel point in two cracks is obtained. The image-based techniques offer significant advantages over traditional methods, such as improved site accessibility, non-invasive approaches, and advanced automation in detection processes [19]. Still, several challenges remain: (i) training can be time-consuming, (ii) accuracy can be affected by the background [5], (iii) methods can be sensitive to environmental conditions, image resolution, noise levels, ambiguous image regions, data deviation from the training distribution and detection of small objects or fine details [11], and (iv) quantifying cracks automatically is difficult due to the unknown scale of the images where a crack size ground truth or scale reference becomes necessary [8].

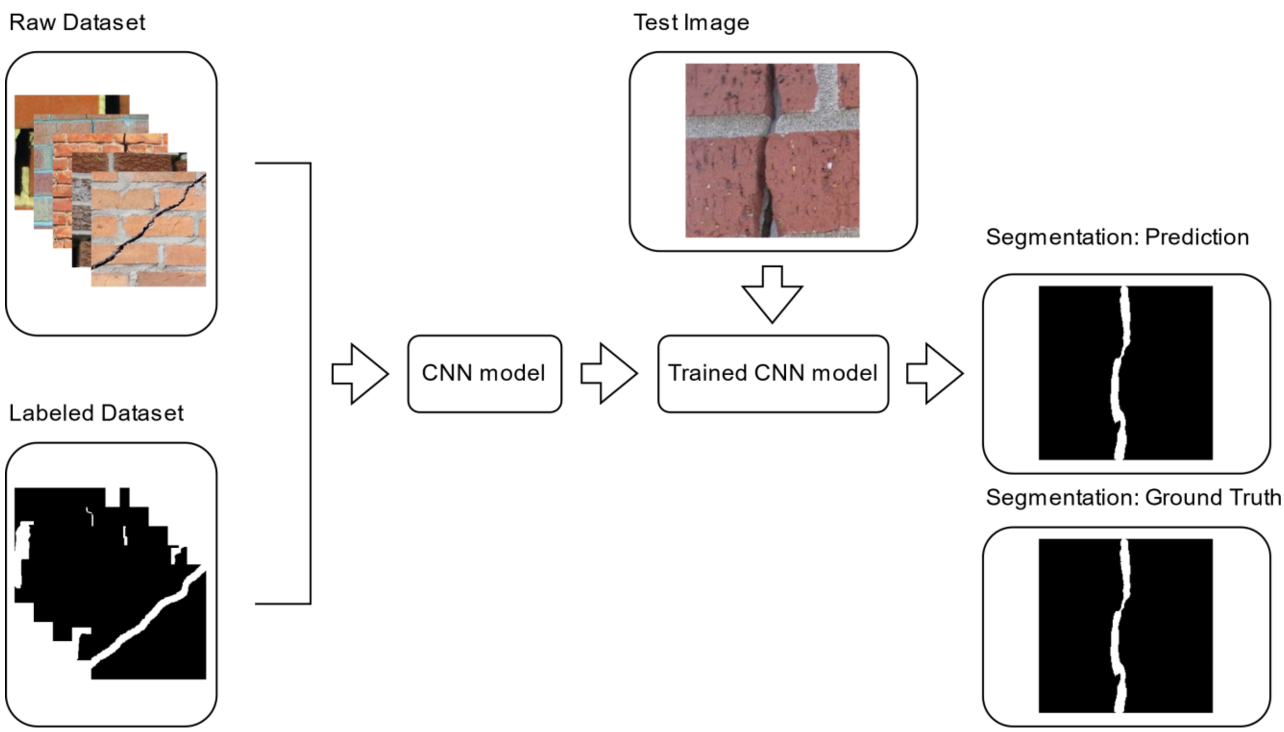


Fig. 3. Crack classification and segmentation pipeline for image-based methods.

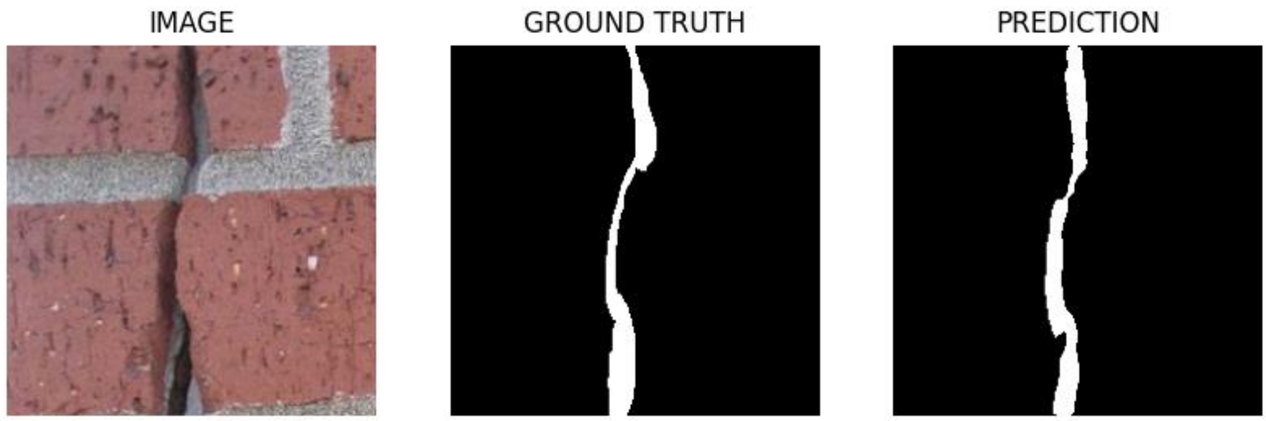
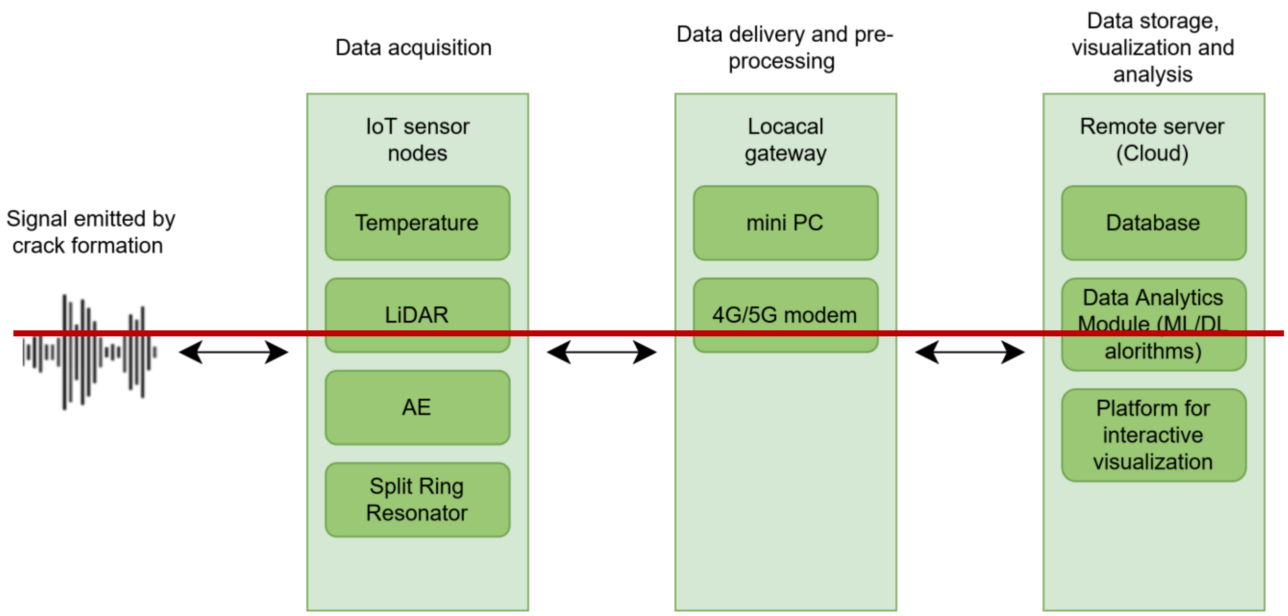


Fig. 4. Crack classification using U-Net model. The first image represents the real crack, the second represents the ground truth and the last image represents the prediction.

Are IoT-based systems sufficient for crack detection and monitoring?

Despite the significant advancements and automation provided by image-based techniques, many crack monitoring applications remain within the domain of the IoT, involving the deployment of physical sensors. IoT-based systems, combined with edge-cloud computing, play a pivotal role in enabling the continuous collection, transmission, processing, analysis, and visualization of data, which is fundamental for SHM applications [3]. A comprehensive overview of the IoT-based pipeline is presented, drawing on the work of [10], which focuses on the real-world deployment of IoT devices for crack detection, and [20], which provides an overview of a typical hardware/software architecture for SHM-IoT systems. The detection phase begins at the sensor nodes, which identify changes in physical phenomena associated with crack formation, such as variations in AE waves, and alterations in crack size and depth. The data collected by the sensor nodes are transmitted via Machine to Machine (M2M) communication protocols to a local gateway.

This gateway facilitates basic services to ensure network functionality and manages data delivery to a remote server. The MQTT protocol, using a publish/subscribe model, is employed for data exchange. The interoperability of these sensors is essential for collecting data from diverse sources; for this reason, approaches like the W3C Web of Things may be employed [20]. The data are then stored in a remote database, enabling efficient querying, anomaly detection, and comparison between new and historical data. Lastly, software services can be deployed on top for data visualization and exploitation. A general hardware/software architecture of the proposed design is illustrated in Fig. 5, which shows the flow of data, and the components involved in the system for crack detection. The primary advantages of IoT systems for crack monitoring refer to the responsiveness feature. Specifically, IoT systems can issue alert notifications when a monitored parameter exceeds safety thresholds, and they contribute to significant time and cost savings by promoting predictive maintenance and enabling the tracking of structural properties over time [18]. The ability to collect data in near real-time and exchange information continuously via the Internet allows IoT-SHM systems to facilitate the update of numerical models that accurately reflect the actual behavior of the monitored structure, based on the Digital Twin (DT) paradigm. Some IoT sensors, if properly synchronized with other sensors nodes through GPS technologies, can provide not only the detection but also the location of a crack [10]. Despite the numerous advantages of IoT systems in SHM applications, several challenges arise, including: the limitation in crack quantification, the complexities associated with methodological heterogeneity (particularly due to the diverse materials), environmental effects, and energy consumption [19], [15]. Moreover, the IoT systems examined in this study primarily focus on crack detection, with limited attention given to crack quantification. For instance, AE and temperature sensors, due to their inherent characteristics, are predominantly used for detecting cracks or correlating changes in physical or environmental phenomena with variations in crack development [12], [16], [17].



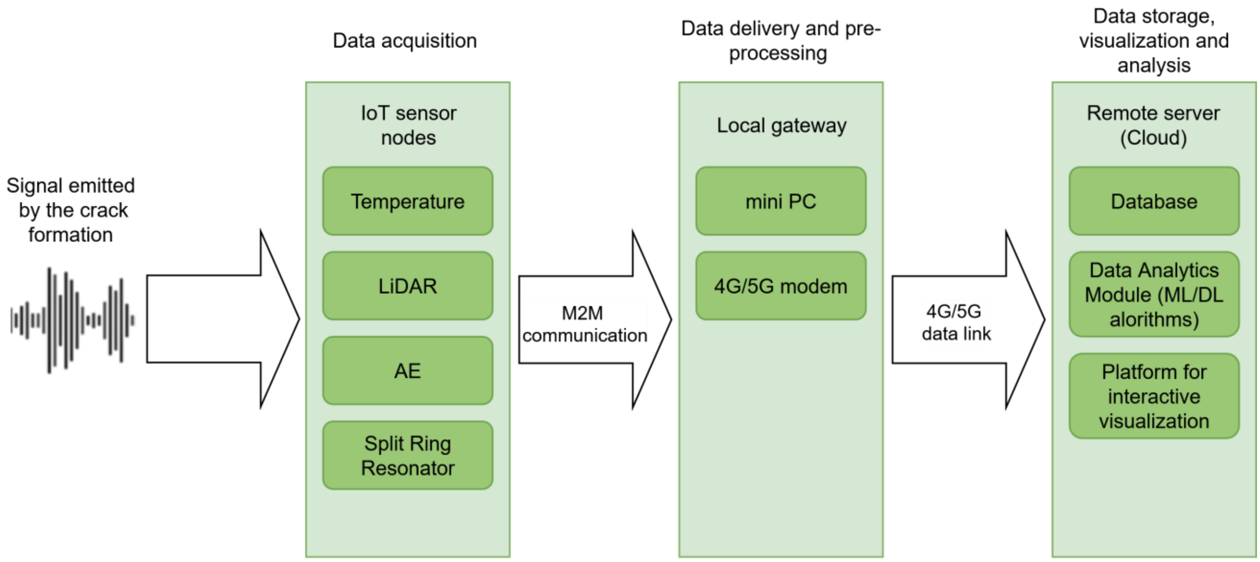


Fig. 5. Data Pipeline for IoT(AE)-based methods of crack detection.

Challenges and perspectives

Although the reviewed articles propose effective methods for crack detection and monitoring, further developments are required to address the complete integration of IoT and image-based techniques. Studies such as in [4] and in [8] demonstrate promising prototypes combining image and IoT approaches, for the case of UAVs equipped with LiDAR sensors. However, the effective integration of these two approaches remains largely unexplored in literature. This gap presents promising research directions, three of which are outlined below.

Challenge 1: Image-based responsiveness improvement

As previously discussed, continuous responsiveness is a characteristic of IoT systems. Image-based techniques require more operational steps before yielding specific crack evaluations, particularly for monitoring applications. An integrated Image-IoT system could address some of the limitations encountered in continuous monitoring with image-based methods. Indeed, deploying a digital camera as an IoT device with permanent installation in front of the monitored surface enables continuous monitoring by transmitting images at regular intervals [3]. Moreover, if the image-based system is not capable of acquiring images or the monitoring accuracy is reduced, due to some adverse environmental conditions (e.g., wind and snow), the IoT component can continue in the monitoring campaign, ensuring higher robustness. To clarify the process behind the fusion of IoT and Image-based system, a schematic diagram is proposed in Fig. 6. The figure conceptually illustrates the robustness of the method to avoid unwanted monitoring interruptions (see the detection and quantification “if” blocks), merging the advantageous resource capabilities of the two technologies involved.

Challenge 2: Crack Source classification

Cracks can originate from various causes, including dynamic actions such as earthquakes or environmental vibrations, as well as static displacements caused by soil failure, structural member degradation, creep phenomena, and other types of failure. In this scenario, crack source classification is intended as the capacity to identify the source of degradation. Accurate crack source classification is vital for determining the appropriate intervention and repair strategies for specific damages. In CH contexts, this is particularly important as it enables restorers to quickly identify the source of degradation and mitigate further damage. While image-based techniques can generally classify degradation, they typically do not provide specific indications of the damage source. This is aggravated by the fact that image-based techniques are able to detect cracks only on the visible surface, ignoring every kind of propagation in the wall thickness. However, these systems are capable of quantifying and determining two key parameters of paramount usefulness for crack source classification: inclination trends and monitoring multiple cracks within the same ROIs [7]. In contrast, the reviewed IoT systems offer additional insights into crack evolution, such as its location (e.g., surface or depth) and specific failure modes (e.g., tensile or shear). Thus, an Image-IoT system can combine these capabilities and utilize data to calibrate and update Finite Element Models (FEMs). This integrated approach can then be used to train DL algorithms for more precise crack classification, based on failure modes, sources of damage, and appropriate repair strategies.

Challenge 3: Cultural Heritage adaptability and scalability

Most of the reviewed studies focus on concrete structures, which represent the majority of civil infrastructure. However, using concrete as the sample material poses challenges for crack detection in existing CH buildings when relying primarily on image-based techniques. CH structures exhibit unique materials, patterns, and geometries, resulting in significant variation that complicates uniform crack detection approaches. This challenge is further complicated by image-specific characteristics—such as brightness, resolution, and noise levels—that hinder ML models' ability to distinguish cracks from backgrounds. In contrast, IoT systems have a long history of successful deployment for SHM applications in the CH domain, where limitations related to computer vision do not arise. Nevertheless, IoT deployment in CH environments faces its own challenges, such as installation restrictions due to strict preservation regulations. Therefore, an integrated Image-IoT approach, leveraging the complementary strengths of both systems, can address these issues as well. For example, in masonry applications, where shadowed mortar joints may be misinterpreted as cracks, IoT sensors can enhance the accuracy of image-based techniques by using different physical parameters (e.g., acoustic emissions) for crack detection. Conversely, for frescoed walls, the installation of sensors must be confined to specific areas, limiting measurement accuracy. In this case, the introduction of image-based techniques, which can be installed at a distance, offers valuable insights for comprehensive surface analysis.

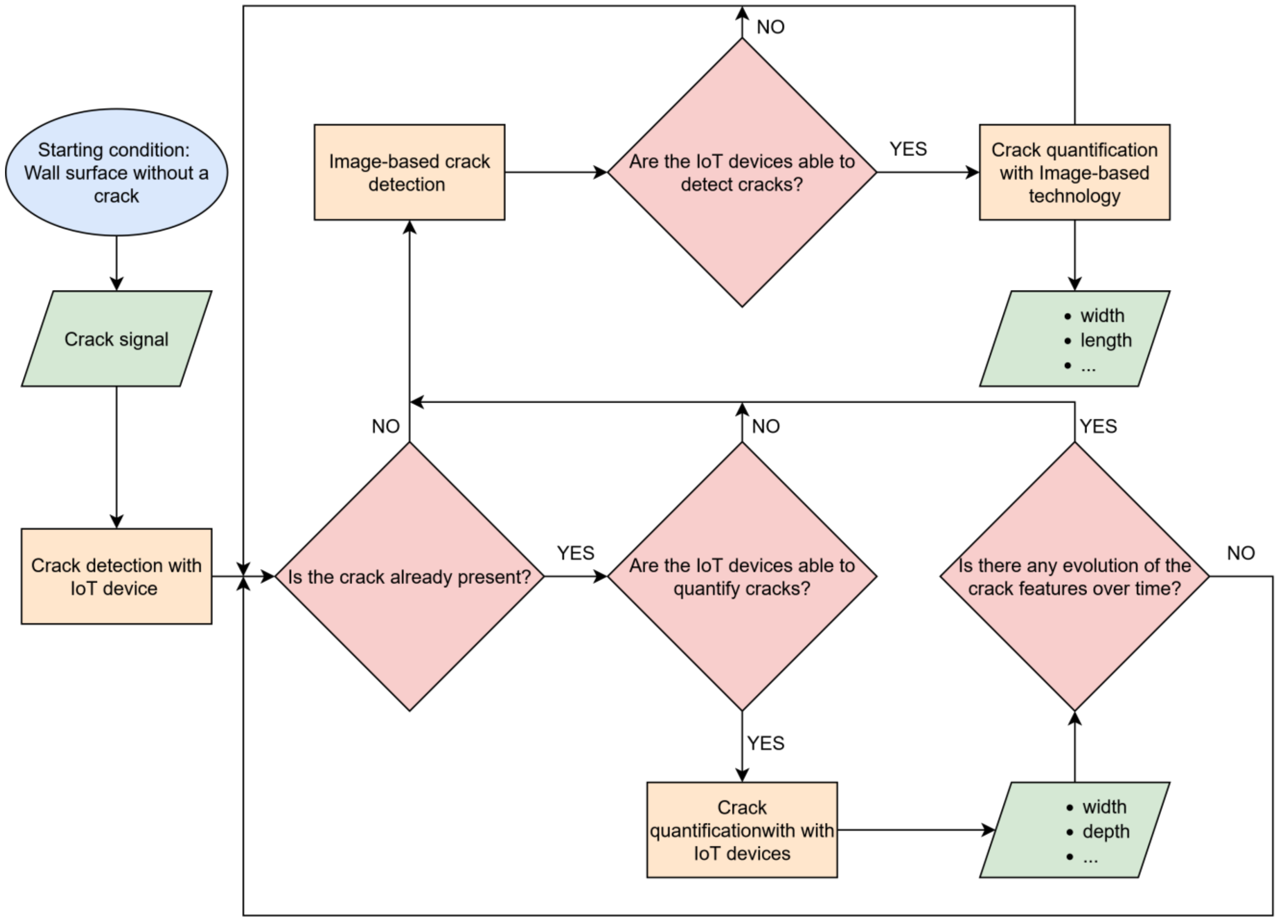


Fig. 6. Flowchart of the Image-IoT system for crack monitoring application.

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