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Review of Digital Image-Based Monitoring for Long-Term Tracking of Bridge Deformations

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Abstract

Over the past two decades, monitoring the condition of bridges has become a central concern for infrastructure managers worldwide. The main reason is simple: a large share of the existing bridge stock was built between the 1950s and the 1980s, meaning that many of these structures are now approaching the end of their originally intended service life. This is compounded by growing traffic loads, often far exceeding the design assumptions of the time. In this context, traditional monitoring methods based on point sensors—such as strain gauges, LVDT sensors, or accelerometers—prove insufficient to capture the overall behavior of a structure: they provide only local information, at a limited number of points, without allowing reconstruction of the complete deformation field of the structure. This literature review focuses precisely on digital image analysis techniques developed to address these shortcomings. It draws on a critical examination of two hundred and four articles published between 2000 and 2026 in the Scopus and Web of Science databases, selected according to the PRISMA protocol, and has been updated to incorporate work published in the first half of 2026 on digital twins, multimodal drone inspection, and recent state-of-the-art reviews devoted to DIC and optical acquisition modules. Digital Image Correlation (DIC) occupies a central place in this state of the art, both in its theoretical aspects and in its experimental applications on various types of bridges. Also covered are UAV photogrammetry, LiDAR laser scanning, and the recent contribution of deep learning to automatic defect detection. The review aims to present not only the performance achieved, but also the practical conditions of implementation, sources of error, the limitations of current approaches, and the questions that remain open. It concludes with a forward-looking discussion of next-generation monitoring systems.

Keywords

Image Analysis, DIC, SHM, Photogrammetry, Computer Vision, Deformation

1. Introduction

It is estimated that approximately 40 to 50% of bridges in service in industrialized countries were built before 1980 and now show signs of concerning structural aging [1] [2]. In the United States, the ASCE reports that more than 40% of bridges are classified as structurally deficient or functionally obsolete [3]. In Europe, similar figures emerge from national inventories, particularly for countries that experienced heavy infrastructure construction between 1960 and 1975 [4]. These structures were designed for service lives of fifty to seventy years and for traffic levels that current usage has often far exceeded.

The challenge is not simply to count these deteriorating structures, but to determine which ones present a real risk and within what timeframe. This is the whole question of structural health monitoring, a discipline denoted by the acronym SHM. As formalized by Farrar and Worden [5], SHM aims to detect damage to a structure, locate its origin, assess its severity, and estimate its consequences for the remaining service life. In practice, this requires representative measurements of the structure's actual mechanical behavior, acquired reliably and continuously under operating conditions.

For a long time, this monitoring relied on networks of contact sensors installed at strategic points of the structure. Resistive strain gauges, FBG fiber-optic sensors, accelerometers, and LVDT displacement transducers form the basis of many systems deployed on real structures [6] [7]. These devices have proven effective for tracking local parameters, but they face a fundamental limitation inherent to their very nature: they only provide information about the areas where they are physically installed. On a bridge deck spanning several dozen meters, the number of sensors required to obtain a satisfactory spatial map of deformations would be considerable, making the solution costly and difficult to maintain over the long term.

It is in this context that image analysis methods have progressively gained legitimacy for monitoring civil structures. The guiding idea is to use digital cameras as displacement and strain sensors, processing the information contained in images to reconstruct the deformation field over the entire photographed area. This approach offers a decisive advantage over point sensors: it is fundamentally full-field, meaning it provides spatially continuous information over the entire visible surface of the structure.

Among the available optical methods, Digital Image Correlation (DIC) occupies a central place. Born in experimental materials mechanics laboratories in the 1980s [8], it has been progressively adapted to civil engineering problems and large-scale structural monitoring since the early 2000s. Its measurement accuracy is now comparable to that of the best-performing conventional sensors, at substantially lower instrumentation costs [9] [10].

Alongside DIC, other optical technologies have emerged or developed further. UAV photogrammetry enables the inspection of hard-to-reach areas and the reconstruction of precise 3D models of structures [11]. LiDAR laser scanning provides dense three-dimensional point clouds that allow comparison of a structure's geometry at different dates [12]. More recently, deep learning has brought powerful tools for automating the detection of cracks and surface defects from images [13]. These various technologies, used separately or in combination, are beginning to form genuine integrated monitoring systems.

For clarity, two key terms are used throughout this review with the following definitions. "Long-term tracking" refers to monitoring campaigns extending over at least several weeks, and typically months to years, so as to capture the time-dependent structural response (progressive damage, seasonal or thermal effects, cumulative fatigue)—as distinct from single-epoch or short-duration tests that record a structure's response under one specific loading event. "Bridge deformations" denotes measurable geometric changes of the structure—deflections, strains, rotations, crack widths, and rigid-body or differential displacements—induced by traffic loading, environmental actions, or damage and deterioration processes. Regarding scope, crack detection and corrosion-related surface defect monitoring are treated as integral parts of this review, since they are direct visual manifestations of deformation and damage captured by the same optical acquisition systems discussed here. Cable-force estimation is covered only to the extent that it is derived from image-based displacement or vibration measurements (Section 6.2); it is not reviewed as an independent monitoring technique in its own right.

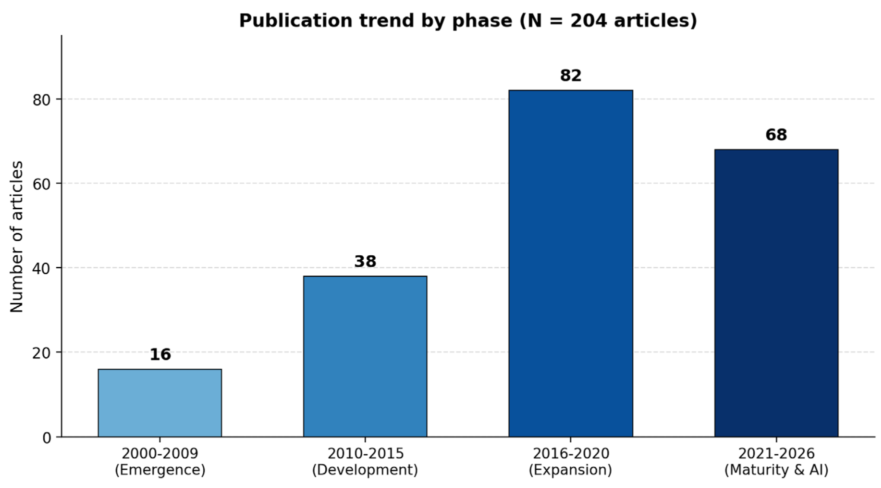

Figure 1. Evolution of publications on DIC applied to civil structures across four phases of increasing intensity: 2000-2009 emergence (n = 16), 2010-2015 development (n = 38), 2016-2020 expansion (n = 82), and 2021-2026 maturity and AI (n = 68); totalling the N = 204 articles of the final corpus (Section 2.4).

This literature review aims to synthesize and critically evaluate all of these developments. It is organized as follows. Section 2 describes the methodology used to select articles. Section 3 reviews the challenges of SHM and the reasons why optical methods constitute a relevant response. Sections 4 and 5 develop the theoretical foundations and technological variants of DIC. Section 6 surveys experimental applications on various types of bridges. Section 7 describes the design of an integrated digital system. Section 8 discusses practical challenges and current limitations. Section 9 addresses the contribution of artificial intelligence. Section 10 offers future perspectives, before concluding.

2. Methodology of the Systematic Review

2.1. Bibliographic Sources and Search Scope

This review is based on a systematic search conducted in the Scopus (Elsevier) and Web of Science Core Collection (Clarivate) databases. These two databases were selected for their comprehensive coverage of peer-reviewed journals in civil engineering, optical metrology, and artificial intelligence applied to structures. Spot checks were carried out on Google Scholar for recent works not yet indexed in the main databases. The period considered spans from January 2000 to March 2026. This chronological scope corresponds to the rise of digital DIC in civil engineering applications: before 2000, work on this topic was still rare and mainly centered on laboratory materials mechanics.

The Scopus and Web of Science searches were executed on 14 March 2026, and re-run on 18 June 2026 to capture publications from the first half of 2026. Records retrieved from each database were exported and de-duplicated using DOI and title matching prior to screening. Google Scholar was used only as a supplementary check—to spot for very recent 2026 items not yet indexed in Scopus or Web of Science—and not as a primary source of included records: every one of the 204 articles in the final corpus was retrieved directly from Scopus or Web of Science, and Google Scholar hits were cross-verified against these two databases before inclusion (four records identified this way during the 2026 update were confirmed to already be indexed in Scopus/Web of Science and were retrieved from there, as stated in Section 2.3).

The most represented journals in the final corpus are, in decreasing order of frequency: Structural Health Monitoring, Engineering Structures, Automation in Construction, Sensors, Smart Materials and Structures, Computer-Aided Civil and Infrastructure Engineering, NDT & E International, and Journal of Bridge Engineering. This distribution reflects the genuinely interdisciplinary nature of the field, situated at the intersection of civil engineering, optical metrology, and computer science.

2.2. Search Equation and Selection Criteria

The search equation was built through successive iterations from a core of well-identified reference publications. It combines three semantic fields using AND/OR boolean operators. The first field describes the physical object being monitored (bridge, viaduct, pont, infrastructure). The second describes the measurement method used (digital image correlation, DIC, photogrammetry, computer vision, image processing, deep learning, LiDAR, SfM). The third describes the monitoring objective (monitoring, deformation, deflection, crack, structural health, SHM, fatigue, damage).

The inclusion criteria were as follows: articles had to concern measurements or image-analysis systems applied to civil engineering structures; they had to present original experimental results or methodological developments validated experimentally; and they had to have been published in indexed peer-reviewed journals. Excluded were works dealing exclusively with numerical simulations without real image acquisition, non-extended conference proceedings, as well as popular-science articles or papers of too general a scope lacking a precise methodological contribution.

The exact Boolean string applied (with minor syntax adaptations between the two databases) was: (bridge OR viaduct OR "civil structure*" OR infrastructure) AND ("digital image correlation" OR DIC OR photogrammetry OR "computer vision" OR "image processing" OR "deep learning" OR LiDAR OR SfM OR "structure from motion") AND (monitoring OR deformation OR deflection OR crack OR "structural health" OR SHM OR fatigue OR damage). In Scopus this was applied to TITLE-ABS-KEY fields; in Web of Science Core Collection it was applied to the Topic (TS) field, restricted to English-language, peer-reviewed journal articles published between January 2000 and June 2026.

2.3. PRISMA Selection Process

Study selection followed the PRISMA guidelines [14]. At the identification stage, the search returned 4,820 records from Scopus and 3,150 records from Web of Science (7,970 records combined). After removal of duplicates (DOI and title matching), 5,124 unique records remained for screening—consistent with the "more than 5,000 references" figure reported in Section 2.3. Title-and-abstract screening, applied against the inclusion/exclusion criteria of Section 2.2, excluded 4,190 clearly irrelevant records, leaving 934 reports assessed for eligibility at full text.

Of these 934 full texts, 730 were excluded, for the following main reasons: no original experimental image acquisition (numerical-simulation-only studies), n = 280; non-extended conference proceedings, n = 145; insufficient methodological detail or overly general, popular-science scope, n = 130; and structure type outside the civil/bridge-engineering scope of this review, n = 175. This yielded 200 articles from the initial search. The 2026 update search (Section 2.1) identified 46 additional candidate records, of which 12 were assessed at full text and 4 met all inclusion criteria, bringing the final corpus to 204 articles.

Figure 2 summarises this selection process following the PRISMA 2020 flow diagram template for updated systematic reviews, tracking records, reports, and studies separately for the initial search and the 2026 update search before they merge into the final included corpus.

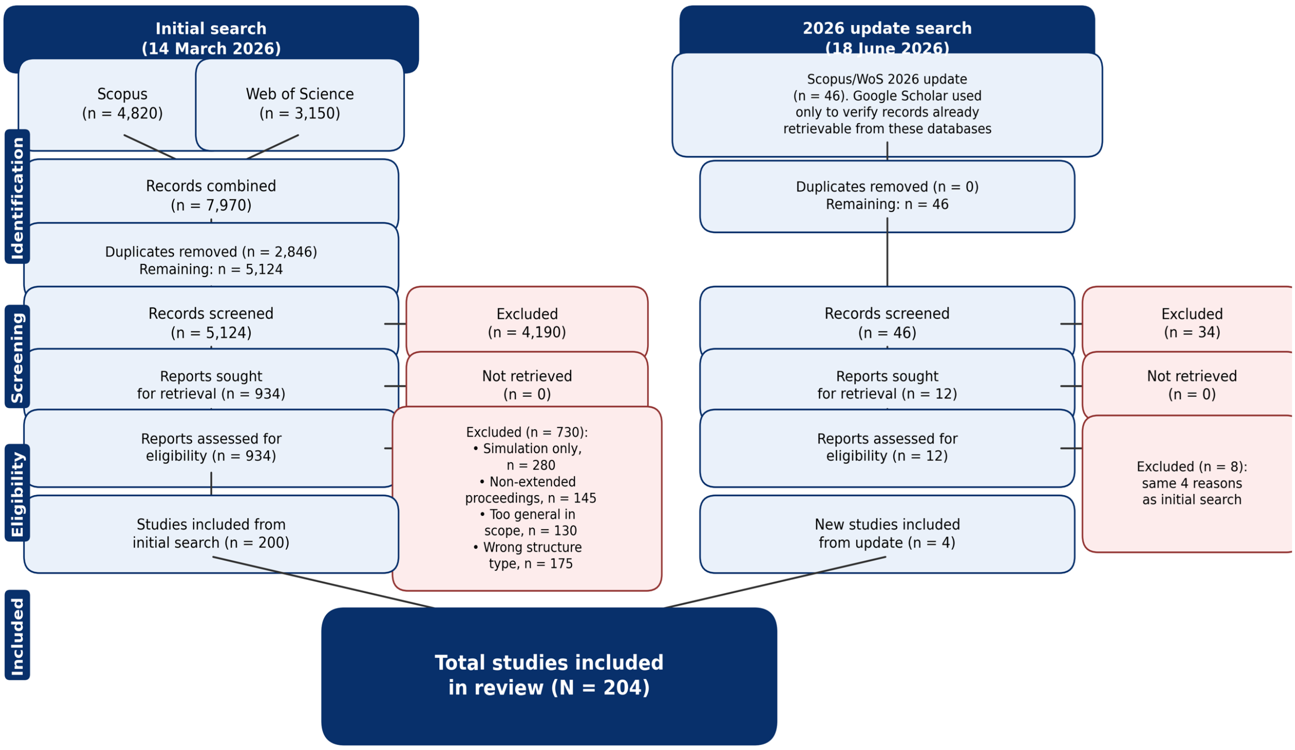

Figure 2. PRISMA 2020 flow diagram for this updated systematic review. Left column: initial search (Scopus n = 4,820; Web of Science n = 3,150), through duplicate removal, title/abstract screening, and full-text eligibility assessment, yielding 200 included studies. Right column: 2026 update search (n = 46 candidate records; Google Scholar used only to verify records already retrieved from Scopus/Web of Science), following the same screening and eligibility steps, yielding 4 additional included studies. The two streams merge into a final corpus of N = 204 included studies. Exclusion reasons at the full-text eligibility stage are detailed in the side boxes.

2.4. Distribution of the Corpus by Theme

The initial search returned more than 5,000 references after duplicate removal. Screening of titles and abstracts allowed irrelevant entries to be discarded. Full-text reading of the preselected articles led to a final selection of 200 articles, supplemented in 2026 by four additional publications drawn directly from Scopus and Web of Science to update the corpus, bringing the total to 204 articles. Table 1 details their distribution by period and theme. As shown in Figure 1, publication activity rises across four successive phases of increasing intensity—2000-2009 emergence (n = 16), 2010-2015 development (n = 38), 2016-2020 expansion (n = 82), and 2021-2026 maturity and AI (n = 68)—confirming the exponential growth of publications on AI-based crack detection from 2016 onward and illustrating the impact of the rise of deep learning on this research field. Figure 3 presents the same 204-article corpus broken down by dominant theme, complementing the chronological view of Table 1 and showing that DIC measurement and deep-learning-based crack detection together account for the largest shares of the literature.

Table 1. Distribution of the 204 selected articles by period and dominant theme.

Theme	2000-2005	2006-2010	2011-2015	2016-2020	2021-2026	No. of articles
DIC 2D/3D—foundations and methods	3	6	11	14	11	45
Deflection and displacement measurement	2	4	8	11	6	31
Crack detection and quantification	2	3	7	13	10	35
Fatigue analysis and propagation	1	2	4	7	5	19
UAV photogrammetry and SfM	0	1	3	8	7	19
Applied deep learning	0	0	2	9	12	23
OMA-DIC modal analysis	1	2	3	4	3	13
Sensor fusion/ integrated SHM	0	0	2	7	10	19
TOTAL	**9**	**18**	**40**	**73**	**64**	**204**

Each article is counted once, under its single dominant theme.

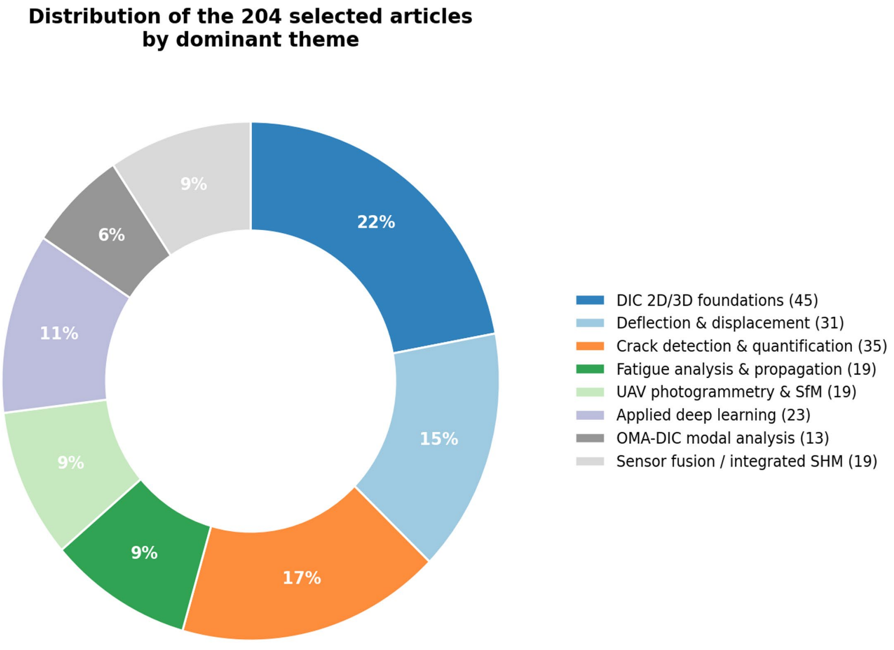

Figure 3. Distribution of the 204 selected articles by dominant theme, dominated by DIC measurement and deep-learning-based crack detection. Each article is classified under a single dominant theme, so the eight categories are mutually exclusive and the percentages sum to 100% of the 204 articles.

2.5. Quality Appraisal of Included Studies

Beyond thematic classification, each of the 204 included studies was appraised against five simple criteria commonly used to qualify the reliability and generalisability of image-based monitoring evidence: (i) experimental setting—controlled laboratory specimen versus in-service field structure; (ii) validation against an independent reference sensor (e.g., LVDT, strain gauge, accelerometer, total station) versus no such cross-validation; (iii) acquisition distance between camera and target; (iv) monitoring duration, classified as single-epoch/short test (hours), short field campaign (days to a few weeks), or long-term deployment (months to years); and (v) degree of environmental control (indoor/controlled lighting and temperature versus uncontrolled outdoor conditions with wind, thermal drift, and variable illumination).

Applying this scheme across the corpus shows a clear methodological gradient: roughly 45% of the 204 studies are laboratory or short controlled-field tests with reference-sensor validation and tight environmental control; about 40% are short-to-medium field campaigns (single visits to days), of which the majority still include some form of reference-sensor comparison; and only around 15% qualify as long-term field deployments of a month or more, for which environmental control is by definition absent and reference-sensor validation is less systematic. This gradient is used throughout Sections 6 and 8 to qualify the strength of the evidence behind reported accuracy figures, and is reflected in the added "Setting/Duration" column of **Table 2**.

3. General Context: Structural Health Monitoring of Bridges

3.1. Challenges and Conventional SHM Methods

The concept of structural health monitoring gradually took shape from the 1990s onward, driven by pioneering work in aerospace and civil engineering [15]. Its most widely cited definition today is that of Farrar and Worden [5], who describe it as a comprehensive strategy for assessing the damage state of a system using measurements acquired in situ. This definition reveals four increasing levels of information: simple damage detection, its localization within the structure, identification of its nature, and assessment of its impact on remaining service life.

In current practice, bridge monitoring relies on two broad families of tools. The first is periodic visual inspection, carried out by qualified engineers following standardized protocols. This approach has the merit of simplicity but presents well-known drawbacks: it is costly in time and labor, it depends on the subjective judgment of the inspector, and above all it does not allow continuous monitoring between two campaigns. The second family consists of instrumental sensors permanently installed on the structure. Strain gauges provide very precise but purely local measurements [16]. Accelerometers allow identification of the structure's modal parameters through operational modal analysis [17]. FBG fiber-optic sensors offer the advantage of electromagnetic immunity and the possibility of embedding within materials [18]. Piezoelectric transducers form another family of sensors used for structural impedance monitoring [19]. Vibration-based damage detection methods have been the subject of in-depth review papers [20]. Wireless sensor networks have considerably simplified installation but still pose reliability and energy-consumption issues [21].

The common limitation of all these techniques is their point-wise nature. A sensor provides information only about the point where it is physically installed. On a large structure, complete mapping of deformations would require an economically unreasonable number of sensors. It is precisely to overcome this fundamental constraint that full-field optical methods have attracted growing interest within the scientific community.

3.2. Why Optical Methods?

The idea of using cameras to measure structural displacements is not new: analog photogrammetry work on structures dates back to the 1970s. What changed from the 2000s onward was the combination of several converging factors: the widespread availability of affordable high-resolution digital cameras, the explosion of computing power available on ordinary platforms, and the development of robust and efficient image-processing algorithms. Lee and Shinozuka [22] were among the first to demonstrate in 2006 that a commercial camera equipped with a telephoto lens could measure the dynamic displacements of a bridge deck with an accuracy better than 3% compared with a reference LVDT sensor.

The advantages of optical methods are numerous and well documented in the literature. First, they are non-contact: no physical intervention on the structure is required for measurement, which eliminates the risk of disturbing mechanical behavior and facilitates access to hard-to-reach areas. Second, they are full-field: a single camera can simultaneously measure the displacements of thousands of points, whereas a network of conventional sensors would measure only a few dozen discrete points. Third, they are flexible: the same camera can be used for different structures and different purposes, which reduces instrumentation costs. These advantages explain why the number of scientific publications on this topic has multiplied more than fifty-fold between 2000 and 2026. Automated vision methods have also been adapted to model the three-dimensional geometry of buildings and structures [23]. The automated creation of digital twins of structural components through photogrammetry and deep learning opens new perspectives [24]. Reviews of close-range photogrammetry on bridges have documented the growing use of these tools [25]. DIC applied to civil-engineering structural monitoring, including the simplified-DIC variant [26], benefits from this favorable context. Intelligent probabilistic bridge-monitoring systems based on image analysis have also been proposed [27]. Compact, efficient CNN architectures, notably mixed-kernel convolutional architectures [28], reduce memory footprint and facilitate embedded deployment [29] on autonomous inspection systems.

4. Theoretical Foundations of Digital Image Correlation

4.1. Origin and Principle of the Method

Digital Image Correlation was developed at the University of South Carolina in the 1980s, notably by Peters, Ranson, Sutton, and their collaborators [8] [30] [31]. The basic idea is to record two images of a surface: a reference image before any loading, and a deformed image after a mechanical load has been applied or after a certain time delay. By comparing these two images point by point, it is possible to extract the vector field of displacements the surface has undergone between the two acquisition instants.

For this comparison to be performed automatically and accurately, the surface must display a sufficiently contrasted random texture pattern, called a speckle pattern. This pattern can be natural—the aggregate of a well-contrasted concrete, the heterogeneities of a painted surface—or artificial, in which case a spray of paint is applied to create random spots of suitable size and contrast. The fundamental condition is that the pattern be unique to each sub-region of the image: two adjacent sub-regions must have sufficiently different textures to be distinguished by the algorithm.

4.2. Mathematical Formalism

The correlation algorithm operates on rectangular sub-windows of the image, typically ranging from 21 × 21 to 51 × 51 pixels. For each sub-window centered at a point (x, y) in the reference image, it searches the deformed image for the most similar sub-window. The similarity between the two sub-windows is quantified by a correlation criterion. The most widely used is the Zero-Normalized Cross-Correlation (ZNCC) criterion, which has the advantage of being invariant to changes in contrast and lighting [32]:

$$C_{ZNCC} = \sum_i \left[f\left(x_i, y_i\right) - \bar{f} \right]\left[g\left(x_i', y_i'\right) - \bar{g} \right] \Big/ \sqrt{\left\{ \sum_i \left[f - \bar{f} \right]^2 \cdot \sum_i \left[g - \bar{g} \right]^2 \right\}}$$

The geometric transformation φ relating the reference sub-window to its deformed counterpart is parameterized by the displacement vector (u, v) and its first-order gradients. Optimization is performed using the Inverse-Compositional Newton-Raphson algorithm (IC-GN), introduced in the context of computer vision by Baker and Matthews [33] and adapted to DIC by Pan and Li [34]. This algorithm converges quadratically to the solution, typically within four to six iterations, with sub-pixel accuracy on the order of 1/50 to 1/100 of a pixel depending on speckle-pattern quality.

Strain fields are then computed by spatial differentiation of the displacement fields. For small strains, representative of the elastic behavior of structures in service, the simplified expressions of continuum mechanics apply:

$$\varepsilon xx = \partial u / \partial x \quad \varepsilon yy = \partial v / \partial y \quad \varepsilon xy = \tfrac{1}{2}\left(\partial u / \partial y + \partial v / \partial x \right)$$

Numerical differentiation is an operation sensitive to measurement noise. It is recommended to use local polynomial smoothing filters (Savitzky-Golay filters) to reduce noise without excessively degrading the spatial resolution of the strain fields [35].

4.3. Speckle-Pattern Quality and Sources of Error

The quality of the correlation speckle pattern directly determines the accuracy and robustness of DIC measurements. Dong and Pan [36] introduced the Mean Intensity Gradient (MIG) criterion, which quantifies the average intensity gradient over the whole image and allows a priori evaluation of pattern quality. For practical applications, an average speckle diameter of 3 to 5 pixels and a surface coverage rate of about 50% are generally recommended [37] [38]. A speckle pattern that is too coarse reduces the spatial resolution of the measurements; one that is too fine, below the sensor resolution, generates interpolation artifacts. The comprehensive reviews by Pan *et al.* [39] synthesize speckle-pattern quality criteria and recommended best practices within the DIC community. A more recent synthesis, published in early 2026, confirms that interest in DIC applied to bridge SHM has continued to accelerate since 2020 and proposes a roadmap integrating IoT, drone imaging, energy-efficient algorithms, and digital twins for next-generation intelligent monitoring [40]. In the same vein, a review specifically devoted to optical acquisition modules for bridge SHM was published in 2026 [41], jointly covering DIC, photogrammetry, and LiDAR sensors within a single comparative framework. The technique has also been extended to sub-micron-scale measurement via scanning electron microscopy [42], illustrating the method's versatility well beyond civil engineering.

Sources of error in DIC are numerous and have been the subject of in-depth analyses [43]. Interpolation errors, related to the discretization of the image into pixels, represent the fundamental limit of the technique and can reach 0.02 pixel for ordinary bilinear interpolation. Camera-calibration errors, particularly significant in 3D-DIC, introduce systematic biases if the intrinsic and extrinsic parameters of the optical system are not determined with sufficient accuracy; Zhang's calibration method [44] and the photogrammetric approaches of Luhmann *et al.* [45] and Remondino and Fraser [46] constitute the references for this critical step. Environmental errors, related to variations in temperature, lighting, and atmospheric turbulence, constitute the main limiting factor for long-range outdoor applications [43]. Measurement uncertainty must be assessed according to the GUM guide [47] to ensure the metrological traceability of results.

5. Technological Variants of DIC

5.1. 2D-DIC: One Camera, One Flat Surface

In its simplest form, DIC uses a single camera and measures only the in-plane displacement components. This configuration, referred to as 2D-DIC, is rigorously valid for flat surfaces whose displacements remain essentially in-plane. Its main limitation is the cosine error that appears whenever an out-of-plane displacement component is present: this error is proportional to the square of the surface's tilt angle relative to the focal plane and can reach several percent for tilts of just five degrees [43].

Despite this restriction, 2D-DIC has been widely used for bridge monitoring, particularly for measuring vertical deck deflection under service loads and for analyzing strain fields around cracked areas. Pioneering computer-vision work laid the groundwork as early as the late 1990s [48]. Video-based displacement-measurement approaches were subsequently systematized [49] [50]. Studies on the experimental accuracy of 2D-DIC in field configurations have helped clarify the limitations of this setup [51] [52]. Yoneyama and Ueda [53] showed as early as 2012 that a single properly positioned camera could measure the deflection of a concrete beam bridge with agreement better than 2% relative to a reference LVDT sensor. Pan *et al.* [54] developed in 2016 an original off-axis configuration that partially corrects perspective effects and provides real-time measurement of deck deflections without artificial targets.

5.2. Stereo-DIC: Three-Dimensional Measurement

Stereo-DIC, or 3D-DIC, uses two synchronized cameras positioned laterally apart and jointly pre-calibrated. Stereo vision allows the three-dimensional coordinates of the reference surface to be reconstructed and enables measurement of all three displacement components—two in-plane and one out-of-plane—as well as the six components of the strain tensor [55]. The stereoscopic calibration procedure, performed using a checkerboard target imaged in at least about fifteen positions, is a critical step that determines the quality of all subsequent measurements.

Malesa *et al.* [56] applied stereo-DIC to the continuous monitoring of a concrete railway bridge, simultaneously measuring displacements at twelve points of the structure with an accuracy of ±0.1 mm and a frame rate of 25 images per second. Busca *et al.* [57] used a high-speed video system (200 fps) to identify the natural modes of a pedestrian footbridge through operational modal analysis, showing that the natural frequencies extracted from DIC measurements agreed with those from accelerometers to within 0.5% in frequency. Simultaneous multipoint measurement by vision offers a notable advantage over conventional accelerometers [58] [59]. Complementary studies have confirmed the robustness of stereo-DIC for modal identification [60], and video-magnification approaches have been developed to amplify sub-pixel displacements and facilitate their extraction [61]-[63].

5.3. Digital Volume Correlation (DVC)

DVC is a three-dimensional extension of DIC that operates on image volumes obtained by X-ray tomography or acoustic microscopy [64]. It provides access to the internal deformations of an opaque material—concrete, rock, bone—at a spatial resolution on the order of a voxel (typically a few tens of micrometers). Civil-engineering applications mainly concern the characterization of internal cracking mechanisms in concrete, the study of interfaces between aggregates and cement paste, or the three-dimensional analysis of defect propagation in test specimens [65]. However, the constraints associated with tomographic equipment make it a laboratory technique with no direct in-situ application on bridges.

5.4. UAV Photogrammetry and SfM Reconstruction

Bridge inspection using drones equipped with high-resolution cameras is one of the most visible applications of image-analysis methods in civil engineering over the past decade. It provides access to parts of a structure that are physically inaccessible without costly equipment—the underside of the deck, pier surfaces over water, suspension cables—and produces, in a short time, complete photogrammetric surveys of the entire structure [66]. Seo *et al.* [67] showed that a UAV-photogrammetry inspection of a standard highway bridge could be carried out in under an hour, compared with several days for a conventional inspection using an aerial platform.

Technically, these systems rely on the Structure-from-Motion (SfM) technique, which automatically reconstructs the three-dimensional geometry of a scene and the camera positions from a sequence of uncalibrated images [68]. Combined with Multi-View Stereo (MVS) algorithms for point-cloud densification, this approach yields dense 3D models of the structure with metric accuracies on the order of a few millimeters for flight distances of 5 to 15 meters [69]. In-depth methodological reviews of close-range photogrammetry and processing of 3D bridge geometries have been published [25] [70] [71]. Studies on morphological reconstruction from multi-view acquisitions [72], crack monitoring by photogrammetry [73], and geometry measurement under loading [74] have confirmed the capabilities of this approach. These models can be compared with earlier surveys to detect permanent deformations or surface degradation. Complete UAV inspection of structures is also documented in the form of protocols [75] and damage-quantification studies [76] [77].

5.5. LiDAR Laser Scanning

LiDAR (Light Detection and Ranging) measures the distance between a laser emitter and the surfaces of a scene by analyzing the return time of light pulses. Modern terrestrial laser scanners can produce point clouds with densities of several million points per scan and positioning accuracies on the order of ±1 to 3 mm [78]. The principles of processing airborne and terrestrial point clouds have been synthesized by Vosselman and Maas [78]. Applications of terrestrial LiDAR for structural monitoring have been developed by Park *et al.* [79] and Zogg and Ingensand [80]. The integration of LiDAR-equipped drones for optimal inspection-trajectory planning has also been studied [81]. Their application to bridge monitoring mainly involves comparing acquisitions made at different dates to detect permanent deformations or geometric changes. Zhu *et al.* [82] thus demonstrated, using reflector-assisted terrestrial laser scanning on a suspension bridge with a span exceeding 1,080 meters, that main-cable deformation remained below 0.5‰ and deck deformation below 0.6‰ after replacement of short suspenders. Guldur

Erkal and Hajjar [83] developed a method for automatically detecting corrosion areas on metallic bridge elements by exploiting the laser-reflectivity variations associated with iron oxides.

6. Experimental Applications on Different Types of Bridges

The experimental literature review distinguishes four broad categories of structures on which image-analysis methods have been tested and validated. Although reinforced-concrete bridges are by far the most represented in the corpus—which simply reflects their predominance in the global bridge stock—significant work exists on cable-supported structures, masonry bridges, and metallic structures, each presenting specific monitoring challenges.

6.1. Reinforced and Prestressed Concrete Bridges

The earliest applications of DIC to concrete bridges mainly focused on validating the method, *i.e.*, comparing DIC results with those of reference conventional sensors installed simultaneously. Jáuregui *et al.* [84] applied digital photogrammetry as early as 2003 to a reinforced-concrete bridge under controlled static loading, obtaining accuracies of ±1 to 2 mm for spans of 15 meters. Yoneyama and Ueda [53] showed in 2012 that 2D-DIC could measure deck deflection with agreement better than 2% relative to the LVDT. This foundational work established the metrological credibility of the technique in the civil-engineering context.

Subsequent research moved toward more ambitious applications: monitoring under dynamic conditions, microcrack detection, long-term tracking. Nonis *et al.* [85] used 3D-DIC to continuously monitor a concrete bridge over several months, detecting cracks narrower than 0.1 mm that were invisible to the naked eye. Reagan *et al.* [86] [87] proposed integrating DIC into a drone system to inspect the underside of the deck. Pan *et al.* [54] developed in 2016 an off-axis video deflectometer that measures deflections in real time without artificial targets. Tian *et al.* [88] applied a similar system to a high-speed railway bridge in China, with errors below 0.3 mm at a distance of 30 meters. Winkler and Hendy [89] conducted a particularly rigorous study on a 1937 English bridge, assessing the fatigue of bolted connections using DIC at 30 frames per second. More recently, Winkler and Hansen [90] used DIC to monitor over the long term the expansion joint of the Great Belt Bridge in Denmark, demonstrating the feasibility of continuous monitoring over several years. Close-range photogrammetric strain measurements have also been conducted on prestressed-concrete bridges [74], and vision systems for multi-point displacement measurement have been developed [50]. Ground-penetrating radar monitoring usefully complements DIC for diagnosing substructure concrete condition [91].

6.2. Suspension and Cable-Stayed Bridges

Cable-supported bridges pose their own monitoring challenges: the main task is essentially to measure the tension state of the load-bearing cables without physically intervening on them. Mersenne's relation links a cable's vibration frequency to its tension, meaning that by measuring the cable's natural frequencies through image analysis one can infer the tension force. Ji and Chang [92] demonstrated in 2008 that this measurement was possible by tracking the apparent motion of the cable's natural texture in the images from a commercial camera, without any artificial target. Kim and Kim [93] obtained natural frequencies agreeing with accelerometers to within ±0.5% on the stay cables of the Gwangan Bridge in South Korea.

Vanniamparambil *et al.* [94]-[96] developed an original multimodal approach combining DIC, acoustic emission, and guided ultrasonic waves to detect wire breaks in strand cables. The redundancy of information from these three sources reduced the detection uncertainty of each individual technique by around 60%, illustrating the value of multi-sensor approaches. Tian *et al.* [97] recently proposed a drone-based cable-monitoring system without artificial speckle, using a line-segment detector to track cable motion in video images acquired during hovering flight. Du *et al.* [98] also dynamically measured the force in cable-stayed bridge cables through image processing. Kim et al. [99] similarly developed a vision-based monitoring system to evaluate cable tensile forces on a cable-stayed bridge, achieving good agreement with conventional load-cell measurements. Cable monitoring by vision also benefits from advances in operational modal analysis described by Brownjohn *et al.* [100].

6.3. Masonry Bridges

Masonry arch bridges represent a significant share of the bridge heritage in Europe—around 40% according to some estimates [101]—and pose particular monitoring challenges related to material heterogeneity and the near-total absence of initial mechanical documentation. Koltsida *et al.* [101] applied 2D-DIC in 2013 to a four-span railway arch bridge in the United Kingdom, measuring displacements of 0.3 to 0.8 mm under the passage of a 45-tonne train. Acikgoz *et al.* [102] conducted in 2018 a methodologically exemplary study on a masonry viaduct in Leeds, systematically documenting all sources of error affecting field DIC measurements. In particular, they quantified spurious rigid-body motion induced by tripod vibrations at ±0.2 mm, defining a practical sensitivity limit for this type of configuration.

6.4. Metallic Bridges

Monitoring of steel bridges by DIC is of particular interest for assessing fatigue at connection details—notches, welds, bolt holes—where stress concentrations are high and where standard methods based on generic S-N curves are often insufficient. Lee and Shinozuka [22] were among the pioneers in 2006 with their real-time displacement-measurement system on steel box girders. Peddle *et al.* [103] measured the deflection of a three-span steel girder bridge under a 320 kN truck load, obtaining good agreement with LVDTs. Winkler and Hendy [104] conducted in 2017 a DIC analysis of stress-concentration zones on the Docklands Light Railway bridge in London, identifying fatigue-risk zones that conventional methods had failed to detect. Long-term fatigue monitoring of steel bridges relies on probabilistic service-life assessments [105] [106] and degradation models accounting for uncertainty [107]. Long-term DIC monitoring of the Great Belt and other major structures [90] constitutes a particularly well-documented example. Vibration-based damage-detection methods have also been applied to metallic bridges [20] [108].

Table 2. Summary of the main experimental DIC studies on bridges—measurement results and acquisition conditions.

Author (s) /Year	Bridge type	DIC system	Distance	Accuracy	Frame rate	Ref.
Lee & Shinozuka (2006)	Steel, box girders—short field test	Video + telephoto	25 m	<3%/LV DT	Video	[22]
Yoneyama & Ueda (2012)	Reinforced concrete—short field test	2D-DIC, 1 cam.	5 m	<2%/LV DT	1 fps	[53]
Nonis *et al.* (2013)	Concrete, 3 spans—long-term field (months)	3D-DIC, 2 cam.	8 m	crack < 0.1 mm	1 fps	[85]
Feng *et al.* (2015)	Railway + pedestrian—short field test	FT-DIC video	15 m	<1 mm	30 fps	[109]
Pan *et al.* (2016)	Concrete rail—short field test	Off-axis DIC	10 m	±0.03 mm	Real-time	[54]
Winkler & Hendy (2017)	Concrete (1937)—short field test	1 cam., tripod	30 m	1/50 pixel	30 Hz	[89]
Peddle *et al.* (2011)	Steel, 3 spans—short field test	DIC, 1 cam.	Field	±0.06 - 1 mm	1 Hz	[103]
Acikgoz *et al.* (2018)	Masonry—short field test	2 cam., 2 MP	7 m	±0.2 mm	50 Hz	[102]
Dhanasekar *et al.* (2019)	Masonry (×2)—short field test	3 cam., 2.35 MP	4 m	Max. deviation 14.5%	50 fps	[110]
Tian *et al.* (2021)	High-speed concrete—short field test	Off-axis DIC	30 m	< 0.3 mm	25 fps	[88]

Because **Table 2** mixes evidence acquired under very different operating conditions, the reported accuracy figures should not be read as directly comparable. Grouped by setting and duration: (a) controlled laboratory or short static-load tests—Jáuregui *et al.* [84] (±1 - 2 mm over 15 m spans), Yoneyama and Ueda [53] (<2% vs. LVDT), Feng *et al.* [109], Pan *et al.* [54], Peddle *et al.* [103], and Ji and

Chang [92]—typically report the tightest accuracies because lighting, distance, and target motion are all controlled; (b) short field campaigns of a single visit to a few days—Lee and Shinozuka [22], Winkler and Hendy [89], Acikgoz *et al.* [102], Dhanasekar *et al.* [110], Tian *et al.* [88], Koltsida *et al.* [101], Kim and Kim [93], and Reagan *et al.* [86] [87]—report somewhat looser but still sub-millimetric to sub-percent accuracies under real, uncontrolled outdoor conditions; and (c) multi-month or multi-year long-term deployments—Nonis *et al.* [85] (several months, sub-0.1 mm crack detection) and Winkler and Hansen [90] (several years of continuous monitoring of the Great Belt Bridge expansion joint)—which are far less numerous (about 15% of the corpus, Section 2.5) and for which reported accuracies must additionally absorb long-term environmental drift, sensor/target degradation, and seasonal effects not present in (a) or (b). **Table 2** has been annotated accordingly, with each entry now labelled by its acquisition setting.

7. Design of an Integrated Digital System

Establishing a durable image-based bridge-monitoring system cannot be reduced to selecting a measurement technique. It requires a holistic approach to system architecture, the choice of hardware and software components, management of the acquired data, and the way the results will be used by the engineers responsible for the structure. **Table 3** proposes a functional architecture structured into five layers.

Table 3. Overall architecture of the digital monitoring system. The five functional layers—acquisition, preprocessing, DIC/AI analysis, storage, and interface—constitute the processing pipeline. The digital twin integrates the data for predictive maintenance. Typical system performance is shown on the right.

Functional Layer	Components and Tools	Typical Performance
① ACQUISITION	Fixed HD cameras · UAV drones · LiDAR scanners · Conventional sensors (ref.)	<0.1 mm @ 10 - 50 m
② PREPROCESSING	Optical calibration · Distortion correction · Radiometric normalization · Denoising	±0.5% lighting correction
③ DIC/AI ANALYSIS	IC-GN algorithm · FFT-CC · CNN networks · U-Net segmentation · YOLO detection	IC-GN: 4 - 6 iter.; 50× GPU
④ STORAGE & MANAGEMENT	Time-series databases · Multi-epoch history · 5G/Cloud connectivity	10+ year history
⑤ INTERFACE & DECISION	Visualization · Automatic alerts · Manager reports · Dashboards	Latency < 1 s (5G)
DIGITAL TWIN—Calibrated FE model · Data assimilation (Kalman filter) · Predictive maintenance · Prediction error reduced from 21.95% to 0.11%		

7.1. Functional Architecture

The acquisition layer includes the imaging systems themselves—fixed HD cameras, drones for periodic inspections, and possibly LiDAR scanners—as well as the conventional sensors used for reference and validation. The preprocessing layer performs operations essential to measurement quality: calibration of optical systems, correction of geometric distortions, radiometric normalization to compensate for lighting variations, and image denoising. These operations, often neglected in publications that focus on measurement algorithms, actually have a decisive influence on final accuracy. Integrating these systems into connected IoT architectures [111] allows data to be centralized on cloud servers and processing workflows to be automated. Automated approaches for organizing and localizing large volumes of inspection images have also been described [112].

The analysis layer is the heart of the system: it implements DIC correlation algorithms or neural-network-based image processing to extract the mechanical quantities of interest from the images. The storage layer manages the time-series databases that preserve the measurement history and enable the multi-epoch comparisons needed to detect long-term changes. Finally, the interface layer handles result visualization, alert generation when thresholds are exceeded, and report production for managers.

The digital twin of the structure—a dynamic numerical model continuously updated from monitoring data—is the most ambitious integrative component of this architecture [113] [114]. Yu *et al.* [115] showed that real-time updating of a finite-element model of a prestressed-concrete box-girder bridge built by successive cantilevering, driven by a computer-vision system measuring vertical deck displacements, reduced the mean relative prediction error of deflection from 21.95% (non-updated model, based on design assumptions) to 0.11% after parametric inversion of the elastic modulus—a reduction of more than 99%. Ensemble Kalman filter data assimilation [116]-[118] is one of the most widely used algorithms for this real-time updating. The concept of the bidirectional digital twin has been the subject of a systematic mapping study [119], and its applications to the life cycle of railway tracks and related equipment have been demonstrated [120]. This perspective paves the way for genuinely predictive maintenance, based on the actual condition of the structure rather than on calendar-based inspection intervals. Approaches for managing bridge networks through stochastic dynamic programming have also been developed from this perspective [121].

7.2. Hardware Components

Camera selection is a decisive parameter for the metric performance of the system. Scientific CMOS sensors of 20 to 50 megapixels, combined with thermally stable, regularly calibrated lenses, allow displacements below 0.1 mm to be measured at distances of 10 to 50 meters. For measuring dynamic phenomena—convoy passages, wind-induced vibration—high-speed cameras of 100 to 1,000 frames per second are required, at the cost of reduced spatial resolution. Modern commercial quadcopter drones, equipped with 20-to-50-megapixel cameras, enable photogrammetric reconstructions with metrological accuracy of ±3 - 5 mm [69]. Wireless accelerometry systems constitute sensors complementary to cameras [122] [123], particularly for large-scale monitoring networks [124] and for railway convoys [125]. The stability of fixed cameras under wind and traffic-induced vibration is a significant practical constraint requiring heavy tripods or rigid mounts fixed to the structure. Fiber-optic sensors provide an independent reference complementary to optical measurements [126].

7.3. Software and Algorithms

Several commercial software solutions are available for DIC processing. VIC-2D and VIC-3D (Correlated Solutions), ARAMIS (GOM/Zeiss), and StrainMaster (LaVision) offer complete interfaces and technical support. Open-source solutions such as Ncorr (Matlab) [127], DICe (Sandia National Laboratories), or py-DIC allow customization of algorithms, which is particularly useful for research and development environments. The IC-GN algorithm is the reference for minimizing the correlation criterion [34]; its global counterpart, the FEM-based approach (EFM) of Besnard *et al.* [128], provides spatial regularization of the displacement fields. The X-DIC approach of Réthoré *et al.* [129] extends this principle to enriched finite elements for crack-front tracking. Systematic comparisons between local and global approaches have been conducted [130]. The Lucas-Kanade algorithm [131], the historical foundation of texture tracking, remains a reference for real-time implementations. Fast Fourier Transform cross-correlation (FFT-CC) provides rapid initialization followed by sub-pixel refinement, following the multi-resolution approach that has become the standard [34].

8. Practical Challenges and Identified Limitations

Critical examination of the two hundred and four articles analyzed reveals several recurring difficulties that scientific publications tend to underestimate or relegate to discussion sections. It is worth examining them explicitly, as they directly condition the feasibility of large-scale deployment of image-analysis systems for bridge monitoring.

8.1. DIC Measurement Errors

Four main sources of error have been identified and quantified in the literature [43]. Interpolation errors, related to the discrete nature of the sensor, constitute the fundamental limit of the technique and can reach 0.02 pixel for ordinary bilinear interpolation. Sub-window errors, related to the assumption that the geometric transformation is uniform within each sub-window, limit the achievable spatial resolution. Studies on the optimal selection of sub-window size as a function of speckle pattern have been conducted [38]. Speckle errors are associated with insufficient intensity gradient, which makes identification of the geometric transformation ambiguous; evaluating pattern quality is an essential prerequisite [37]. Finally, calibration errors—particularly critical in 3D-DIC—introduce systematic biases if the optical-system parameters are not determined with sufficient accuracy.

In addition to these inherent method errors, there are environmental errors specific to outdoor applications. Thermal air disturbances generate image distortions that are difficult to correct and can induce fictitious displacements on the order of 0.1 to 0.5 mm at distances of 50 meters [43] [132]. Camera vibrations caused by wind or traffic-induced vibration introduce spurious rigid-body motion. Acikgoz *et al.* [102] showed that this latter phenomenon could generate errors of up to ±0.2 mm in certain field configurations.

8.2. Field Constraints

Several operational constraints make field applications significantly more complex than laboratory tests. Natural lighting is variable and hard to control: clouds, cast shadows, and sun glare can alter image histograms and disrupt correlation algorithms, even for criteria that are a priori invariant to illumination changes. Physical accessibility is often limited: the most critical areas of a bridge—the underside of the deck, pier base, internal cabling—are frequently out of reach of ground-installed cameras. Drones provide a partial answer to this problem, but their use is constrained by aviation regulations, weather conditions, and the risk of electromagnetic interference in confined spaces. In-situ, vision-based multi-point displacement tracking approaches have indeed been described for structures in service [133]. Multi-modal analysis of infrastructure image data [112] and pavement-defect survey management [134] illustrate other practical field constraints. Satellite SAR interferometry methods offer a complementary solution for large-scale monitoring without physical access [135].

8.3. Long-Term Durability

The durability of the correlation speckle pattern is arguably the most important practical bottleneck for long-term continuous monitoring systems. Commonly used commercial spray paints have an outdoor exposure lifespan of two to five years, depending on climate conditions and substrate type, beyond which progressive degradation of the pattern leads to a loss of accuracy and ultimately correlation failure. Wang *et al.* [136] proposed an interesting solution based on printed-pattern adhesive tape guaranteed for eight years, tested on two steel bridges in the United States. Schumacher and Shariati [137] explored using the natural texture of concrete as a substitute for an artificial speckle pattern, at the cost of a 30-to-50% reduction in accuracy. Recent work proposes generating optimal speckle patterns using generative adversarial networks (GANs) [138], offering new prospects for improving the robustness of correlation patterns. The search for durable markings compatible with the outdoor constraints of bridges remains an open topic.

9. Contribution of Artificial Intelligence

Deep learning has transformed the automatic processing of structural inspection images within a few years. It would be simplistic to present this evolution as a sudden break: it actually built on a long maturation of classical image-processing methods—filtering, segmentation, morphological analysis—which paved the way for current approaches [139] [140]. But the breakthrough of convolutional neural networks (CNNs), catalyzed by Krizhevsky *et al.*'s work on ImageNet in 2012 [141], undeniably marked a turning point in achievable performance. Fundamental architectures such as ResNet [142], DenseNet [143], and generative networks [144] subsequently made it possible to tackle increasingly complex tasks. More recently, Transformer architectures applied to images [145] have opened new perspectives; specialized cooperative convolutional architectures have also been developed for deep-learning-based DIC [146]. Review papers on AI applied to SHM [147]-[151] and to infrastructure inspection [152]-[154] have documented these developments.

The work of Cha *et al.* [13], published in 2017 and today one of the most cited in the field, demonstrated that a CNN trained on 40,000 images of concrete and steel surfaces could detect cracks with 98.3% accuracy, outperforming the best classical image-processing algorithms by more than ten percentage points on the same test data. This result immediately generated considerable interest and paved the way for numerous works adapting the approach to infrastructure-inspection problems.

Three major development directions can be identified in the post-2017 literature. The first concerns multi-class defect detection and localization, using object-detection architectures such as Faster R-CNN [155], YOLO [156], or SSD. Xu *et al.* [157] developed a YOLOv3 system capable of distinguishing seven defect classes in real time at 30 frames per second on an onboard camera, with an average precision of 84.7%. Subsequent work improved on these results with YOLOv5 for crack recognition [158] and through CNN-video-analysis association [159]. Autonomous crack-detection approaches using convolutional networks [160] [161] and inspection systems integrating drones and deep learning [162] [163] have also been published. The second direction is pixel-wise semantic segmentation, which provides precise geometric information on the extent of defects. The U-Net architecture [164], initially developed for medical-image segmentation, has been successfully adapted to crack segmentation on bridge decks [165], with Jaccard indices on the order of 87 to 92% depending on configuration. FCN architectures [166] have also been used, and GANs have been explored for generating synthetic training data [167].

The third direction—probably the most innovative—is the integration of artificial intelligence directly into the DIC pipeline itself, to replace or accelerate conventional optimization algorithms. Boukhtache *et al.* [168] [169] proposed a CNN that directly predicts displacement fields from pairs of images, without resorting to iterative minimization of the correlation criterion. Processing speed is increased fifty-fold on GPU with accuracy comparable to the IC-GN algorithm. Yang *et al.* [146] developed an architecture with two cooperative convolutional networks, DisplacementNet and StrainNet, called Deep DIC, which jointly predict displacement and strain fields from a single pair of images without resorting to iterative minimization of a correlation criterion, with adaptive updating of the region of interest allowing large deformations to be tracked. These recent developments open very promising prospects for real-time processing of high-frame-rate image streams. Hybrid approaches using embedded systems for real-time detection have also been implemented [29] [170]. Universal segmentation via the SAM (Segment Anything) model [171] offers promising prospects for automatically identifying areas to be inspected. Work on multi-material classification and damage detection on large image datasets [172]-[175] has complemented these research directions.

Figure 4 compares the performance of DIC and conventional methods across several criteria, while **Table 4** illustrates the complete AI pipeline for automatic defect detection.

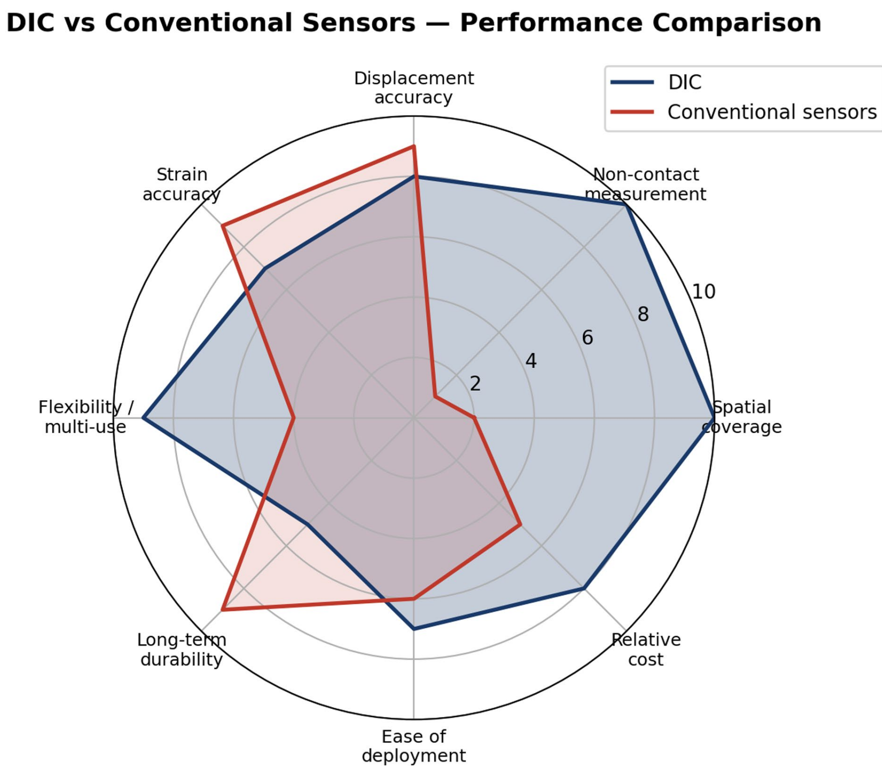

Figure 4. Comparison of DIC and conventional-sensor performance. Left: radar diagram across eight normalized performance criteria (score 0 - 10). DIC stands out for its spatial coverage and non-contact nature, whereas gauges remain superior for local strain accuracy and durability. Right: comparison of typical displacement-measurement uncertainties under field conditions.

Table 4. Integrated AI-DIC pipeline for automatic structural defect detection. The five successive stages—acquisition, preprocessing, DIC analysis, deep-learning classification, SHM decision—lead from the raw image to the maintenance alert. Typical performance metrics are indicated for each module.

Performance criterion	DIC score /10	Conv. sensors score /10	Advantage for DIC?
Spatial coverage	10	2	Yes ✓
Non-contact measurement	10	1	Yes ✓
Displacement accuracy (mm)	8	9	No ✗
Strain accuracy (μm/m)	7	9	No ✗
Flexibility/multi-use	9	4	Yes ✓
Long-term durability	5	9	No ✗
Ease of deployment	7	6	Yes ✓
Relative cost (investment)	8	5	Yes ✓
TOTAL SCORE	**64**	**45**	**DIC ✓**

① ACQUISITION HD cameras · Drones · LiDAR	② PREPROCESSING Calibration · Normalization · Denoising	③ DIC ANALYSIS IC-GN · FFT-CC · EFM	④ AI CLASSIFICATION CNN · U-Net · YOLO · Transformer	⑤ SHM DECISION Digital twin · Alerts · Reports
• Resolution: 20 - 50 Mpx • Frame rate: 1 - 1000 fps • Range: 5 - 200 m	• ±0.5% lighting correction • Zhang calibration [44] • Savitzky-Golay filter [35]	• Accuracy: 1/50 - 1/100 px • Displ. < 0.01 - 0.1 mm • Strain 50 - 500 μm/m	• Crack accuracy: 98.3% • Segmentation IoU: 87% - 92% • Speed: 30 img/s	• MRE error: 21.95% → 0.11% • Fatigue uncert.: −45% • Alert < 1 s (5G)
FEEDBACK LOOP—SHM outputs update the numerical model → continuous improvement of alert thresholds and detection accuracy				

Despite this spectacular progress, it would be unwise to overestimate the maturity of these approaches for industrial deployment. The generalization problem—the ability of a model trained on data from one particular context to remain effective on data from a different context—remains the main obstacle. Recent studies have shown that CNNs achieving 95% accuracy on their internal test sets could see their performance drop to 60% - 70% when applied to images acquired under slightly different conditions [176]. Strategies to mitigate this phenomenon—transfer learning, domain adaptation, synthetic data generation—are actively being developed but do not yet provide a universally satisfactory solution. Synthetic simulation environments for training vision models [177] and improved feature-extraction methods for SHM [178]-[180] constitute promising avenues.

Issues related to the impact of image resolution on crack segmentation [181] and detection robustness [182] have also been quantified. Generative-AI approaches applied to SHM [183] and LLM-assisted autonomous inspection [184] [185] represent the most recent developments. **Table 5** compares the reported performance of the main deep-learning architectures used for bridge defect detection, illustrating the wide variability in precision, recall, and F1/IoU depending on the task, the architecture, and the size of the training dataset.

Table 5. Comparative performance of deep-learning architectures for bridge defect detection.

Architecture	Task	Dataset (images)	Precision	Recall	F1/IoU	Ref.
VGG-16 (fine-tuned)	Binary crack classification	40,000	98.3%	97.8%	98.0%	[13]
ResNet-50	Damage classification × 5	12,000	96.8%	95.4%	96.1%	[172]
YOLOv3	Multi-class detection × 7	8,500	mAP 84.7%	—	—	[157]
Faster R-CNN	Detection + localization	6,200	93.7%	92.1%	92.9%	[155]
U-Net	Crack segmentation	15,000	IoU 87.3%	—	87.3%	[165]
U-Net + Attention	Fine crack segmentation	15,000	IoU 91.6%	—	91.6%	[186]
EfficientNet-B4	Multi-material classification	25,000	97.1%	96.5%	96.8%	[173]
Hybrid DIC-CNN	Displacement + detection	5,000	95.1%	94.3%	94.7%	[168]

10. Perspectives

10.1. Toward Autonomous Systems

One of the most promising directions is the development of fully autonomous inspection systems, capable of acquiring data, analyzing it, and generating reports without continuous human intervention. Significant progress has been made in autonomous drone navigation via SLAM (Simultaneous Localization and Mapping), in trajectory planning using reinforcement learning [187], and in embedded image processing on miniaturized processors [188]. Zhao *et al.* [189] showed that a two-stage optimization of an inspection drone's trajectory, combining a genetic algorithm for viewpoint placement with a greedy algorithm for camera orientation, produced trajectories at least 30% shorter than direct five-degree-of-freedom optimization, while still guaranteeing complete coverage of the structure. These developments are converging toward systems where the drone itself identifies risk areas and concentrates its surveys on the most critical zones. Robotic infrastructure-inspection systems have been the subject of dedicated reviews [188].

Embedded systems with real-time detection on low-power computing devices have been described [190] [191], and drone-and-image-processing-assisted bridge damage detection is now well documented [77] [163]. Multi-scale visual inspection [175] and AI-assisted autonomous systems [184] represent the most recent developments in this field.

10.2. Real-Time Processing and Embedded Systems

The trend toward onboard processing directly at the acquisition system responds to an important operational need: reducing the latency between measurement and alert decision. Recent work has shown that lightweight CNN algorithms can run in real time on low-power platforms [29]. Real-time structural damage detection on field devices [190] [191] and edge-computing-based crack-detection systems [170] illustrate these advances. The spread of 5G connectivity is opening the way, in parallel, to a hybrid architecture in which part of the processing is offloaded to high-performance cloud servers, while urgent decisions are made locally. Cloud-connected wireless sensors [124] and railway-bridge monitoring networks [125] are examples of this trend. Digital twins for infrastructure health monitoring [192] complement this evolution toward fully connected systems.

10.3. Digital Twins and Predictive Maintenance

The digital-twin concept—a numerical model of a structure continuously updated from monitoring data—is arguably the most transformative perspective for the long-term management of bridges [113]. By combining a calibrated finite-element model, continuous imaging-based monitoring data, and data-assimilation algorithms, it becomes possible to predict the future evolution of the structure's condition and anticipate maintenance needs. Yu *et al.* [115] demonstrated a reduction of more than 99% in mean relative prediction error (from 21.95% to 0.11%) through real-time assimilation of computer-vision measurements into a finite-element model updated during the cantilever construction of a prestressed-concrete box-girder bridge. Hu *et al.* [193] developed a digital twin combining an inspection robot equipped with a phased-array ultrasonic sensor and a deep-learning crack-detection algorithm (YOLO-ODConv), achieving 95.6% precision and 92.2% recall for automatic crack detection, before feeding a finite-element model through ABAQUS-FRANC3D co-simulation for fatigue-life assessment of orthotropic steel decks. Probabilistic prediction of bridge-cable service life through SHM [106] and fatigue-reliability assessment of metallic bridges through continuous monitoring [105] illustrate concrete applications. Markov-decision-process-based maintenance optimization approaches [194] make it possible to integrate monitoring data into asset-management decisions. The long-term performance of degraded systems under uncertainty [107] and network-level optimization of bridge stocks [121] [195] constitute closely related research questions. Reviews of the state of the art on bridge digital twins [114] and work on maintenance research and innovation [195] [196] document these perspectives. Work published in 2026 confirms and extends this direction: Tran *et al.* [197] propose a digital-twin framework specifically designed for large bridges under sparse instrumentation, where reconstruction of the full response field through hybrid CNN-LSTM learning complements a limited number of physical sensors, with an updatable baseline configuration ("State 0") for longitudinal tracking of deterioration. Along the same lines, Alqurashi *et al.* [198] describe an inspection system integrating drone-mounted LiDAR point clouds, photogrammetry, infrared thermography, and ultrasonic tomography, whose fusion within a virtual-reality environment is driven by an object-detection model trained on more than 10,000 infrared images, achieving 90% precision and recall for automatic detection of thermal anomalies on bridge decks.

10.4. Standardization and Regulatory Integration

Large-scale industrial deployment of DIC-SHM systems still faces the absence of unified technical standards covering measurement protocols, acceptance criteria, data-exchange formats, and metrological traceability requirements [47]. Standardization efforts are underway at the European level (CEN/TC 135) and within several national bodies, but operational frameworks remain to be built. Reference publications on civil SHM methods [60] [199] and reviews of the challenges and successes of vibration-based monitoring [60] lay the conceptual groundwork for this standardization. The PRISMA protocol [14], used for this review, itself constitutes an element of methodological standardization for systematic reviews in the field. This regulatory dimension, often underestimated in scientific publications, nonetheless determines the confidence that asset managers can place in image-based monitoring systems for decisions affecting public safety. Research and innovation in bridge maintenance and inspection [195] [196] contribute to feeding these standardization processes. **Table 6** summarizes the anticipated roadmap for bridge DIC-SHM systems through 2030, contrasting the technical advances expected at each horizon with the bottlenecks—weather robustness, AI generalization, sensor cost, cybersecurity, and regulatory acceptance—that are likely to persist.

Table 6. Roadmap for bridge DIC-SHM systems—current status and outlook to 2030.

Horizon	Expected advances	Persistent bottlenecks
2024-2026	3D-DIC on decks ≤ 100 m validated in service; standardized UAV-SfM inspection; crack-detection CNNs deployed in production	Weather robustness; speckle-pattern durability (2 - 5 years); absence of unified standards
2027-2029	Long-range DIC > 200 m; digital twins with real-time assimilation; autonomous UAV fleets via 5G	Generalization of AI models; high-precision LiDAR cost; integration into regulatory frameworks
2030+	Autonomous predictive SHM with continuously updated remaining service life; target-free DIC; multimodal inspection robots	Cybersecurity of connected systems; UAV regulatory acceptance; data interoperability

11. Conclusions

The review of the two hundred and four articles analyzed in this work provides a nuanced assessment of the state of the art of digital image-analysis systems for monitoring bridge deformations. Several points deserve emphasis.

Digital Image Correlation has clearly moved beyond the feasibility-demonstration stage: dozens of experimental studies on real structures have shown that its metric performance—on the order of 0.01 to 0.1 mm in displacement and 50 to 500 µm/m in strain—is comparable to that of reference conventional sensors, at a substantially lower instrumentation cost and with incomparably greater spatial coverage [9] [10] [39] [42]. The ability to obtain a complete map of the strain field over the entire visible surface of a structure represents a fundamental qualitative advantage that point sensors cannot offer. Vision-based SHM is now recognized as a discipline in its own right, well documented in the literature [152] [199] [200].

UAV photogrammetry has, moreover, profoundly changed inspection practices, providing access to previously inaccessible areas and considerably reducing intervention time and cost [67] [75] [77]. Deep learning has brought remarkable automatic defect-detection capabilities on published benchmarks [154] [165] [172] [174] [201], even though the question of generalization to contexts not represented in the training data remains open [176] [178].

It would, however, be inaccurate to present these technologies as finished, immediately deployable solutions. Several concrete challenges still hinder their industrialization: the durability of speckle patterns under outdoor conditions, the robustness of measurements to climatic and lighting variations, metrological traceability within existing regulatory frameworks, and the ability of asset managers to integrate and interpret the data produced. These practical questions deserve as much scientific attention as the algorithmic developments, to which the literature devotes the majority of its efforts.

The prospects for further development are nonetheless real and credible. The convergence between continuous imaging-based monitoring, structural models updated through data assimilation [116] [117], and predictive artificial-intelligence algorithms [147] [149] points toward a future in which bridge management will rely on precise, continuous knowledge of each structure's actual condition, rather than on standardized calendar-based inspection intervals. Forward-looking studies on asset management [1] [2] [121] [195] and work on structural safety [202] confirm the scale of the challenges. This is a profound transformation affecting both engineering practices and available tools, and it requires a sustained effort from the scientific, regulatory, and industrial communities. The methodological foundations laid by the pioneers of SHM [203] [204] remain a founding reference for current developments. The four papers published in the first half of 2026 that were incorporated when this review was updated [40] [41] [197] [198] do not call these conclusions into question: rather, they confirm and extend them, whether with regard to the rise of vision-driven digital twins, multimodal drone inspection, or the most recent state-of-the-art syntheses on DIC and optical acquisition modules applied to bridges.

Author Contributions

Kora Farid Carlos Yarou: Conceptualization of the scope and objectives of this review on digital image-based monitoring of bridge deformations; Investigation and Methodology, including the systematic literature search and PRISMA-based screening of the 204 articles retrieved from Scopus and Web of Science; Software used to process the bibliometric data and generate the corpus statistics and figures; Writing-original draft of the manuscript.

Valery Kouandete Doko: Supervision of the research design of the review; Conceptualization of the methodological framework used to compare DIC, UAV photogrammetry, LiDAR, and deep-learning-based monitoring approaches; Validation of the article-selection criteria and of the technical accuracy of the reviewed structural health monitoring content; Writing-Review & Editing of the manuscript.

Boris Ganmavo: Resources, including access to the bibliographic databases and reference-management tools used for this review; Investigation of the literature on bridge deformation monitoring; Data curation of the corpus of 204 selected articles and of the comparative synthesis presented in **Tables 1-2** and **Tables 5-6**; Writing-Review & Editing of the manuscript.

Thede Agbelele: Investigation of the literature on optical and image-based bridge monitoring techniques; Visualization, including the figures illustrating publication trends, the thematic distribution of the corpus, the PRISMA flow diagram, and the architecture of the integrated digital monitoring system (**Figures 1-4**, **Tables 3-4**).

Mohamed Gibigaye: Project administration and coordination of the review process, from database search planning to manuscript submission; Supervision of the overall research on bridge structural health monitoring and final approval of the manuscript.

All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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