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Review

Structural Health Monitoring of Concrete Bridges Through Artificial Intelligence: A Narrative Review

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Abstract: Concrete has been one of the most essential building materials for decades, valued for its durability, cost efficiency, and wide availability of required components. Over time, the number of concrete bridges has been drastically increasing, highlighting the need for timely structural health monitoring (SHM) to ensure their safety and long-term durability. Therefore, a narrative review was conducted to examine the use of Artificial Intelligence (AI)-integrated techniques in the SHM of concrete bridges for more effective monitoring. Moreover, this review also examined significant damage observed in various types of concrete bridges, with particular emphasis on concrete cracking, detection methods, and identification accuracy. Evidence points to the fact that the conventional SHM of concrete bridges relies on manual inspections that are time-consuming, error-prone, and require frequent checks, while AI-driven SHM methods have emerged as promising alternatives, especially through Machine Learning- and Deep Learning-based solutions. In addition, it was noticeable that integrating multimodal AI approaches improved the accuracy and reliability of concrete bridge assessments. Furthermore, this review is essential as it also addresses critical gaps in SHM approaches and suggests developing more accurate detection techniques, providing enhanced spatial resolution for monitoring concrete bridges.

Keywords: concrete bridge inspection; structural health monitoring; machine learning; crack detection; automation; digitalisation

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1. Introduction

Bridges are essential infrastructure that facilitate connectivity for the advancement of society and the economic condition of any region [1]. They can be constructed over rivers, two adjoining ocean/sea masses, roads, railway tracks, or valleys. Bridges facilitate the perpetual and easy flow of raw materials, consumer durables, and manufactured items from factories and suppliers to houses, customers, distributors, and many more. Several types of infrastructure malfunctions can have a catastrophic impact on the structure of a bridge, such as accidental overload [2], lack of maintenance [3], scour [4], faulty design [4], corrosion [5], and mistakes encountered due to construction and supervision [6]. In addition, forces like tension, torsion, shear, and resonance can also compromise structural integrity [7]. Moreover, catastrophic atmospheric events can substantially impact the health of bridges and increase their fragility [8]. Bridges are standard in coastal areas, connecting two adjacent or distant land masses. These bridges are exposed to highly aggressive environments, which leads to durability problems, affecting their service and necessitating intensive inspection regimes. In general, bridges are constantly used, exposing them to damage that can reduce their serviceability and lifetime, leading to an increased risk of collapse and causing economic and physical damage [9].

Bridge structures have different structural typologies that are often dictated by the environmental setting and geography, span, expected load, visual impact, and design requirements. Due to their different operational environments and loading conditions, bridges and other civil structures like buildings and dams have different structural health monitoring (SHM) methods. Vehicles, trains, and people burden bridges make vibration-based monitoring essential for structural changes. Bridge integrity is often assessed using modal analysis, which includes natural frequencies and damping ratios [10]. Dams are examined for seepage, foundation subsidence, and internal erosion threats, while buildings are primarily static and require SHM systems focusing on wind-induced vibrations and seismic resilience [11]. Bridges use accelerometers, strain gauges, and weigh-in-motion sensors at piers and mid-spans, while buildings use tiltmeters and seismic sensors, and dams use piezometers and water pressure sensors [12]. Failure modes and maintenance practices distinguish bridge SHM from other structures. Bridges need regular inspections, Artificial Intelligence (AI), drones, and real-time monitoring for predictive maintenance due to fatigue cracks, corrosion, and scour [13]. Structures can collapse during seismic events, while dams can overtop or collapse owing to seepage, requiring geotechnical monitoring. SHM in predictive maintenance plans has improved infrastructure resilience, especially in bridges where ageing and dynamic stress are essential [14]. These differences highlight the need for SHM methods tailored to each structure's characteristics and risk factors.

Concrete is the most exploited construction material globally and lends itself effectively to most bridge applications and complex structures. Concrete bridges are durable and versatile, not only when they take their final shape but also during the process of construction, and these qualities are not commonly found together, making concrete the substance of choice in the construction of modern bridges. Other qualities of concrete that make it highly desirable are its strength, aesthetic quality, economic impact, simple construction, and quick deployment technique. All these qualities make concrete the best material for constructing any bridge, irrespective of its size, use, or type. Enhanced construction flexibility can be achieved by the varied forms of cement-based materials available on the market, and the associated technologies in reinforced and prestressed concrete make it an adaptable solution suitable for the highly challenging types of bridges and other ancillary structures, such as bridge support structures, abutments, and piers [15,16].

Several methods have been developed to assess the structural health and conditions of in-service civil infrastructure, which include visual inspections based on expert and skilled personnel who gather and analyse data [17,18]. However, these methods can be highly time-consuming, dangerous, and expensive [19]. Monitoring using technological solutions is required to enhance safety and reduce maintenance and inspection costs. Yet, the spatial resolution of the captured data can be compromised or might depend on the sensors. The method of utilising fixed sensors is widely used and prevalent, but access to these sensors after installation can be highly challenging [18,20]. In cases where only periodic monitoring is needed, contact sensors can incur significant costs as ample time will be invested, while sensor systems require maintenance. Conventional image processing tools depend on boundary detection methods, viz., template matching and Sobel edge/morphological detector for feature extraction from images and are highly susceptible to environment-related elements like shade, light, distortion, and occlusion.

SHM techniques are customised to accommodate the specific attributes and possible failure mechanisms of different structural materials, such as concrete, steel, and composites. SHM in concrete constructions emphasises identifying defects, including cracks, delaminations, and voids. Methods such as infrared thermography and ground penetrating radar are frequently utilised for this objective. Recent improvements have offered methods that integrate optimised Grey-Level Co-occurrence Matrix (GLCM) studies with other techniques to improve the detection of structural faults in concrete [21]. Steel constructions, however, are vulnerable to issues such as corrosion and fatigue-related fractures. Non-Destructive Testing (NDT) procedures, including ultrasonic testing and acoustic emission monitoring, are extensively employed to monitor these concerns. SHM must consider the complications resulting from the interaction of diverse materials in composite constructions [22].

SHM is a broad umbrella that includes processes and presents reliable data on any structure's current condition. The appropriate bridge monitoring and deterioration diagnosis require essential tools related to bridges: their functional state and structural integrity. A series of measurement sensors can be applied under SHM to detect the deterioration of structures and bridges over a given time, and particular studies of bridge monitoring have been vast and varied [23]. When talking in terms of sensors, the hardware and software elements of SHM should be considered. The sensors and related instruments constitute the hardware, and damage detection and modelling techniques for damage identification are included in the software elements of SHM [24]. Table 1 gives a list of the variety of techniques that are incorporated in SHM.

Table 1. Structural health monitoring techniques.

S. No.	Technical Aspects of SHM	Function Performed	References
1.	Impregnation of sensors	Monitor the condition of the specific structure	[24–26]
2.	Data acquisition techniques	Gather real-time data that help to track structural integrity	[24,25]
3.	Signal processing tools	Help to analyse data collected in the previous step	[27]
4.	Damage detection	Assist in damage detection	[24,27]
5.	Remote monitoring	Help in monitoring structures remotely	[24,26]
6.	Acoustic emission	Detect and locate different damage in reinforced concrete structure	[26]

Bridges are affected either by man-made or natural elements that cause deterioration with time [28]. Most bridges are expected to remain in service for long timespans; thus, any damage can propagate with time and eventually cause catastrophic failure. This makes it mandatory to have regular inspections of the bridges to determine the structural stability, potential hazards, and progression of defects over time [28]. A SHM system is used to diagnose damage, identify the spread of damage, and determine the health status of any bridge; however, either assumption or development of the bridge's pre-damage state is mandatory for damage understanding [29]. It is required to know the prior state of the bridge for accurate estimation of the impact and to determine damage extension and location. The SHM system is used to analyse and compare a new model of the bridge with an older one and figure out any discrepancies between the two successive models [30]. Under the broad category, SHM can be divided into model-driven and data-driven types. Model-driven SHM is based on a finite element analysis model and sensitivity matrix [31,32]. Major hindrances to the model-driven SHM model are that it is time-consuming, the calculations are generally complex, and the model needs validation on an experimental basis [33,34]. Another hindrance includes vibrations in the surrounding environment, which induce measurement noise and false boundaries. Data-driven SHM reduces ambiguity and unanticipated issues attributed to computational intelligence [35]. Data-driven techniques can be applied along with model-driven approaches [36]. Data-driven techniques in SHM offer significant advantages but also face the following limitations, and their solutions are discussed below:

1. Challenges in Dataset Collection: Data-driven techniques require large datasets for thorough training. The lengthy and costly process of collecting run-to-failure data makes it impractical for novel systems. Guaranteeing that the data encompasses all possible future operating scenarios is nearly impossible, resulting in model prediction efficacy issues [37].
2. Data Quality Issues: The effectiveness of data-driven SHM techniques heavily depends on the quality of the collected data. Elements such as noise, missing data, and inconsistencies may adversely affect the effectiveness of these methods. Despite the critical significance of data quality, there has been very limited focus on establishing comprehensive data quality indicators and metrics within the SHM community [38].
3. High-Dimensional Feature Spaces: Data-driven techniques often analyse several features, creating high-dimensional feature spaces. Complexity may limit the model's generalisation and require dimensionality reduction, which may lose important information [39].
4. False Positives and Negatives: Image-based SHM methods using computer vision and Machine Learning (ML) can produce false positives and negatives, especially in changing environments. This vulnerability can misread structural integrity, especially when damage events are rare [40].

The challenges in the dataset collection can be tackled using the following approaches:

- Transfer learning and synthetic data generation [41].
- Deploying large-scale sensor networks across multiple infrastructures can help diversify datasets [41].
- Integrating physical knowledge (such as finite element models) with data-driven approaches reduces dependence on large labelled datasets [42].
- Emphasising data collection for ambiguous cases diminishes the necessity for comprehensive data acquisition [43].

The challenges in data quality issues can be solved using the following approaches [44]:

- AI-based imputation methods, such as autoencoders or KNN imputation, may effectively manage missing or noisy data.
- Employing real-time anomaly detection methods, such as statistical outlier detection and AI-driven validation, can improve data integrity.
- Establishing data quality benchmarks guarantees uniformity in SHM datasets.

The challenges associated with high-dimensional feature spaces can be mitigated using the following approaches [45]:

- SHAP (SHapley Additive exPlanations), Principal Component Analysis (PCA), and autoencoders effectively preserve pertinent features while diminishing dimensionality.
- Developing domain-specific characteristics (e.g., modal frequencies, strain energy measures) enhances model precision.
- Sparse coding and dictionary learning facilitate the extraction of significant features while preserving information integrity.

The challenges associated with false positives and negatives can be minimised using the following approaches [46]:

- Integrating physics-based models with AI classifiers can enhance reliability.
- Employing context-sensitive thresholding that adapts according to environmental factors.

- Employing Bayesian Deep Learning (DL) and ensemble techniques (e.g., Random Forest, XGBoost) to enhance reliability.
- Regular model retraining with updated data mitigates environmental bias.

AI-driven SHM employs ML and DL techniques to evaluate structural integrity. Principal problems encompass damage identification and categorisation, defect localisation, and the prediction of residual usable life. AI models analyse extensive sensor data, extract features, and identify abnormalities while synthesising multimodal data from accelerometers, LiDAR, and computer vision [47]. Real-time SHM utilising edge AI, uncertainty quantification, and transfer learning improves adaptability across various structures. Three-dimensional reconstruction and digital twins facilitate virtual inspections and predictive maintenance. These AI methodologies enhance precision, efficacy, and decision-making in SHM applications. Integrating AI into SHM boosts the reliability of concrete bridge assessments through automated inspections, refined data analysis, and the facilitation of predictive maintenance programmes [48]. Conventional approaches like manual inspections and vibration-based techniques have proved essential in SHM of concrete bridges, but issues with precision and efficacy are frequently encountered. Although specific accuracy percentages for these conventional procedures are not constantly recorded, they are typically regarded as less precise due to human error and environmental impacts. Conversely, AI-driven SHM methodologies have exhibited substantial enhancements in precision. The literature indicated that Machine Learning algorithms can identify cracks and fatigue in bridge structures with over 90% accuracy [49].

Concrete is the construction material most exploited globally in structural and infrastructure works. It has been a widely used construction material in bridge construction over the past decades, and several bridge structures rely on cement-based materials [50]. Concrete offers several possibilities for different types and forms of bridge construction. Most bridges globally consist of concrete or rely on composite solutions with concrete featuring as a primary material; due to its versatility, strength, and durability, it lends itself to different typologies of reinforced and prestressed, including post-tensioned, concrete bridge construction [51]. For instance, a study conducted by Znidaric et al. [52] in six European countries showed that there were more concrete-based bridges constructed over the past decade than steel bridges. Similarly, according to the United States (U.S.) Department of Transportation Federal Highway Administration [53], concrete bridges significantly outnumber steel bridges in the U.S. Therefore, this supports the need for robust inspection and assessment methods, justifying the global efforts in inspection and monitoring of concrete bridges. This is especially relevant since, in the case of reinforced concrete, due to the degradation mechanisms involved, early detection and maintenance can support an early intervention and hence extend the lifetime of the asset. Late identification of defects and progressing degradation may require replacement of the asset, besides safety concerns and economic losses.

Conventional SHM of concrete bridges is highly dependent on the skills and knowledge of the expert humans involved and is highly susceptible to errors and manipulation. In addition, the process is expensive, laborious, and inconsistent as various parameters should synchronise for a fruitful outcome. Furthermore, during the inspection, the traffic has to be diverted or blocked for several hours, which causes changes, disrupts travel plans, and hinders emergency response in providing services [54]. AI algorithms have markedly enhanced SHM by facilitating the autonomous analysis of large datasets, encompassing sensor data and images, to identify structural defects such as cracks, corrosion, and deformation. DL techniques, especially CNNs, have proved pivotal in precisely detecting and localising damage in real-time [55,56]. Hence, the focus of this review was limited to concrete bridge monitoring and damage detection using AI, mainly ML and DL techniques. For this purpose, a narrative review was conducted to evaluate the available research articles on SHM of concrete bridges through AI. This review provides insight into AI, ML, and DL solutions for inspection processing when detecting cracks and defects in concrete bridges.

1.1. Problem Statement

Conventional SHM methods, including visual inspections and fixed sensor monitoring, exhibit constraints regarding accessibility, resolution, and dependability. Furthermore, image-based approaches employing conventional computer vision techniques encounter difficulties due to environmental noise, occlusions, and fluctuating illumination conditions, resulting in erroneous positives and negatives in defect identification. The issue is exacerbated by problems in extensive data gathering, high-dimensional feature spaces, and the limited generalisability of AI models across various bridge architectures and contexts. This work emphasises the need for sophisticated, resilient, and interpretable AI models proficient in detecting, localising, and classifying defects such as cracks, spalling, corrosion, and delamination in concrete bridges. It emphasises the necessity of integrating physical knowledge with data-driven methodologies, utilising edge AI, transfer learning, and digital twins to facilitate predictive maintenance and real-time monitoring, thus guaranteeing bridge infrastructures' long-term safety and sustainability.

1.2. Motivation

Bridges are essential infrastructure that facilitate uninterrupted land connectivity and commercial exchange. Their structural integrity is perpetually jeopardised by overload, corrosion, natural disasters, inadequate maintenance, and environmental degradation, especially in coastal and marine settings. Conventional manual inspection techniques are labour-intensive, expensive, inconsistent, and prone to human mistakes. They frequently necessitate partial or whole bridge closures during assessments, resulting in public inconvenience and economic detriment. Advancements in AI, especially in ML and DL, have created substantial opportunities for automating bridge health monitoring systems. This paper is motivated by these advancements and hence aims to investigate and assess the potential of AI-driven methodologies to enhance the accuracy, efficiency, and cost-effectiveness of SHM for concrete bridges.

2. Causes of Bridge Failure

There are several parameters that contribute to bridge failure, such as overloading and material degradation [57]. Factors that impact bridge failure closely depend on the bridge's structural type, user services, and material type. Most bridges are based on reinforced and prestressed concrete with cement-based materials and steel reinforcement. Cracking in concrete structures is a critical parameter and affects their service time. Also, as cracks appear, Young's modulus of concrete, which is nearly constant at low-stress phases, begins to decline at enhanced stress levels [58]. Cracks result in hardened concrete due to actions acting on the structure or structural elements. Concrete durability performance is important and depends on the material's intrinsic properties, the environment where the structure is located, and other parameters such as structural detailing and workmanship at the time of construction.

Concrete characteristics such as porosity and permeability are important parameters. Therefore, cracks in concrete result from different stages of the bridge life cycle and can be due to different actions or processes. Concrete is the basic bridge-building material widely applicable to several typologies of bridges or bridge components. Consequently, the cracks, including their size, extent, pattern and location in the structure, the technology used, and the bridge typology, together with the supporting engineering system, provide essential and valuable information concerning the structure's health. The changing crack pattern over time during the lifetime of the bridge structure is also of fundamental importance and requires monitoring [59].

Although all bridges are exposed to harsh extrinsic environments and unavoidable internal degenerative processes, bridge infrastructure in coastal areas presents more significant challenges and is more likely to experience degradation. Such bridges can be severely impacted by their external surroundings, e.g., in the marine environment, concrete is primarily degraded due to transport mechanisms in the material with penetrating fluids, leading to damaged reinforcement bars induced by carbonation of concrete or chloride attack. Bridges are affected by air-borne salts but are particularly vulnerable to damage when exposed to seawater in a splash zone or an area prone to wetting and drying cycles. Bridge structures may also be exposed to de-icing salts that degrade the material. The primary focus of this work is concrete bridges, which present essential solutions in infrastructure but are also vulnerable to deterioration over time [60].

2.1. Historical Bridge Failures

There have been several historical examples reporting damage and losses caused by the disruption of bridges [2–4]. Over 70 people died when the under-construction Quebec Bridge, Levis, Canada, collapsed in 1907 [61]. The Quebec Bridge was the longest cantilever bridge ever attempted until 1907. The final design had a clear span measuring 548.6 metres (1800 feet) in length. In the same vein, in 1967, the Silver Bridge, Ohio, United States, collapsed, taking the lives of around 50 people along with other damage to adjoining structures [5,6]. Another under-construction bridge, the Tuojiang Bridge, Sichuan, China, collapsed in 2007, resulting in a huge economic loss of approximately CNY 40 million and deaths and casualties totalling 200 [7]. A magnificent bridge located in Italy collapsed during service in 2018. This one was the Morandi Polcevera Viaduct, Genoa, Italy and its collapse caused the death and injury of around 50 people and an economic loss of around EUR 12.6 million [62,63]. A bridge supporting a tram line partially collapsed in Dresden, Germany. The Carola Bridge is one of the four structures over the Elbe River. The abrupt shutdown of the 100-metre bridge caused a significant interruption to the city's transportation, encompassing both the tram and maritime transport. The bridge is a primary transit corridor connecting Dresden's Old Town and New Town, utilised by vehicles, pedestrians, and bikes [64]. The problem of bridge deterioration is severe even in most advanced countries like the USA and China. For instance, the study conducted by Lee et al. [8] reported 1062 bridge failures in the USA alone from the year 1980 to 2012. Another study that was conducted by Xu et al. [65] reviewed the collapse of more than 300 bridges, specifically mentioning location failure causality and bridge type. The above-mentioned statistics highlight the importance of adequate bridge inspection methods to avoid such failures.

2.2. Natural Causes of Bridge Failure

Causes of bridge failure can be both internal (construction errors, design errors, poor maintenance) and external (collision, overload, hydraulic) [66]. Earthquakes, floods, and winds can cause bridge failure and collision [57]. The usage of defective material in bridge construction accounted for more than 30% of bridge failures in Colombia [3]. These were some region-specific studies, and when looking at the global platform, it has been reported that 65% of bridge failures happen because of floods, earthquakes, and avalanches [67]. A recent study further confirmed that more than 70% of bridge failures occur due to natural calamities and faulty construction materials. In contrast, other failure factors included design, accidental load, and durability [59,68].

2.3. Failure Due to Poor Maintenance

Among the several causes of bridge failure, particularly in the United States, it was observed that most failures could have been avoided through regular maintenance. In contrast, bridges in China fail due to large-scale construction elements [69]. Figure 1 shows the global classifications of bridge failure causes based on the above analysis by various authors. Figure 2 shows the timeline of major bridge failures in history from 1907 to 2024.

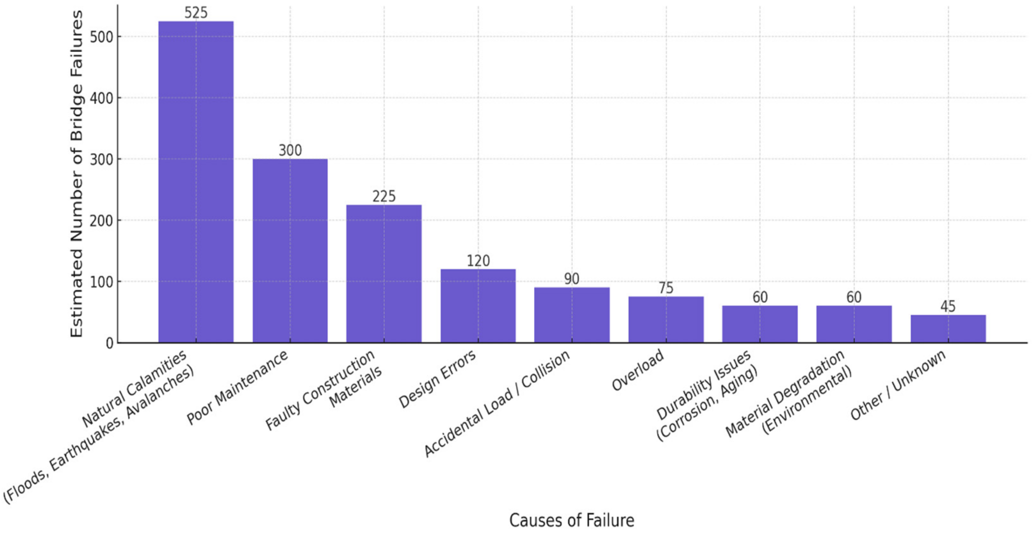

Figure 1. Global classification of bridge failure due to different causes.

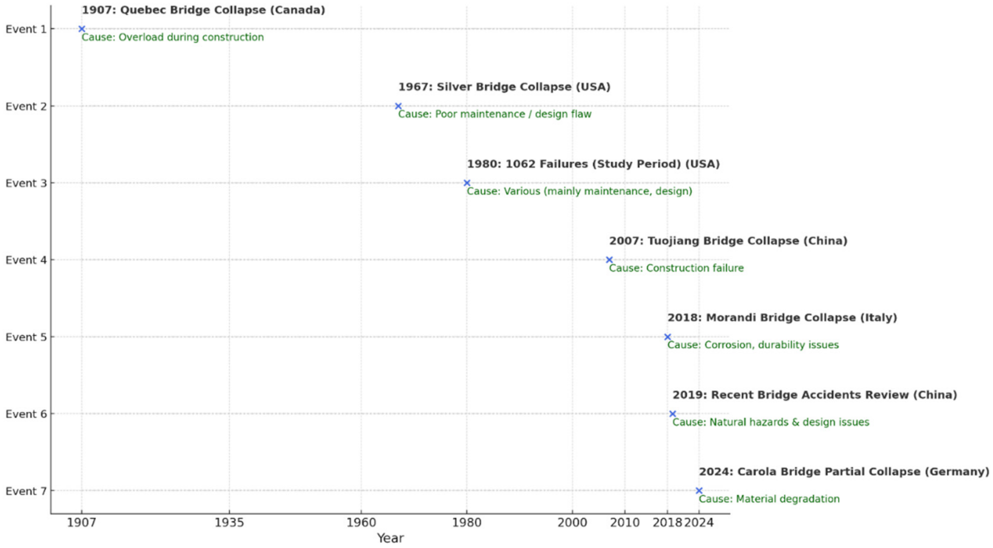

Figure 2. Timeline of major bridge failures.

Hence, there is a need to identify bridge health using ML and DL methods so that the problem of poor maintenance can be addressed and taken care of to prevent large-scale future losses globally. A study by Zhang et al. [70] revealed that out of most field bridges, about 70% were constructed using steel and concrete. Major bridge failures in the United States occur in steel bridges, followed by concrete bridges, even though there are more concrete bridges [8]. Poor infrastructure knowledge and lack of annual maintenance were the two prominent reasons for major bridge failures in the United States. This reinforces that computer-assisted and ML-initiated bridge inspection should be mandatory even in developed nations. Around 80% of bridges in China are made of concrete, so many failures were observed in their structure [71]. Looking at bridge management and maintenance in developed countries, the situation is much better than in less developed countries, and bridge safety guarantee plans exist, including long-term bridge programmes and sustainable bridges [69,72].

3. Bridge Inspection

Bridges are vital for daily transport and communication across cities and land masses. Regular and close inspections are necessary to ensure their safety, integrity, and service-rendering ability. Bridge inspections ensure the detection of faults/kinks in the preliminary stages and directed maintenance can be planned and executed. Bridge inspections in Europe typically incorporate several types of inspections. The first is a routine or regular visual examination; the other is a significant inspection due to particular events or concerns. There is also a special inspection that involves the microscopic examination of specific components or the conduct of a loading test for the formulation of a diagnosis [73]. Irrespective of the type of inspection carried out, all of them lead to holistic conclusions about the health of the bridge and its functional capability. Alongside this, it also ensures maintenance strategies and solutions for risk mitigation.

NDT techniques enable timely management and maintenance of bridges under a bridge management system without causing damage themselves [74]. Various NDT techniques are now readily available, ensuring high-intensity inspections to conduct structural monitoring and detailed inspections [75]. One such technique at the network level is the Interferometric Synthetic Aperture Radar (InSAR), which is self-sufficient for continuous bridge monitoring. Its major characteristics include the microscopic detection of surface changes with good precision [76]. As a constant monitoring system, it surpasses conventional inspection methods. It might, however, overlook some upcoming deterioration changes or changes in dormant periods (the time lapse between two scheduled periodic inspections) [77].

Among the technologies that can be applied during the inspection phase are LiDAR (light detection and ranging) and GPR (ground penetrating radar). Both effectively work at the surface and sub-surface levels to give a grounded assessment of bridge conditions [78]. They both provide baseline data related to bridge condition and reference points for future inspections to enable the assessment of the deterioration rate. The only shortcoming is differentiating gathered data from data integration and visualisation aspects. This shortcoming can be mitigated if the bridge management system functions as a unified unit combining high-resolution point clouds provided by LiDAR and sub-surface information made available by GPR. These data, with visual and structural inspection information, provide a comprehensive overview of the bridge condition, thereby enhancing the accuracy of condition assessment and facilitating precise decision-making for the maintenance of the bridge.

Structural Health Monitoring

The SHM of bridges is neither predictable nor monotonic. Certain uncertainties while the bridge is being constructed create structural behaviour changes that were not included in the bridge's design. After completion and being put to active use, bridges are subjected to evolving patterns of loads and other actions. Integrated SHM systems have enhanced bridges' maintenance, management, and decision-making processes through continuous monitoring and assessment of operational conditions [79]. The uncertainties created during design and construction or while the bridge is in active use all bring unexpected challenges to the engineers and institutions in charge of the bridge's safety, maintenance, and operation.

Superficial maintenance by only surface observation and relying on the type of model of the bridge is risky and will also hamper efficient resource utilisation. However, regular inspection can be highly beneficial in deciding and detecting uncertainties, although this also has limitations. The observation of the structure surface is performed for a short time, and then a long inactive phase occurs, with damages that go unnoticed in the manual inspection. SHM aims to render reliable data on the actual conditions of the bridge, scrutinise its evolution, and detect any appearance of new degradation [80]. Different types of sensors can be installed according to the relevance of the structural condition and other environmental factors, which will render a clear and detailed picture of the state and evolution of the bridge. When this observation is carried out with the help of digital technology and devices, it is known as digital health monitoring and can perform better than modelling and visual inspection [19].

Having healthy bridges is a prominent need everywhere, including in coastal regions. The appearance and presence of cracks are typical in bridges, which can be due to many factors like weathering, ageing, improper loading, and, in the case of coastal bridges, constant proximity to saline water. Several methods have facilitated crack detection in civil infrastructures like bridges, roads, buildings, dams, tunnels, walls, etc., including hiring human visual inspection [81]. To overcome human error, several studies are now being conducted to replace human detection with scientific and computer-aided techniques that include image processing [82], computer vision [83], and classical ML [84]. None of the methods are absolute and all have their respective limitations [85]. Nowadays, AI has marked its presence in several types of fields, including AI-powered disruptive technology [86], CNNs [87,88], and many other object detection techniques [9].

The role of AI-powered technologies can be better understood by looking at a few examples, like Chen et al. [89], who applied CNN to reinforced concrete bridges in China for multi-category damage detection and recognition. Li et al. [90] conducted a study on cracks on bridges using drones and Faster-RCNN. The results of this study indicate that automated bridge fracture detection with UAVs and Faster R-CNN can achieve good efficiency while preserving high accuracy. CNN-based crack detection has encountered two pivotal issues: complex network architecture and a high number of training parameters [91]. The CNN model consists of millions of parameters (weights and biases) that must be learned during training. Thus, it is right to say that the optimisation problem is adjusting the model's internal parameters (e.g., weights) and the associated computational cost.

These pivotal issues can be solved by applying an object detection method broadly classified as a one-stage or two-stage object detection model. There is a simple differentiation between these two types of models, where the one-stage model consists of a single shot-multibox detector (SSD) [92] along with a series of You Only Look Once (YOLO) architectures [93]. The one-stage model does not incorporate a Region Proposal Network (RPN) and does not deliver end-to-end object detection, which is why they are fast. Still, the level of precision achieved is limited. The two-stage model contains architectures like Faster R-CNN [94] and Spatial Pyramid Pooling Network, SPP-NET [95]. These models' object region detection networks are trained as per the RPN [96]. The two-stage models are slower, but the degree of precision achieved is generally higher than that of the one-stage counterparts. Object detection capacity depends on the accuracy and speed of the algorithms applied [97]. YOLOv5 is an efficient object detection example, giving excellent detection accuracy and inference speed compared to YOLOv3 and YOLOv4. YOLOv5 exhibited a mean average precision (mAP) enhancement of 5% to 16% compared to YOLOv4 across diverse evaluation settings utilising the Common Object in Context (COCO) dataset. YOLOv5 can process the data at 38.4 Frames Per Second (FPS), in contrast to YOLOv4's 23.5 FPS, signifying a 63% enhancement [98].

There can be two methods for damage detection in infrastructure. The first method is destructive models that deploy the removal of structural sample masses for damage assessment. Another is NDT, which can predict the presence or absence of damage without any impact on the structure [99]. The signal-based techniques are built on the latest innovative computing algorithms and sensors [100]. Three signal-based techniques are reported in the literature, viz. time domain techniques [101,102], frequency domain techniques [103,104], and time–frequency domain techniques [105,106]. Under the class of frequency domain methods, there are several NDT, including natural frequency, model curvature [107,108], frequency response function [109,110], power spectral density [111,112], and model strain energy [107,113]. Among these, power spectral density finds wide application in damage detection, where a sensitive non-linear function of structural factors is used to create a transfer function of the second order [114]. Structural damage identification is achieved using the model update approach. Increasing the frequency points utilised for damage identification can diminish the selection of measurement sites. The results are derived from modifying the impaired parameters utilising the sensitivity of power spectral density. It not only diminishes the size of the analytical model required for model updating but also reduces the uncertain parameters necessitating updates, facilitating a swift convergence of the iterative process [111]. Several recent studies have been conducted based on this power spectral density technique, such as Hadizadeh-Bazaz et al. [112], which evaluated corrosion-induced damage on coastal bridges. Bayat et al. [115] conducted failure detection tests in concrete bridges using least squares. A Spanish study [116] examined the environmental impact of chloride on a coastal reinforced concrete bridge (Arosa, Spanish region of Galicia) using the power spectral density method. The type chosen was a reinforced concrete bridge constantly eroded by chloride ions. According to this study, chloride corrosion can be subdivided into different levels. The partial spectral density method was compared with conventional techniques. It was concluded that the method applied could diminish the probable harmful effects on the environment by around 14% in the deck and by around 30% in the columns of the bridge in the state of bridge repair and maintenance. In the initial phase, the quantity of chloride ions is below the chloride threshold. Then follows the propagation phase, which includes corrosion followed by structure cover cracking leading to the serviceability state and, finally, the limit state [117]. Table 2 shows a few region-specific case studies using these techniques in crack detection and SHM of concrete bridges.

Table 2. AI- and ML-based crack detection and SHM techniques.

Reference	Objective	Place of Study	Technique	Dataset	Special Highlight	Outcome	Limitations/Future Direction
[118]	SHM	United States	Vibration-based mechanisms, along with ML	NA	Fibre optic system for harsh cold conditions.	The study deployed local measurement sensors, train and displacement sensors, and Artificial Intelligence algorithms.	An extensive focus on vibration-based analysis was laid out, but no attention was paid to feature extraction.
[119]	Crack detection in UAV-based bridge inspection	Norway	CNN	SDNET2018 [120], Hetrogenious (308 images), Homogeneous (400 images) UAV-based images of 3000 × 4000 pixels	Extensive training time, a multitude of parameters RCNN, and YOLO.	Crack identification accuracy of CNN is 81%.	Proposed that the Atrous convolution method permits the usage of a sizeable receptive field without compromising the resolution.

Table 2. *Cont.*

Reference	Objective	Place of Study	Technique	Dataset	Special Highlight	Outcome	Limitations/Future Direction
[121]	Identification and classification of cracks in concrete bridges	China	A fully connected layer comprising 256 neurons was placed ahead of the Softmax layer in the VGG network	2000 images of 224 × 224 pixels were used in 4:1 ratio of training and testing	BN layer amidst convolution and pooling layers normalised gradient depression. TL reduced the network's training time.	Achieved more than 90% training and testing accuracies.	Although high accuracy was achieved, practical application is attainable only with CNN. Overfitting was successfully managed.
[122]	Cracks, spallings, and water erosion detection in concrete bridges	China	A model based on FCN pixel-level identification was used to study concrete bridge delamination and reinforcement exposure	1647 images of 224 × 224 pixels	A pre-trained model was utilised for TL and tested on data exhibiting damage to concrete bridges.	Twin fold improvement viz. the SPP module showcased a 1.3% mAP improvement, and 21% (20.9%) mAP improvement was attained through TL.	The pre-training sample deployed was relatively small.
[123]	Structural damage detection in bridges	New Zealand	A model based on YOLO v3 with the help of the Spatial Pyramid Pooling (SPP) module	Structural ImageNet [124], and 330 images of high resolution	It also works in emergencies, like just after an active earthquake.	After the sensitivity analysis, an accuracy of 84.7% was obtained.	Achieved results included 88% for damage detection, while for spalling, it was 63%.
[125]	Damage segmentation of the bridge using FCN	Japan	FCN pixel-level identification for concrete bridge delamination and reinforcement exposure	734 images of very low resolution of 1 Mpx	FCN surface damage detection was accomplished (automated semantic segmentation).	Despite using a large dataset, an accuracy of 89.7% for delamination was achieved. Reinforcement exposure was just 78.4%; however, the weighted F1 score was around 81.9%.	A large dataset was assembled to justify the proposed model on regions of agreement, thereby diminishing the risks of highly unpredictable in-field inspections.
[90]	Bridge crack detection with UAV	China	Bridges were studied for damage detection induced by earthquakes and other seismic events	6069 images of 224 × 224 pixels	An end-to-end CNN model was used, with a total of 28 layers (16 were convolutional layers, while 3 were max-pooling layers) 10 CNN layers were attributed to the Atrous Spatial Pyramid Pooling (ASPP) module.	No pre-trained model but achieved 96.37% accuracy in crack identification. Data augmentation was used to fulfil the required data.	Developed CNN outperformed conventional models. The adaptable model can be ingrained in any CNN for feature extraction.
[126]	Bridge crack detection with UAV	Korea	UAVs and R-CNN were applied to expose and pinpoint cracks in bridge surfaces	384 images of 256 × 256 pixels	With the help of extracted crack image blocks, both area-based and width-dependent crack parameters were exhibited.	It was a two-step process: initially, a basic background model formulated using a point cloud-based method was made. Surface cracks were later identified using R-CNN and TL.	It was based on CNN. The Cifar-10 dataset was used.

4. AI and ML in Bridge Inspection

AI and ML are new tools that are being adopted in construction to improve productivity. They enhance the project's evaluation and contribute to the monitoring and inspection of infrastructure. Nowadays, AI and ML are becoming common in bridge inspection. Hence, this section is further categorised into NN-based techniques, YOLO-based techniques, and other techniques used for bridge inspection.

4.1. Neural Network-Based Bridge Inspection Techniques

Table 3 gives a summary of recent research on CNN- and ANN-based bridge inspection.

Table 3. Description of recent studies based on neural networks.

Reference	Objective	Technique	Dataset	Outcome	Feature/Limitations
[127]	To develop a crack detection model using TL.	Image augmentation was achieved using rotation, offset, flip, fill, clip, and zoom. CNN and VGG16	A total of 167 RGB images of 1024 × 768 pixels.	Enhanced accuracy and robustness, along with a stupendous F1 score.	5% enhancement in accuracy. Model was trained on a very small dataset.
[128]	Reviewed ML-based algorithms used for the SHM of buildings.	ANN, CNN, and SVM	NA	Data processing achieved by the Hilbert–Huang transform or the wavelet packet transform yielded good results.	Emphasis was placed only on using fog devices to minimise noise filtering and enhance data compression and data fusion after seismic events.
[129]	To investigate the link between enhanced computational intelligence and SHM solutions.	ANN, Hybrid ANN- ICA, Hybrid ANN-GA	NA	ICA and GA were intermingled with pre-developed ANN and hybrid ANN to formulate two hybrid models. Improved prediction error.	Learning outcomes of pre-developed networks improved along with the prediction error with the help of advancements in ANN. The study used vibration data from controlled laboratory conditions. No explicit comparison with real-world damage scenarios.
[130]	To Improve the mAP.	R-CNN	Canon EOS 5DS R camera captured 1000 digital images of 8688 × 5792 pixels	The results were better than those of faster R-CNN with predefined anchor points. 84.56% was the average identification accuracy achieved.	Besides cracks, other types of damage, like spalling and exposed reinforcement, were also detected. Damage quantification was not conducted. No consideration of environmental and operational variations.
[131]	To detect sub-surface damage in bridges using NDT technology and GPR.	CNN	The training dataset (75%) contains 17,388 CNN data points. The testing dataset featured 2898 GPR signals. The validation dataset uses a sample with the same amount of samples.	A high accuracy of around 84% was obtained with the proposed model.	The proposed model has already surpassed ML-based GPR data networks. The dependability of the 1D-CNN is dependent on the quality and uniformity of GPR data. Disparities in data gathering techniques, climatic conditions, and device calibration may influence model efficacy.
[132]	To explore several ML techniques in structural design, construction quality management, bridge engineering, and reinforced concrete bridge inspection.	ANN CNN SVM	NA	ANN is best suited for classification and regression tasks. CNN is best suited for image information, processing.	Reinforced concrete bridges were explored in microscopic detail; however, feature extraction techniques are missing.

Table 3. *Cont.*

Reference	Objective	Technique	Dataset	Outcome	Feature/Limitations
[133]	Identify and classify surface and sub-surface corrosion in steel bridges.	Faster R-CNN	A dataset of 36 3D CbCr-IR images. The training included 72 images, including 36 rotated versions (180 degrees) of the original images.	Promising results were obtained: 88.64% mAP for surface corrosion and 88.59% for sub-surface corrosion.	The combination approach (vision and infrared images) enhanced the reliability of damage detection. The model was trained and tested on only two bridges' data (First Jindo Grand Bridge and Deung-Sun Bridge in South Korea).
[134]	To propose a deep-learning system, Faster R-ConvNet, to detect pavement distress.	Faster R- CNN	The testing dataset was divided into 300, 500, and 900 MHz transmission frequencies. The ratio of GPR images in the three transmitting frequencies was 1:1:1.	Maximum effective results in terms of accuracy were attained by the proposed Faster R-CNN when there were 0.3 anchors and a 0.7 ratio. Results in accuracy were reflection cracks (88.31%), water-damage pits (90.56%) and uneven settlements (88.51%); While IoU was-reflection cracks (86.53%).	Not only cracks were detected, but other damage types, such as reflection cracks, water damage pits, and uneven settlements, were also detected. GPR's data lower resolution or unsuitable frequency ranges can reduce detection accuracy due to image detail loss.
[135]	An automated computerised system can reduce time, faulty inspection, and inspection cost.	CNN	Cellular phones and FLIR 6.8 mm f/1.3 thermal imaging drones captured 2086 crack and non-crack images of 838 × 638 pixels.	Inception V2 was applied to a faster R-CNN model and exhibited about 80.35% accuracy.	The combination approach delivered enhanced damage detection and accuracy. The post-training model displayed 98% accuracy. The dataset was collected from the University of Tennessee at Chattanooga's old library parking garage ceiling.
[136]	The vision-based solution uses deep convolutional neural networks (CNNs) to detect concrete cracks without calculating fault attributes.	CNN	Out of 332 raw images, 277 images of 4928 × 3264 pixels were utilised for training and validation, while 55 images of 5888 × 3584 were used for testing.	A comparison of the proposed model with Canny and Sobel edge detection methods revealed better results. The designed CNN is trained achieving around 98% accuracy.	Extravagant crack detection of minute cracks was achieved despite of limiting environmental factors. The study lacks specifics regarding the model's performance across various cracking types, widths, and orientations.
[137]	Multiple damage detection in reinforced concrete (RC) bridges.	CNN Xception and Vanilla	CODEBRIM [138].	Xception was better, with 94.95% accuracy. Vanilla rendered 85.71% accuracy.	Detected five types of bridge damage: cracks, corrosion, efflorescence, spalling, and exposed steel reinforcement. Real-world validation of the model is missing.
[139]	Detect cracks at the bottom of bridges.	Faster R-CNN and BIM	A total of 637 images, each 512 × 512 pixels, were captured using a DJI M210-RTK UAV.	Promising corollaries were attained, viz. 96.54% recall and 92.03% accuracy.	Different types of crack families, viz. longitudinal/transverse/turtle cracks could be identified. The study fails to consider potential difficulties in synchronising and updating BIM models with real-time inspection data.
[140]	Drone photography of concrete cracks was studied in detail using ML tools.	CNN	3000 Images having a size of 512 × 512 pixels are captured using UAV.	The improved CenterNet model reduced FPS by 123.7 Hz, with 62 MB GPU memory enhancement.	Stable GPU memory occupancy while training. Remarkable real-time performance, accuracy, and robustness were encountered. The study lacks sufficient details regarding the dataset utilised, encompassing its provenance, image dimensions, and collection methodologies.

Table 3. *Cont.*

Reference	Objective	Technique	Dataset	Outcome	Feature/Limitations
[141]	Assessing cracks on concrete surfaces using UAVs.	A combination version of FRCNN and ResNet model	1000 images of 640 × 480 pixels from diverse datasets were used.	The proposed combination model gave a 93.3% precision rate and a quick inference time of 59.7 ms.	Unremitting real-time crack, especially, was possible within a reasonable budget. The investigation may inadequately assess the model's capacity to generalise across diverse concrete constructions with varying textures, colours, and compositions.
[142]	To detect cracks in millimetre units (not in pixels).	Custom CNN and U-Net models	NYA-Crack-Data [143].	Attained accuracy of 99.22% for the classification model and 96.54% for the segmentation model.	Crack detection in millimetres rather than pixels is more accurate and practically applicable. The study is dependent on laser calibration to measure the crack in millimetres.
[144]	Crack detection in structures including bridges.	CNN ViT	SDNET2018 [120] dataset.	About 92.81% accuracy was achieved in bridge crack detection.	A combination model was developed using vision transformers and CNN. The model's effectiveness in detecting very fine or hairline cracks is not thoroughly evaluated.
[145]	Crack detection in concrete bridges.	CNN	A total of 20,000 images of 227 × 227 pixels in each category of cracked and non-cracked dataset.	A 99% accuracy was featured with moderate expenditure.	All examined models had a minimum of 99.1% G-mean values. The model's performance across varied environmental conditions, such as different lighting scenarios, surface textures, and crack morphologies.
[146]	Crack detection in concrete bridges.	Lightweight deep CNN and unmanned aircraft system (UAS)	A total of 6000 images with image resolution of 200 × 200 pixels were used for training, validation and testing in 7:2:1 ratio.	The model exhibited 97.42% accuracy, 97.62% precision, and 97.23% recall and attained 93.25% IOU.	The technical changes made the proposed model suitable for local cross-channel interaction, securing the dimensionality element. The effectiveness of the model in detecting very fine or hairline cracks is not thoroughly evaluated.
[147]	Crack detection in concrete bridge.	CNN Square/strip convolution	BlurredCrack [148], CrackLS315 [149], CFD [150].	Precision: 73.74%, recall: 77.04%, F1: 75.30%, IoU: 60.48%.	Performed better than CNNs as they fail in background noises and long-range dependencies between crack regions; background noises. The study does not elaborate on how MFSA-Net's outputs can be integrated into broader structural health monitoring frameworks.
[151]	Crack detection on the surface of concrete infrastructure.	TensorFlow CNN and image processing	6000 images of 227 × 227 pixels.	The proposed model exhibited an accuracy of 97.11% and 97% F1 score.	Effective and accurate crack identification was possible. The study fail to perceive long-range dependencies between crack regions, and has weak suppression ability for background noises, leading to low detection precision of bridge cracks.

Dung et al. [127] conducted a comparative study for the preliminary detection of fatigue cracks (three types) by inputting relevant data into a shallow CNN and VGG16. Gomez-Cabrera and Escamilla-Ambrosio [128] explored CNN, ANN, and SVM techniques and compared them for their applicability to concrete bridge crack detection. The basis of comparison was input data, type of feature selection applied, data size, stage of damage under consideration, and achieved accuracy of the deployed ML model. It was observed that several combination techniques rendered promising results, such as when data are generated by fusing multi-sensor information. Also, data processing achieved by Hilbert–Huang transform or wavelet packet transform (both damage-sensitive feature extraction methods) yielded good results. Emphasis was laid on using fog devices to minimise noise filtering and enhance data compression and fusion after seismic events. Hybrid approaches (physics- and data-based) were explored to overcome the bottlenecks of stand-alone modelling. Studies revealed that accuracy can improve if anomalous sensor data are combined with real-time monitoring. Gordan et al. [129] stated that conventional human detection methods and normal statistical actions must be more accurate for damage detection, besides being hefty and expensive. To overcome these, the MAE of various models was compared. The learning outcomes of the pre-developed networks improved along with the prediction error with the help of advancements made in ANN. Vibrational information extracted from models under testing was utilised to arrive at the results.

Yu et al. [130] used an algorithm based on k-means clustering to obtain anchor sizes corresponding to damages. Fixed focal length and shooting distance were maintained throughout the data acquisition phase to secure an explicit visual of damage size. The optimised solution developed by the authors was better than Faster R-CNN, improving mean average precision (mAP). Besides cracks, other types of damage, like spalling and exposed reinforcement, were also detected. It was applied to the Anzac Bridge in Christchurch to study various structural damages, and the results outmatched those of faster R-CNN with predefined anchor points. Cracks, spalling, and exposed reinforcement had an 84.56% average identification accuracy.

Ahmadvand et al. [131] deployed a 1D CNN neural network and ground penetrating radar (GPR) system to detect bridge decks. GPR data were obtained from human-generated damage on eight experimental samples. The efficiency of GPR was augmented using a few pre-extracted features. The type of CNN used was a one-dimensional type (1D) to discover concrete bridge decks. Laboratory-based GPR consisted of artificially created sub-surface defects and defect-free samples to classify the entire collection. A thoroughly investigative study deploying ML algorithms for SHM in bridges, paying special attention to reinforced concrete bridges, was carried out by Fan et al. [132]. Many aspects, like design, construction, quality management, and bridge engineering work, were explored. The study supported the idea that ANN is best suited for classification and regression tasks. ML algorithms like SVM and Random Forest (RF) are easy to use and find the optimal parameters related to the problem because of their smaller number of hyperparameters. CNN is best suited for image information, processing, and establishing a connection between the dependent and independent variables of high dimensions.

Lim et al. [133] explored reinforced concrete bridges using vision and infrared thermography. The hybrid image combines images captured with RGB cameras with infrared camera data. The hybrid images were input into Faster R-CNN, which yielded details about the corrosion-induced damage of bridges on the surface and also sub-surface damage. Faster CNN led to automated corrosion detection. Practical application and sub-surface corrosion, often missed in single modalities, were easily pinpointed.

Gao et al. [134] input more than 3750 scanned images into a Faster R-CNN to identify structural faults in concrete bridges. The proposed Faster R-CNN attained better results in terms of accuracy when there were 0.3 anchors and a 0.7 ratio. Qurishee et al. [135] performed bridge crack detection using a combination of Faster R-CNN and infrared thermography. By applying Inception V2 to execute feature extraction for Faster R-CNN, a model was developed that exhibited about 80.35% accuracy. The combination approach delivered enhanced damage detection and accuracy. Cracks on the surface were identified using a shallow CNN proposed by Cha et al. [136]. Comparative studies were conducted to examine the performance of the proposed CNN using traditional Canny and Sobel edge detection methods. The results reported show that the proposed method performs better and can find concrete cracks in realistic situations like strong light, spots, and shadows. Image processing techniques can be obstructed in real-world situations, and this study proves a practical and applicable solution to these by detecting extremely minuscule cracks up to 1.5 mm.

Abubakr et al. [137] researched different damages, including cracks on reinforced concrete bridges, to analyse their safety levels, plan maintenance, and understand serviceability capacity. The image classification process detected five defects, including cracks, using a combination of CNN's Xception and Vanilla models. Gan et al. [139] conducted a study to detect cracks at the bridges' bottom portion using faster R-CNN and building information modelling (BIM) techniques. Crack images correlate with a BIM model designed for the selected bridge and the box girder family exhibiting cracks, along with three categories of cracks: transverse, longitudinal, and turtle. This unique combination of bridge crack detection, consisting of UAVs and modelling techniques, helped detect remote cracks, which are otherwise difficult to detect in manual inspection, and thus has practical applicability in civil engineering.

Kang et al. [140] carried out drone photography of concrete cracks and evaluated the gathered information using ML tools like CNN; also, a model called the CenterNet model based on CNN was proposed. In the first step, the conventional CNN model introduced a channel-space attention mechanism, imparting the ability to analyse the image closely. After that, a feature selection module was incorporated to scale the feature map. This module served a dual purpose; in the downsampling stage, it combines images of similar sizes in the channel dimension. On the other hand, in the upsampling stage, this module figures out combined features and allows their fusion with the output features of upsampling. In the final stage, target size loss is balanced through a smooth L1 loss to IoU loss. This is carried out to diminish its inefficacy in adapting according to target size. Outcomes from this study showcased a reduction in FPS by 123.7 Hz, enhancement in GPU memory by 62 MB, increment in FLOPs by 3.81 times/sec, and increase in the AP by 15.4% when viewed in contrast to the primordial (original) model. The collateral advantage of CenterNet was that real-time performance and robustness were attained while GPU memory stability was maintained throughout the entire operation, making the model practicable.

Kim Bubryur et al. [141] undertook safe and practical experimentation to detect surface cracks in concrete structures, allowing real-time assessment with the help of a combination deep neural network and an autonomous UAV. The study used Fast Region-based CNN (FRCNN) and Residual Network (ResNet), which permitted the real-time and accurate detection of cracks through the ongoing live-video feeds. The study was based on real videos transmitted by the UAV to a computer platform equipped with tools for spotting surface cracks. About 1000 images from a diverse dataset were used to train the FRCNN-ResNet model. The reported precession rate is 93.9% with a 59.7 ms inference time. The model allows for improved safety and cost savings of civil infrastructures made of concrete, including bridges. Sermet and Ishak [144] conducted a crack detection study on bridges, roads, and concrete walls. A combination of vision transformers and CNN was used to diagnose cracks in these three structures automatically. The performance of the combination model was improved through various strategies like transfer learning, optimised hyperparameters, and data augmentation.

A study conducted by Shahin et al. [145] aimed towards the crack detection of concrete bridges across the USA with the help of a combination model consisting of a visual transformer (ViT) having image enhancement detector algorithms. Traditional crack detection techniques frequently prove inadequate due to their substantial dependence on time and resources for implementation. Thus, the proposed model was a solution because combining ViT with diverse image enhancer techniques led to better accuracy when detecting cracks in concrete bridges. The CNN model achieved around 99% accuracy, and the proposed model was per the Industry 4.0 rubric; it also exhibited automatic manual inspection at low cost, allowing accurate and timely crack detection. Negative results can be obtained for normal concrete if extra sophisticated specific tests are applied for crack detection. Therefore, it is important to determine what type of test should be applied under what occurrence and type of concrete. These innovations ensure safety through dependable detection and prompt maintenance while aligning with Industry 4.0 goals by automating manual inspections, lowering costs, and promoting technological integration in public infrastructure management.

Song et al. [146] conducted a study using unmanned aircraft images and a lightweight deep CNN to detect concrete bridge damage to achieve pixel-level crack segmentation. Along with the conventional encoder–decoder unit architecture, an hourglass-shaped depthwise separable convolution structure was used to reduce the model parameters. This was followed by introducing a lightweight channel attention module to enhance the model's fuzzy ability and segmentation accuracy. Local cross-channel interaction could be achieved irrespective of dimensionality reduction, and there was a significant improvement in the segmentation performance of the model because it was based on lightweight and efficient attention modules.

According to Zhang et al. [147], many methods based on square kernel struggle to view and capture crack features efficiently; they also fail to reveal long-range probability, and background noises become a limiting feature because of their restricted suppression ability. All of these elements lead to reduced efficiency of bridge crack detection. To overcome this problem, a multi-stage feature aggregation and structure awareness network (MFSA-NeT) was proposed to detect concrete bridge cracks at the pixel-level. In the coding stage, square and strip convolutions were combined to perceive a linear picture of cracks in the concrete. Square convolution helped gather microscopic-level information. In contrast, strip convolution interacted with local features to maintain the long-range dependent relationship between various crack areas. Strip convolution also achieves suppression of the immediate background around the crack region. Sharpened edges of the concrete bridge crack were achieved using a feature attention fusion block that allowed for fusing features from the encoder and decoder at the same stage. To fully utilise shallow detail features and deep semantic features, the mix-up of features obtained from different stages was conducted to extract fine-grained segmentation outcomes. Shashidhar et al. [151] developed a method for crack detection in concrete structures. The method was based on TensorFlow CNN and image processing tools, and thousands of cracked and non-cracked images obtained from the structure surface dataset were used to develop the model. Training efficiency was enhanced by extracting image features in the pre-processing stage.

4.2. YOLO-Based Bridge Inspection Techniques

Many researchers have focused their work on the YOLO architecture for bridge inspection techniques, which is described in Table 4. The main advantages of YOLO-based solutions are that they are fast, allow near real-time object detection, and achieve high accuracy in several applications. This subsection reviews studies using this architecture.

Table 4. Description of recent studies based on YOLO.

Reference	Objective	Technique	Dataset	Outcome	Features/Limitations
[152]	To accurately and autonomously calculate reinforcing bar cover thickness and diameter.	The extracted thickness range became the input data for a 1D CNN, besides EMI (electromechanical impedance) data	EMI data for 1D CNN training. GPR data for YOLOv3 training.	Accuracy obtained in sand pit experiments was 96.8% for overburden thickness and 90.3% for reinforcement diameter.	Besides CNN, other methods usually used, like ANN, were overlooked. The models were trained and validated on a limited dataset. Pre-processing data from GPR and EMI in all fields is not possible.
[153]	Coarse and fine crack analysis of concrete bridges based on double detection and single segmentation.	Object detection network model (ODNM); YOLOv5; U-Net	A total of 2068 images of 1024 × 1024 pixels with various disturbances, including mud stains, water spots, shadows, and blurriness were used in 8:1:1 ratio of training, testing, and validation.	U-Net model's accuracy was 98.37%.	U-Net is used for semantic segmentation. Detecting cracks that occupy a very small area relative to the overall image remains challenging.
[154]	Detecting fine-grained concrete cracks using pseudo-labelling techniques.	STL-ELM	SDNET2018 [120], METU Campus Buildings dataset [155], 28309 images of 450 × 450 pixels [156].	The proposed method was better in mAP by around 2.62%, and the F1 value improved by 4.40% compared to existing studies.	Efficiency was better than other normally used methods. The proposed approach erroneously identified some samples from the no-crack category as images depicting cracks.
[157]	Automatic and robust crack detection in concrete installations.	YOLOv8 models	A total of 6315 crack images of 450 × 450 pixels with labels derived from a crack segmentation dataset.	The study reports 89.62% precision and 0.88 scores for IoU. The minimum inference time/image was 27 milliseconds, representing at least a 5% improvement.	Three types of YOLOV8 models were compared, with YOLOv8x giving the best results with a precision of 93.13%, recall of 91%, and mAP of 90.13%. These are better results compared to the U-NET and U-NET++ models. Combining inference results with IoU thresholding may not consistently yield the most effective fusion, particularly when overlapping or unclear cracks are present.
[158]	Crack detection using YOLO in concrete bridges.	Different types of YOLO and YOLOR are used for crack detection in concrete bridges.	A total of 7009 images of 3264 × 2448 pixels from concrete bridge defect (CBD) dataset.	The proposed model's efficiency was enhanced, with an accuracy of 97.5% and an mAP improvement of 2.7 %.	Not only concrete cracks but nine different types of bridge damage were identified (including cavity, leakage, and reticular/single crack). The model's testing in real-world circumstances, such as on-site bridge inspections, is not addressed. The model's efficacy in identifying subtle or early-stage defects that are less conspicuous is not addressed.
[159]	Multidamage identification in high-resolution concrete bridge.	YOLOv5 and AWCM	A dataset was created having cracks (4980), spallation (5225), holes (5211), and rebar (5020).	94.2% mAP for all classes was attained; other values were as high as spallation 98.1% and rebar 99.4%.	Several types of concrete bridge damage, including cracks, were successfully identified. Fluctuations in light, shadows, and image resolutions can influence detection precision and accuracy.
[160]	Concrete damage detection in reinforced bridges in Hong Kong.	YOLOv8, with slight modification, a decoupled head with two components, viz. Detection head and classification head.	A total of 3960 images (3320 images of 224 × 224 from BSD dataset and 640 images from Hong Kong bridge crack dataset (HKBCD).	A precision of around 97% and almost 95% recall was obtained.	Superordinate flexibility so that one can grapple with disparate tasks. The model may encounter difficulties detecting minute or faint cracks, especially in intricate backdrops or when cracks are partially concealed.

Table 4. *Cont.*

Reference	Objective	Technique	Dataset	Outcome	Features/Limitations
[161]	Identified cracks in concrete bridges.	YOLOv5-TS with the following output features-mAP@0.5 (0.752), mAP@0.5:0.95 (0.518), and recall (0.794)	ZJU SYG [162].	Four types of mechanical cracks were distinguished viz. horizontal cracks (0°–20°), low-angle cracks (20°–45°), vertical cracks (70°–90°), and high-angle cracks (45°–70°).	Twin benefits were achieved by using transposed convolution–enhanced network capacity that enabled it to self-learn weights and minimise characteristic information loss. Although DCGAN is utilised to enhance the dataset, the initial deficiency of authentic crack images presents difficulties.
[163]	Crack detection in concrete bridges at pixel-level.	A combination of U-Net, Gabor filters, and Convolutional Block Attention Modules.	The authors created a multi-source, annotated crack dataset of 1200 images of 200 × 200 pixels,	Outcomes surpassed Intersection over Union (IoU) of 60.62% and an F1 score of 74.49%.	A generalised investigation takes care of detecting cracks across various domains and backgrounds. The integration of UNet with Gabor filters and CBAM increases the model's complexity.

YOLOv3 was chosen by Li et al. [152] to study scanned images and their reflected signals of bridges, especially reinforcement types. An overall idea of the thickness range of the reinforcement bar was thus estimated. Ma et al. [153] studied double detection and single segmentation preliminary detection of crack images using a Deep Learning-based initial crack detection network. A few rectangular boxes that contained cracks were obtained. Then, in each rectangular box, a Deep Learning-based fine crack detection network was employed to identify and locate the actual detected crack region to extract the accurate location of the crack. The detected cracks were then put through image semantic segmentation to segment the identified cracks. There were two detection stages. In the course detection stage, the complex background was excluded, leading to the identification of regions that contain cracks. The results from this stage were further processed during the fine detection stage, reducing false detection and enhancing detection accuracy. In the segmentation stage, the detected cracks were scrutinised in detail to quantify the crack width. Sohaib et al. [154] pinpointed that generalising infrastructure inspection is equally important despite of the enormous data available on measuring cracks in concrete using deep learning methods; only some models can be used without re-training. So, this study was executed with the help of step transfer learning (STL) and extreme learning machines (ELMs) to create an automated mechanism to figure out surface cracks in concrete infrastructure. From a diverse set of source images, STL can meaningfully generalise abstract features while ELM enables the proposed model to overlook the limitations of the optimisation of conventional ANNs. Hence, the model achieved automatic inspection and provided generalisation ability. Fine-grained crack detection in concrete buildings was conducted by Sohaib et al. [157]. Due to pseudo-labelling, the model can be effectively used on a limited data size. This model allows real-time implementation because of the integration of quantised YOLOv8 models. The integration deployed in this study provides good crack detection performance, mitigates overfitting, and reduces inference time. Three different YOLOv8 models were used, and each model exhibited promising results. During the training phase, YOLOv8x exhibited maximum precision, recall, and mAP values. Three-fourths of the images were used to train the three YOLOv8 models, and the leftover images were deployed as inference data to evaluate each model's performance. The training dataset images were subdivided into three subsets for three models. The incongruous and complex background did not present any bottlenecks when working on the proposed models.

A multi-apparent detection of damage on concrete bridges based on YOLOR was proposed by Sun et al. [158]. A concrete bridge defect (CBD) dataset comprising more than 7000 images was chosen to distinguish as many as nine bridge defects, including cavity, single crack, pockmark, reticular crack, rust expansion, leakage, whitening, spalling, and exposed rebar. Using the CBD dataset, comparison experiments on performance were conducted among YOLOv3, YOLOv4, YOLOR-640, and YOLOR-1280 to finally choose the best model. A model called YOLOR-BDIM was developed, and it was selected after taking care of defects in bridges, choosing suitable anchor boxes, and localising loss function.

Tang et al. [159] conducted a Deep Learning analysis for multi-damage identification in high-resolution concrete bridge component imagery. For efficient and better learning of damage features by the network, the high-resolution images are converted into sub-images using the help of the Auto-adaptive Window Cropping Method (AWCM) proposed in this study. The advantage of such a cropping method is that cropped images justify their label information, and damaged features are protected from destruction during cropping. A balance in the volume of different types of damage had to be maintained to prevent overfitting. This balanced dataset can be applied to train the DL network and prepare a multi-damage identification model. The restoration of sub-images into their actual high-resolution image and prediction boxes of damage can be achieved after identification. The results show that this model performed better than the other three conventional models (direct input of original images, sliding window cropping method, along with random centroid cropping process) tested.

Xiong et al. [160] conducted a study in Hong Kong, one of the most populated cities globally that witnesses jam-packed traffic all year round. This makes automated bridge inspections more desirable. A modified version of YOLOv8 was proposed along with added features of a global attention module and Intersection over Union loss function to accomplish correct determination of cracks and also ameliorate the generalisation ability of the proposed model, which was named YOLOv8-GAM-Wise-IoU. The proposed model was highly economically effective because it maintained a modest size of 93.20M parameters and cut down the cost of training and inference processes. The model exhibited a high success rate in maintaining the safety and integration of reinforced concrete bridges in the Hong Kong environment.

Zhang et al. [161] identified cracks in concrete using YOLOv5-TS (this initial model was deployed in combination with SPPCSPC) to achieve better adaptive image output and extract multiple-size receptive fields. Four types of mechanical cracks (based on crack inclination) were distinguished, viz., horizontal cracks (0°–20°), low-angle cracks (20°–45°), vertical cracks (70°–90°), and high-angle cracks (45°–70°). An applicable and practical model was the end product of the study, which was YOLOv5-TS with the following output features: mAP@0.5 (0.752), mAP@0.5:0.95 (0.518), and recall (0.794). Experiments were executed on the ZJU SYG crack dataset. Twin benefits were achieved using transposed convolution–enhanced network capacity that enabled it to self-learn weights and minimise characteristic information loss. According to Zoubir Hajar et al. [163], cracks on bridge surfaces can severely hamper their safety and serviceability properties. Typically, available manual bridge inspection methods are restricted because of the severe workload of data processing and are also highly dependent on the subjective judgement of the inspecting professionals. This study was based on crack segmentation methods that involved U-Net, Gabor filters, and convolutional block attention modules. Hence, both spatial and frequency domains were focused so that ameliorated crack detection could be obtained and the impact of image disturbances could be reduced. The authors created a multi-source annotated crack dataset to train and evaluate their proposed model. The entire setup was designed to expose the model to different types of crack appearances and complex backgrounds that honed the model's generalisation capacity. A few important results achieved by the model are an IoU of 60.62% and an F1 score of 74.49%, transcending benchmark segmentation networks. The model allows cross-domain feature fusion and multi-source data utilisation in crack segmentation in situations with multiple patterns and diverse backgrounds.

4.3. Other Techniques for Bridge Inspection

This subsection presents another set of studies that have emphasised the use of general techniques in SHM for bridge inspection, and they are summarised in Table 5.

Table 5. Description of recent studies based on other techniques.

Reference	Objective	Technique	Dataset	Outcome	Features/Limitations
[164]	Develop real-time, pixel-level crack detection.	The mask branch ProtoC1 keeps the quality of the instance masks the same as the original branch, reduces parameters and complexity, and speeds up the processing speed of the prototype branch.	The 600 underwater concrete crack images of 704 × 480 pixels include uneven cracks of varying degrees.	Accuracy was achieved at 0.945 at 129 FPS. Reduction in volume; suitable for low-lying devices.	Training cost was minimised, and enhanced robustness was achieved. Model volume can be achieved by replacing the backbone with LCANet, slightly altering the accuracy. Compared to the baseline YOLOv8n-seg model, there is a 3% reduction in detection accuracy.
[24]	Advancements in AI and new technologies for bridge SHM.	Drone technology and 3D printers.	NA	Urged to replace visual inspection with drone-aided technology. Drones can fly at high altitudes and have hi-tech cameras.	Along with several AI tools, other methods of drone technology and 3D printers were also discussed. The performance of SHM systems using AI, drones, and sensors is not deeply analysed in this study.
[165]	Develop an automated bridge crack evaluation method.	Sub-surface bridge damage and delamination were detected.	800 high-resolution (HR) images and 100 low-resolution (LR) images were randomly picked from the DIV2 K dataset for training and validation.	Only actual damage (cracks) was detected. False results were efficiently diminished (accuracy by 49.91% and recall by 13.31%).	Poor bridge condition was held responsible for the false indication. Identifying very fine or propagating cracks remains challenging. Fluctuations in light and surface conditions might influence the precision of crack identification algorithms, resulting in either false positives or negatives.
[166]	Prioritise bridge safety maintenance due to noise and hazy images.	STDC-Net.	The training dataset has 28,800 images, the testing set has 9600, and the validation set has 9600.	The proposed DBR-Net was tested on three datasets, rendering 97.54% accuracy on the authors' self-made dataset.	The combination of STDC-Net creates a new DBR-Net. In the case of real-time, the crack detection rate was as good as 37.0 images/sec. The technique may exhibit diminished efficacy in identifying minute cracks owing to the resolution constraints of the input images. The model may have difficulty differentiating cracks from background noise, resulting in either false positives or missed detections.
[167]	Detect different types of defects in both regular and thermographic images in a timely and cost-effective manner.	VGG 16 model.	NA	MobileNetV2 detected several damage types in thermal images, identifying 79.7% damage.	A study on infrared thermography and the VGG 16 model and its applicability in concrete damage detection; however, other ML tools were overlooked. The chances of false detection were minimal. The study focuses on severely compromised concrete structures, potentially restricting the relevance of the findings to those with milder damage.

Table 5. *Cont.*

Reference	Objective	Technique	Dataset	Outcome	Features/Limitations
[168]	Automatic corrosive environment detection of bridge decks from GPR data.	SSD.	Trained on 10316 B Scan images of 300 × 300 pixels and tested on 2578 images.	SSD was able to figure out 677 bars; accuracy—98%.	With the assistance of this extracted reinforcement information, a contour map could be created displaying bridge deck corrosion. Establishing precise ground truth for model training and validation is difficult.
[169]	Perform damage segmentation by entering varying data sizes.	Pre-trained VGG was used to pre-train U-Net.	The data were collected by manually labelling 200 steel corrosion images and 500 rubber-bearing crack images.	HR images were compressed into the network. In the next step, the HR image was cropped to 224 × 224 pixels, which was also input into the network.	The second method was better for large damage (corrosion), while the first method was successful for large damage (corrosion). Relatively small and specific dataset used for training and evaluation.
[170]	Pixel-level crack detection in concrete.	Median Absolute Deviation (MAD); Median Absolute Deviation (for edges).	This study collected images of concrete cracks between 0.1 and 1.5 mm. An AF-s Nikon 24–70 mm f/2.8 G ED lens and Nikon D810 digital camera were used for imaging.	Performance was determined using probability of detection (POD) curves that displayed 94% success in narrow crack detection and 100% for wider cracks.	Cracks as small as 0.1 mm was also detected. The system used performed well compared to conventional Otsu and Niblack methods. Overestimated the width of the cracks due to selection of higher k-value. Some noise is still detected as cracks, which may lead to false positives due to the detection of cracks up to 1 mm.
[171]	Crack detection in concrete bridges using drones, Deep Learning geofencing.	Cracks were segmented and identified as per their georeferenced coordinates.	A total of 15298 images were extracted from the 11 existing public datasets.	The spawned framework gave a precision of 77.5% and 76.5% recall.	The practical application of the proposed model on a real bridge delivered accurate and relevant outcomes. Environmental variables, including light fluctuations, shadows, and surface reflections, can affect the accuracy of crack detection during drone operations.
[172]	Concrete crack detection on structures, including bridges.	Varied image (taken by Nikon camera and iPhone 7 Plus) processing methods were used.	A subset of the public dataset SDNET2018 [120], along with the experimental laboratory sample.	The result for crack detection in terms of the F1 score was 98.87% in the case of bridges.	Cost-effective and user-friendly model adept in crack exploration on discriminable concrete structures. No large training data were sought. Furthermore, images were captured using iPhone. Poor image quality can lead to inaccurate detection results.
[173]	Crack detection in concrete bridges at pixel-level with the help of drones and Deep Learning.	Computer vision and Deep Learning.	A self-prepared dataset of 2500 images of 600 × 400 and 1200 × 800 pixels.	The loss function of the presented model confirmed a smooth decline. Real-time efficient crack detection was justified by 35.04 FPS detection efficiency.	The model performed well even in diffused/dim light and a complex background. The research fails to address the issue of perspective distortion that may arise when UAV cameras are not perpendicular to the inspected surface.
[174]	Pixel-level concrete crack identification with quantification.	ResNet-50.	A large-scale concrete crack image dataset consists of 1242 images of 227 × 227 pixels.	Segmentation performance was better than regular models, giving an 83.07% IoU.	Pixel-level quantitative analysis of the exigent geometric parameters, including crack area, crack length, crack mean width, and crack max-width, was applied. The current dataset is self-made and relatively small. The existing dataset comprises pictures taken using standard cameras, constrained by ambient factors like lighting. These cameras are limited to capturing two-dimensional images and lack the capability to convey further spatial information such as distance or depth.

Wu et al. [164] proposed a lightweight, real-time, pixel-level crack detection method based on an improved instance segmentation model. The new prototype mask branch ProtoC1 keeps the instance mask quality identical to the original branch, significantly reduces the parameters and complexity in the prototype mask branch, and speeds up the processing speed of the prototype branch. The reduction in volume, with minimal computational prerequisites makes it practically suitable for low-lying devices. Training cost was minimised, and enhanced robustness was achieved by applying a cross-domain transfer learning strategy. Zinno et al. [24] conducted a unique study deploying AI tools with the most trending techniques of drone technology and 3D printers to carry out SHM for bridges. They emphasised replacing visual inspection with added technology because they could study the condition of bridges from all possible angles and figure out specific damage caused by their high flight altitude. They can fly in different weather conditions, are equipped with high-tech cameras, and can take pictures continuously while monitoring bridges, which can later be processed by ML, DL, and the Internet of Things.

Jang et al. [165] detected bridge cracks using an ML system based on deep super-resolution segmentation. Accurate crack identification was achieved at 100μm by combining images of two forms. Sub-surface bridge damage and delamination were detected with less input effort and costs. Poor bridge condition was held responsible for such a false indication. Along with a unique ML method, infrared images were also combined to obtain good-quality results. Li et al. [166] garnered a fruitful and effective combination of a Short-Term Dense Concatenate Network (STDC-Net) and a refinement network developed to explore and study cracks using bridge surface crack segmentation. It improved the crack detection rate and fully harnessed information obtained from binary cross-entropy loss and dice loss. The entire setup was used to observe and unravel segmentation results by refining the segmentation results provided by the offset map based on the training and test stages. The STDC-Net and a refinement network were combined to create a new dense boundary refinement network (DBR-Net). In the case of real-time, the crack detection rate was as good as 37.0 images/s.

The work of Pozzer et al. [167] considered that damage in dark or internal places often goes unnoticed by conventional images. This study tried to overcome this using thermal (infrared) images and ML models. These images were fed to a VGG 16 model and exhibited enhanced righteousness as chances of false detections were minimal. The results from two concrete bridge decks proved that many varied damage types could be detected by MobileNetV2 in thermal images, identifying 79.7% of damage, including patches, delamination, cracks, and spalling on concrete. Zhang et al. [168] conducted extensive and detailed research on the most recent available trends and limitations, where DL algorithms can be utilised for SHM in the case of bridges. The study showed that vibration-based and vision-based processes can be used for damage detection/diagnosis. With the assistance of this extracted reinforcement information, a contour map displaying bridge deck corrosion could be created.

Shi et al. [169] directed their study to explore the application of a U-Net to find bridge corrosion and cracks. This study used a pre-trained VGG architecture to pre-train the U-Net, using compressed high-resolution input images. Two image input methods were covered to obtain the segmentation results. One approach is Squashing Segmentation, which inputs compressed high-resolution images straight into the VGG-UNet model, whereas Cropping Segmentation uses cropped images sized 224 × 224 as input. The second method was better for large damage (corrosion). In contrast, the first method was successful for large damage (like corrosion). Avendano et al. [170] developed a bridge crack detection model that outperformed the traditional Otsu and Niblack methods in achieving better accuracy, precision, and F1 score values. This model was developed on Median Absolute Deviation in images, and the pre-processing steps were highly restricted. Crack edges were determined using Laplace as the detection method, while width was obtained for each centreline point. The structure's performance was calculated using the probability of detection curves that revealed actual crack size, and the model was efficient in detecting cracks of 0.1 mm narrowness with 94% probability. In contrast, cracks of larger width were 100% detected.

Hu et al. [171] proposed the combination of drones and DL methods for automatic crack detection of bridge decks. A three-tier framework that embodied orthomosaic map generation, crack detection oriented on DL, and georeferencing and visualisation in a geographic information system (GIS) platform was proposed. Georeferencing coordinates were vital in segmenting, identifying, and extracting lateral impregnated cracks into a GIS platform. This step enabled magnified visualisation and spatial crack analysis. The model was applied to a real bridge, and the outcomes revealed that it can detect and analyse cracks accurately and efficiently. Also, this framework is adaptable and can be applied to diverse infrastructure types.

To counterbalance the obstacles of traditional image processing that conduct crack detection based on pixels, [68] used more practical units of measurement (millimetres) to measure concrete cracks in bridges. The investigation followed three steps that harnessed DL and image processing methods for conducting crack classification, segmentation, and its measurement. Custom CNN and U-Net were used for crack classification and segmentation in the first two stages. The final module used a laser calibration method that facilitated the measurement of a crack in millimetres. The main absolute error for crack was described to be 0.16 mm. This showed that combining Deep Learning with laser calibration is a promising solution. Also, because the measurement is carried out in millimetre units, it provides details of structural damage better than the conventional pixel-based methods, making this type of experimentation more practical in the field.

Shalaby et al. [172] conducted a crack detection study on bridge decks, concrete cubes, and walls. The proposed algorithm was randomly tested on 825 images extracted from two random datasets, viz., the authors themselves obtained 225 concrete cube samples, and 600 images were obtained from the open dataset SDNET2018 [120]. The dataset had images with crack sizes ranging between 0.06 mm (narrow) and 25 mm (wide). A 16 MP Nikon camera was used to take these images from a distance of 500 mm without zoom. The 225 images taken by the authors of concrete cubes were captured with an iPhone 7 Plus, consisting of dual 12 MP wide-angle and telephoto cameras.

Song et al. [173] investigated the efficacy of combining DL and UAV photography in the pixel-level crack detection of concrete bridges. The model used a ResNet-18 and the pyramid scene praising network (PSPNet). The study was aware that cracks on the surface of the bridge can have a variety of shapes and backgrounds; therefore, a spatial position self-attention module was introduced in PSPNet to improve its detection accuracy. The model performed well in most common UAV-detected problems in scenarios of improper light, background roughness, different crack types, and heterogeneous background conditions. Yuan et al. [174] carried out an automatic pixel-level crack detection study using deep CNN and, in parallel, also executed quantification of crack morphology at the pixel-level. Various crack parameters like crack area, crack length, crack mean width, and crack max width at the pixel-level were studied using the applied model. Images were carefully labelled at the pixel-level, which was used to train the model. This value illustrates that crack quantification results were closer to reality and that this method has enhanced segmentation performance compared to other contemporary models. RestNet-50 was used as a backbone to extract features from images. The model had a feature pyramid network with dense blocks that permitted the fusion of shallow and deep features, also permitting feature reuse. On the other hand, the channel and position attention modules helped strengthen dependency between features. The entire setup enabled the model to analyse vital geometric parameters at a pixel-level quantitatively.

5. Discussion

AI-driven SHM has significantly increased bridge inspection efficiency, precision, and automation, alleviating many manual restrictions. Despite these advances, several challenges and research gaps remain to improve the robustness and practicality of AI-based structural health monitoring methods.

The identification, categorisation, and quantification of concrete bridge cracks and other structural flaws have significantly improved because of AI-driven methods like DL and CNNs. UAVs and AI-driven image processing have permitted broad and rapid inspections, reducing manual work and traffic disruptions [56]. In addition, advanced image processing methods together with YOLO [153,158], Faster R-CNN [133,139,141,142], and U-Net [142,153,157,169] can detect cracks and damage with a high precision and accuracy of 95%. AI-driven predictive maintenance allows authorities to eliminate likely structural flaws before they escalate, enhancing bridge safety and longevity.

AI-driven SHM techniques remain limited in practice despite these advancements. Training dataset quality and diversity are major issues. AI models need large, high-quality annotated datasets to generalise across climates, structural materials, and bridge types. Many datasets that train these models lack diversity and fail to simulate real-world unpredictability, affecting model resilience and adaptability. Image quality, including illumination, weather, occlusions, and structural details, greatly impacts defect detection in AI models [175]. A major limitation is false positives and negatives. AI models are accurate but can make mistakes, especially when distinguishing cracks from surface defects or shadows [176]. Misclassification might lead to unnecessary maintenance or undetected significant damages that pose a safety risk.

Real-time SHM techniques also face processing challenges. Advanced Deep Learning models require large computational resources for training and inference, making them difficult to execute on edge devices or real-time processing systems. The lack of explainability and interpretability in AI models, especially Deep Learning-based ones, limits their use in SHM. Engineers and decision-makers need explicit and interpretable AI models to understand fault discovery and evaluation.

AI-driven SHM has many research gaps. First, standardised benchmark datasets with different bridge structures, weather conditions, and structural defects are needed. Current datasets are often regional or narrow, making constructing AI models that can generalise across numerous geographies and bridge designs challenging. Multimodal data fusion is a new field with little research. Failure identification may be improved by combining infrared thermography, LiDAR, GPR, and acoustic emission sensors with Artificial Intelligence models [177]. Together, sensor and optical data can better assess bridge health. AI model practicality is a major research need. Most AI models are developed on curated datasets and may perform poorly in complex field scenarios. Domain adaptation and transfer learning can increase AI models' flexibility to innovative bridge architectures without costly retraining.

Numerous aspects will shape AI-driven SHM. Developing self-supervised and unsupervised learning methods is promising. These methods allow models to learn from unannotated data, making AI-driven SHM more scalable and cost-effective. Another trend is using Explainable AI (XAI) to create DL models that are more interpretable. Transparency in AI decision-making helps engineers and stakeholders understand fault evaluations and trust AI-driven structural health monitoring solutions. Additionally, edge AI- and IoT-based SHM systems are growing [56]. AI models on low-power edge devices provide rapid defect identification and monitoring without centralised computer infrastructure, which can significantly reduce latency and increase bridge inspection system responsiveness. SHM, with digital twin technology, has a bright future. Digital twins of bridge structures are updated with real-time sensor data for predictive maintenance and structural evaluations with unmatched precision [178].

Large-scale bridges are essential for social and economic development. If they are not adequately monitored and maintained, they can be subject to precarious breakdowns and catastrophes. The causes of such failures can be complex, including safety issues, material degradation, corrosion, structural damage, cracks on the surface and in the sub-surface, performance ignominy, functional failure, and several other damages or diseases induced by load, erosion, and natural disasters. All these listed bottlenecks, damages, and faults affect bridges' regular and normal functioning and reduce the safety parameters that can pose paramount security risks to the bridge itself and the surrounding environment. This makes checking the bridge's structural health mandatory in real-time. Visual inspection has several restrictions, which are time- and skill-dependent. Therefore, conducting SHM with the help of technology is a promising option that can help assess civil infrastructures. SHM primarily depends on three basic steps. The initial step is the close monitoring of structures through the information collected by the sensors, which is followed by extracting the damaged features and finally analysing the damaged features to evaluate the actual condition of the structures. This is why many new bridges are installed with real-time SHM systems. A large amount of data related to the management and maintenance of bridges accumulate, which is otherwise difficult to manage. Techniques like data processing, computing algorithms, and Machine Learning tools used for data analysis have smoothed the data analysis path and incorporated processes like data pre-processing, data fusion, pattern recognition, and data visualisation.

6. Conclusions and Future Scope

This study has reviewed the AI-driven strategies for SHM of concrete bridges due to their necessity in today's world. A narrative review was conducted, and several relevant studies were explored. It was observed that AI-based SHM methodologies, such as CNNs and Faster R-CNN integrated with UAVs and LiDAR systems, have demonstrated superior accuracy in identifying critical structural defects. However, AI-driven SHM still faces significant challenges, including false positive detections, data quality and environmental variations, high-dimensional data complexity, and limited generalisability of models. These challenges underline the necessity for further research and the development of advanced AI methods. This review is crucial because it identifies explicit gaps in conventional SHM and highlights how AI-driven methodologies significantly enhance inspection accuracy, reliability, and decision-making, thus improving overall structural integrity and public safety. Such AI-driven solutions are necessary for the proactive and precise assessment of concrete bridges, leading to improved reliability and extended service life of bridge infrastructures worldwide. Data analysis has become an important part of SHM in bridge engineering and is expected to remain a fundamental part of infrastructure maintenance in the future. AI and ML are transforming SHM, so future research should focus on the following:

- Integrating multimodal data sources like LiDAR, infrared thermography, and ground penetrating radar into AI-driven bridge inspection models. Integrating these data sources improves fault detection, damage categorisation, and bridge integrity evaluation. For resilient, real-time monitoring solutions, self-learning models that adapt to changing structural conditions without manual retraining are essential.
- Examine how temperature, humidity, and air pollutants affect AI-driven fault detection systems to improve model generalisation across many climates.

- Autonomous UAV-based bridge inspection systems can be used with real-time AI analytics. UAVs could automate bridge inspections. However, flight stability, data processing latency, and problem localisation remain issues. Future advances should concentrate on edge computing with UAV-based SHM systems to enable onboard AI inference, reduce cloud-based post-processing, and improve real-time decision-making.
- Adding XAI methods to SHM models to increase transparency and regulatory acceptance of defect assessment. Standardised AI frameworks and benchmarking datasets are needed to scale and replicate AI-driven structural health monitoring solutions across infrastructure systems.

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Abbreviation

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
ASPP	Atrous Spatial Pyramid Pooling
AWCM	Auto-adaptive Window Cropping Method
BIM	Building information modelling
BN	Batch Normalisation
CBD	Concrete Bridge Defect
CNN	Convolutional neural network
COCO	Common Objects in COntext
DBRNet	Dense boundary refinement network
DL	Deep Learning
ELMs	Extreme learning machines
FCNs	Fully Convolutional Networks
FRCNN	Fast Region-based CNN
FPS	Frames Per Second
GA	Genetic Algorithm
GIS	Geographic information system
GLCM	Grey-Level Co-occurrence Matrix
GPR	Ground penetrating radar
ICA	Imperial Competitive Algorithm
IoU	Intersection over Union
InSAR	Interferometric Synthetic Aperture Radar
LiDAR	Light detection and ranging
MAE	Mean Absolute Error
mAP	Mean average precision
ML	Machine Learning
NDT	Non-Destructive Testing

PCA	Pricipal Component Analysis
PSPNet	Pyramid scene praising Nntwork
ResNet	Residual Network
RF	Random Forest
RPN	Region Proposal Network
SHM	Structural health monitoring
SHAP	SHapley Additive exPlanations
SPP	Spatial Pyramid Pooling
SSD	Single Shot-multibox Detector
STDCNet	Short-Term Dense Concatenate Network
STL	Step transfer learning
SVM	Support Vector Machine
TL	Transfer learning
UAV	Unmanned Aerial Vehicle
VGG	Visual Geometry Group
ViT	Visual transformer
XAI	Explainable AI
YOLO	You Only Look Once

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