





Digital Image Processing and Advanced Artificial Intelligence Techniques in the Identification of Pathological Manifestations on the Facades of Historic Buildings: A Systematic Literature Review

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ABSTRACT

Introduction Historic building façades are continuously exposed to physical and chemical degradation processes, leading to pathological manifestations that may compromise structural safety and cultural value. Due to heritage protection constraints, diagnostic methods must be accurate, non-destructive, and compatible with conservation principles. In this context, digital technologies have emerged as promising tools for the identification and analysis of building pathologies. This paper presents a systematic literature review aimed at identifying and analyzing scientific contributions related to the use of digital image processing, diagnostic engineering, and Industry 4.0 technologies in the identification of pathological manifestations in historic building façades. The review followed established systematic review protocols, including structured searches in national and international databases, predefined inclusion and exclusion criteria, and qualitative and quantitative analyses of the selected studies. The findings reveal a significant growth in research focused on the digitalization of built heritage, highlighting techniques such as photogrammetry, infrared thermography, 3D laser scanning, unmanned aerial vehicles, and Heritage Building Information Modeling (HBIM). However, the results also indicate a relevant research gap concerning the direct application of advanced machine learning and semantic segmentation techniques for the automated diagnosis of pathological manifestations in historic façades. It is concluded that the integration of traditional diagnostic approaches with advanced digital tools represents a promising research avenue, with strong potential to enhance conservation, documentation, and restoration decision-making processes for historic buildings.

RESUMO

As fachadas de edificações históricas estão constantemente sujeitas a processos de degradação física e química, resultando em diferentes manifestações patológicas que podem comprometer sua integridade, segurança e valor cultural. Diante das restrições impostas pelo tombamento histórico, torna-se fundamental adotar métodos de diagnóstico precisos, não destrutivos e compatíveis com a preservação do patrimônio. Nesse contexto, o uso de tecnologias digitais tem se destacado como uma alternativa promissora para o mapeamento e a análise dessas patologias. Este artigo apresenta uma revisão sistemática da literatura com o objetivo de identificar e analisar as contribuições científicas relacionadas à aplicação do processamento digital de imagens, da engenharia diagnóstica e de tecnologias associadas à Indústria 4.0 na identificação de manifestações patológicas em fachadas de prédios históricos. A metodologia adotada seguiu protocolos consolidados de revisão sistemática, com buscas em bases nacionais e internacionais, aplicação de critérios de inclusão e exclusão e análise qualitativa e quantitativa dos estudos selecionados. Os resultados indicam um crescimento expressivo das pesquisas voltadas à digitalização do patrimônio edificado, com destaque para técnicas como fotogrametria, termografia infravermelha, escaneamento a laser 3D, uso de drones e modelagem HBIM. Entretanto, observa-se uma lacuna relevante na integração dessas tecnologias com técnicas avançadas de aprendizado de máquina e segmentação semântica aplicadas diretamente ao diagnóstico automatizado de fachadas históricas. Conclui-se que a convergência entre métodos tradicionais de diagnóstico e ferramentas digitais avançadas representa um campo promissor de pesquisa, com potencial significativo para aprimorar os processos de preservação e restauração do patrimônio construído.

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Introduction

The preservation of built historical heritage demands technical approaches that reconcile conservation, safety, and respect for the cultural values associated with listed buildings. In this context, historical listing establishes guidelines for restoration processes, which must be grounded in thorough analyses of building pathologies and appropriate diagnostic methods (IPHAN, 2015; Souza & Ripper, 1998). Diagnostic engineering, combined with the development of damage maps, stands out as an essential tool for identifying and understanding degradation mechanisms in historic buildings, supporting more effective interventions that are compatible with the original structure (Helene, 1981; Tinoco, 2009). At the same time, the advancement of Industry 4.0 has enabled the incorporation of digital technologies into the inspection and monitoring process, increasing the precision of analyses and contributing to the intelligent management of the built heritage (Silva Junior et al., 2020; Volk et al., 2014).

Based on preliminary searches in international databases and editorial repositories (with emphasis on journals in engineering, conservation, and the built environment), a recent growth in studies connecting pathology diagnosis in historic buildings to digital technologies can be observed. The literature is divided into two main approaches: the first evaluates conservation through non-destructive testing (NDT), with emphasis on applicability and limitations according to material and damage type (Bocacci et al., 2024; Hussain & Akhtar, 2017). The second approach concerns the digitization of heritage through photogrammetry and laser scanning, focusing on Heritage Building Information Modeling (HBIM), documentation, lifecycle management, and decision support (Ma et al., 2025; Penjor et al., 2024). These findings indicate that "historical listing," "restoration process," "diagnostic engineering," and "damage map" have been progressively articulated with technologies associated with Industry 4.0, particularly to increase the precision, traceability, and repeatability of assessments (Deng et al., 2021; Hu et al., 2022).

Despite this progress, scientific output remains fragmented by focus area (pathology/diagnosis, documentation, modeling, monitoring) and by disciplinary fields, which makes the conduct of a systematic literature review especially relevant. Systematic reviews help reduce selection bias, make inclusion/exclusion criteria explicit, and synthesize comparable evidence, allowing for the identification of methodological gaps and future directions with greater robustness than narrative reviews (Deng et al., 2021; Hu et al., 2022). On this specific topic, the need is even more evident because intervention decisions regarding listed buildings require technical-documentary support and heritage compatibility, and the convergence between "damage map," "diagnostic engineering," and "digitization/monitoring" is not always addressed in an integrated manner in publications (Cui & Wu, 2025; Penjor et al., 2024). Thus, an SLR (Systematic Literature Review) is strategic for organizing the state of the art, mapping

recurring methods (e.g., HBIM, NDT, photogrammetry/TLS, sensors), and comparing how each approach supports diagnosis and restoration planning.

Regarding existing reviews, the literature presents: (i) reviews on NDT applied to the assessment of historic structures and monuments, systematizing techniques and indicating benefits and limitations according to structure type and expected defects (Boccacci et al., 2024; Hussain & Akhtar, 2017); (ii) reviews and frameworks on HBIM and heritage digitization, discussing acquisition workflows (laser scanning/photogrammetry), modeling, and interoperability and adoption challenges (Cui & Wu, 2025; Penjor et al., 2024); and (iii) reviews on digital twins and Industry 4.0 enablers in the built environment, with broad syntheses on IoT (Internet of Things), data integration, and lifecycle management (Baghdadi, 2025; Deng et al., 2021; Hu et al., 2022). Even so, these reviews tend to address topics in a sectoral manner (focused either on HBIM, or on NDT, or on digital twins), without consolidating, within a single protocol, the relationship between listing, restoration processes, pathology/diagnostic engineering, damage maps, and Industry 4.0 technologies. Furthermore, the volume of recent publications on "smart heritage," automation, and AI applied to heritage has been growing, which reinforces the relevance of a new and more current review, capable of updating evidence, harmonizing terminologies, and proposing an integrative framework to support technical decisions in historic buildings (Baghdadi, 2025; Cui & Wu, 2025; Ma et al., 2025). Given this, the objective of this review was to identify, systematize, and critically analyze the literature regarding the mapping of pathological manifestations on historic facades with an emphasis on digital technologies.

Theoretical Framework

Technologies Used in Damage Mapping of Facades

The technologies used in facade damage mapping have evolved significantly, providing greater precision, speed, and safety in the pathological diagnosis of buildings. Among the main tools employed, digital photogrammetry, the use of drones (UAVs), infrared thermography, and non-destructive testing stand out, assisting both in the identification of visible manifestations (cracks, stains, detachments) and in the detection of anomalies not visible to the naked eye, such as moisture and internal delamination (ABNT, 2020; Bertolini, 2010; Maldague, 2001). Drones allow the inspection of hard-to-reach areas with greater safety, while also generating high-resolution records for subsequent processing and mapping in specific software (Melo & Melo, 2023). Infrared thermography, in turn, is widely applied to locate thermal variations associated with infiltrations, adhesion failures, and coating detachments, contributing to more complete and reliable damage maps (Maldague, 2001).

Furthermore, BIM (Building Information Modeling) has been incorporated as a tool for organizing, tracking, and monitoring pathologies over time, integrating inspection data,

photographs, test results, and maintenance history into the building's digital model, which improves decision-making and intervention planning (ABNT, 2020; Sacks et al., 2018). Complementary techniques, such as systematized visual inspections and non-destructive testing (e.g., ultrasound and rebound hammer testing), contribute to increasing diagnostic reliability and guiding repair and prevention strategies, aligned with building inspection guidelines and the construction pathology literature (ABNT, 2020; Bertolini, 2010).

Chart 1 presents the main technologies used in the facade damage mapping process.

Table 1.

Main technologies used in facade mapping

Softwares	Function
3D laser scanning (TLS)	This technique is considered one of the best solutions for the 3D digitization of cultural heritage. With TLS, it is possible to detect certain defects such as surface delamination, cracks, displacements, and deflections in walls. This technology also allows defects to be measured using information acquired in a CAD (Computer Aided Design) system (Alencastro et al., 2019)..
Infrared thermography (IRT)	Infrared thermography (IRT) is a non-destructive technique that has been applied in building inspection as an important diagnostic tool. The principle is based on measuring the distribution of radiant thermal energy emitted by an object (Birch, 2006). This technology has been used to detect surface defects such as moisture, air leakage in walls, detachment, and cracks in certain types of coating (Antunes, 2010). Furthermore, it presents some limitations related to the significant cost of high-resolution infrared cameras.
Photogrammetry and Remote Sensing (PRS)	Photogrammetry and remote sensing (PRS) is a technique capable of determining the 3D geometry of physical objects through the analysis and measurement of 2D photographs. It is divided into aerial and terrestrial photogrammetry (BAUER et al., 2006).
Digital image processing (DIP)	Digital image processing is a technique for extracting information from images with various applications in engineering and architecture. This technique requires the use of software to perform image processing on digital images. There are two main areas of application: a low level, which involves the enhancement of pictorial information for human interpretation, and a high level, for processing scene data for autonomous machine perception, giving the system the ability to interpret and understand an image (Bordalo et al., 2010).
Drones (UAV)	Advances in programming and autopilot systems, along with the miniaturization of components such as gyroscopes and GPS units, have made machines smaller, cheaper, and easier to fly. Currently, drones, or more formally known as Unmanned Aerial Vehicles (UAVs), have gained great popularity, and the technology has reached a level of maturity that makes it more user-friendly and affordable (Bordalo et al., 2010).

Machine learning and semantic segmentation

The construction industry has many separate automated systems ranging from the design process to logistics and planning, but these information systems are often incompatible with one another, which is a limitation for the creation of effective machine learning and artificial intelligence systems (Miyamoto, 2004).

However, the digital transformation of processes in construction is expressed as weak compared to other industries. The potential of artificial intelligence-based solutions can only be realized through the integration of all heterogeneous data sources (Braga; Amorim, 2023).

Machine Learning (ML) is an area of Artificial Intelligence (AI) that uses statistical and computational techniques to enable systems to learn from data without being explicitly programmed to do so. According to Cerri and Carvalho (2017), the purpose of the Machine Learning process is to obtain knowledge from data, aiming at the construction of models that allow the prediction or classification of new data.

Artificial Intelligence is a branch of computing dedicated to creating algorithms and systems capable of performing tasks that were previously only possible for human beings, such as voice recognition, computer vision, and decision-making (Gomes, 2010; Ludermir, 2021).

The main areas of AI application in civil construction will be project management, risk prediction, and data analysis for decision-making. It should also be noted the importance of considering the social and economic impacts of AI application in civil construction, such as the need for workers to adapt to new technologies and the possibility of increased social inequality resulting from the replacement of workers by machines (Gomes, 2010; Ludermir, 2021; Silva & Mairink, 2019; Teixeira et al., 2020).

Artificial neural networks are a set of algorithms and techniques based on the functioning of the human brain to perform complex tasks. These networks are formed by interconnected artificial neurons that process input information and generate an output. Neural networks have been widely used in various fields, such as medicine, engineering, robotics, and artificial intelligence, and have been the subject of study by many researchers (Fleck et al., 2016; Rauber, 2005; Vargas et al., 2016; Waziri et al., 2017).

Convolutional neural networks are a special type of neural network that has achieved success in computer vision tasks, such as image recognition, object detection, and semantic image segmentation. They are composed of convolutional layers, which apply a convolution between the input and a set of learned filters, pooling layers, which reduce the dimensionality of the data and increase the robustness of the network, and fully connected layers, which perform the final classification (Ferreira, 2017; Juraszek et al., 2014; Vargas et al., 2016).

Materials and Methods

Design and protocol of the review

A Systematic Literature Review (SLR) was conducted with a focus on identifying knowledge gaps at the intersection of built heritage, diagnosis/restoration, and semantic segmentation methods, covering the period from November 2017 to December 2025. The review was conducted according to internationally recognized best practices for systematic review, with prior registration of the scope, search strategy, eligibility criteria, and extraction/synthesis plan (Kitchenham & Charters, 2007; Page et al., 2021). The reporting follows, where applicable, the PRISMA 2020 recommendations to increase transparency and reproducibility (Booth et al., 2016; Page et al., 2021).

Thematic scope and research questions

The review was structured to: (i) map the state of the art regarding the treatment of historic built heritage in diagnosis and restoration processes; (ii) identify semantic segmentation approaches and techniques with potential application in historic buildings; and (iii) highlight knowledge gaps at these thematic intersections (Gough et al., 2012; Tranfield et al., 2003).

Information sources and databases

To maximize comprehensiveness and disciplinary coverage, the following databases and portals were consulted: CAPES Journals, SciELO Brasil, Google Scholar, Scopus, and Web of Science. The selection combines regional and open-access databases (e.g., SciELO) with highly curated international databases (Scopus and Web of Science), mitigating coverage biases (Falagas et al., 2008; Mongeon & Paul-Hus, 2015). Furthermore, a complementary bibliometric step was carried out on the Dimensions platform for the quantification of output, citations, and trends (Hook et al., 2018; Snyder, 2019).

Support and organization tool

The specific review on semantic segmentation was structured with the support of the START (State of the Art Through Systematic Review) software, used to standardize the search chain, screening, and organization of records (Kitchenham & Charters, 2007). The tool's decisions were audited through search records and screening logs, in accordance with best practices (Booth et al., 2016).

Search strategy

Two families of descriptors were employed:

1. For the heritage/diagnosis/restoration axis: "Historical listing," "Restoration process," "Construction pathology," "Diagnostic engineering in historic buildings," "Damage map," "Industry 4.0."

2. For the computer vision axis: "Semantic segmentation" and "Semantic segmentation in civil construction."

Initially, searches were executed without filters, respecting the default configuration of each database (Falagas et al., 2008). Subsequently, a two-level screening was applied: (i) title and (ii) abstract (Page et al., 2021). To enable comparability across databases and reduce algorithmic ordering bias, the quantification considered only the first two pages of results in each database for the main queries — a pragmatic and explicitly stated cutoff strategy (Booth et al., 2016; Haddaway et al., 2015).

Transparency note: although the two-page cutoff optimizes feasibility, it is acknowledged that such a decision may underestimate relevant records positioned beyond this limit, especially in engines with relevance/citation-based ranking (Haddaway et al., 2015). This potential bias is acknowledged in the study's Limitations.

Eligibility criteria and selection process

Inclusion and exclusion criteria were defined prior to the start of screening, encompassing: thematic adherence to the scope, type of academic document (prioritizing articles and reviews), text availability, and quality/relevance inferred from title and abstract. Duplicate records across databases were identified and removed before eligibility assessment (Booth et al., 2016; Page et al., 2021).

The eligibility flow (identification → title screening → abstract screening → full reading when necessary) is summarized in Figure 1, in a diagram compatible with PRISMA (Page et al., 2021).

Data extraction, organization, and synthesis.

From the eligible studies, metadata and substantive variables were extracted: authors, year, journal, indexing database, objectives, methods, metrics/indicators, contributions, gaps, and trends. Organization and version control were carried out using StART and supporting spreadsheets. The synthesis combined:

- Thematic qualitative analysis to identify conceptual axes and gaps (Booth et al., 2016; Gough et al., 2012).
- Quantitative/bibliometric analysis (annual number of publications, citations, temporal trends, most influential works and journals) conducted in Dimensions, aiming to map the dynamics and densities of the field (Hook et al., 2018; Snyder, 2019).

This quali-quantitative approach (mixed methods) allowed for the integration of interpretive depth and empirical traction through indicators, increasing the validity and robustness of inferences (Creswell & Clark, 2017; Tashakkori & Teddlie, 2015).

Study classification

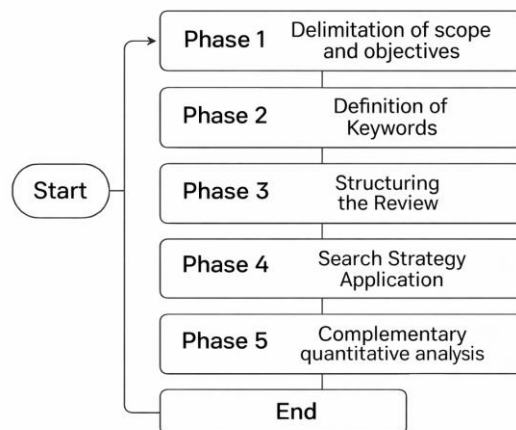
In terms of purpose, this is exploratory research, as it aims to map the state of the art and identify gaps related to the investigated topics (Gil, 2019; Tranfield et al., 2003). Regarding procedures, it is bibliographic research, supported by scientific articles indexed in academic databases, with no collection of primary data (Booth et al., 2016; Marconi & Lakatos, 2017). Regarding nature, it is basic research, aimed at expanding scientific knowledge (Gil, 2019; Gough et al., 2012).

Quality control and biases

The following practices were observed to reduce biases: (i) use of multiple databases with complementary profiles; (ii) explicit recording of keywords and filters; (iii) reporting of the selection flow (Figure 1). As limitations, the following are acknowledged: (a) the cutoff at the first two pages of results, which may exclude relevant studies; (b) possible coverage biases across databases (Haddaway et al., 2015; Mongeon & Paul-Hus, 2015).

Figure 1.

Flowchart



As observed in the flowchart (Figure 1), the operational steps were divided into:

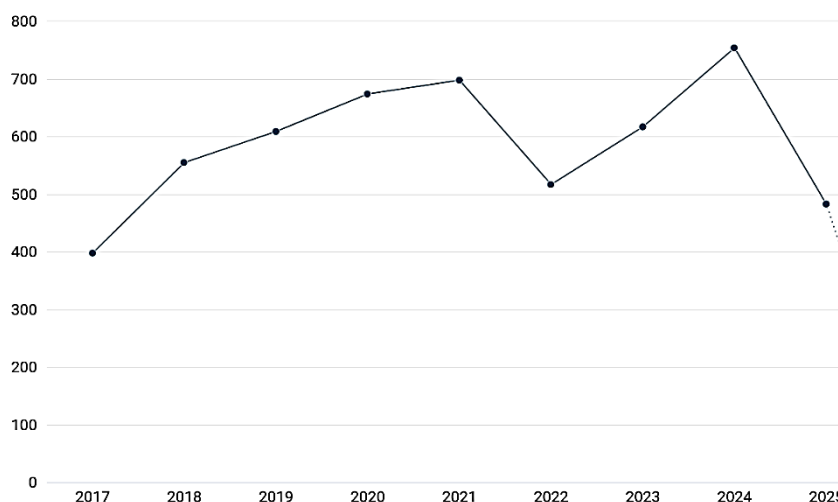
1. Phase 1 – Temporal delimitation and objective: SLR conducted between Nov/2017 and Jun/2025, focusing on knowledge gaps in the subject matter (Tranfield et al., 2003).
2. Phase 2 – Keywords: Definition of descriptors: "Historical listing," "Restoration process," "Construction pathology," "Diagnostic engineering in historic buildings," "Damage map," "Industry 4.0," "Semantic segmentation," and "Semantic segmentation in civil construction."
3. Phase 3 – Structuring (semantic segmentation): Use of StART to standardize the search, screening, and organization process (Kitchenham & Charters, 2007).
4. Phase 4 – Databases: CAPES Journals, SciELO Brasil, Google Scholar, Scopus, and Web of Science (Falagas et al., 2008; Mongeon & Paul-Hus, 2015). Search and filters: Search without filters in the first instance; quantification restricted to the first two pages of results; filtering by title and abstract in sequence (Haddaway et al., 2015; Page et al., 2021).

6. Phase 5 – Complementary quantitative analysis: Dimensions for output metrics, citations, and temporal trends (Hook et al., 2018; Snyder, 2019).

Results and discussion

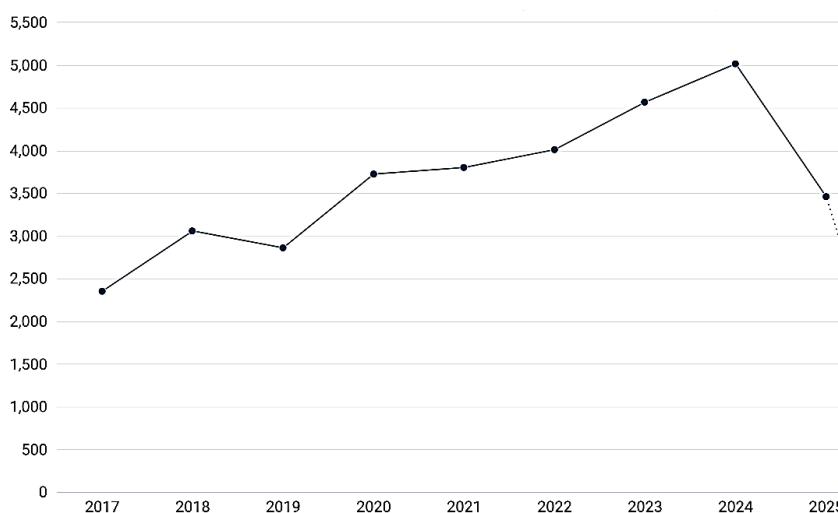
The presentation of results begins with a display of how the topics addressed here appear quantitatively in annual publications since 2017. Figures 1 to 7 allow the visualization of the number of publications for each topic. In Figure 2, it is possible to observe the evolution of publication counts on the topic of "Historical Listing."

Figure 2.
Time series of publication quantities on the topic of historical preservation.



The topic "historical listing" is relevant and reached a peak in publications in the year 2024. Continuing the analysis, Figure 3 presents the results regarding the topic "Restoration Process."

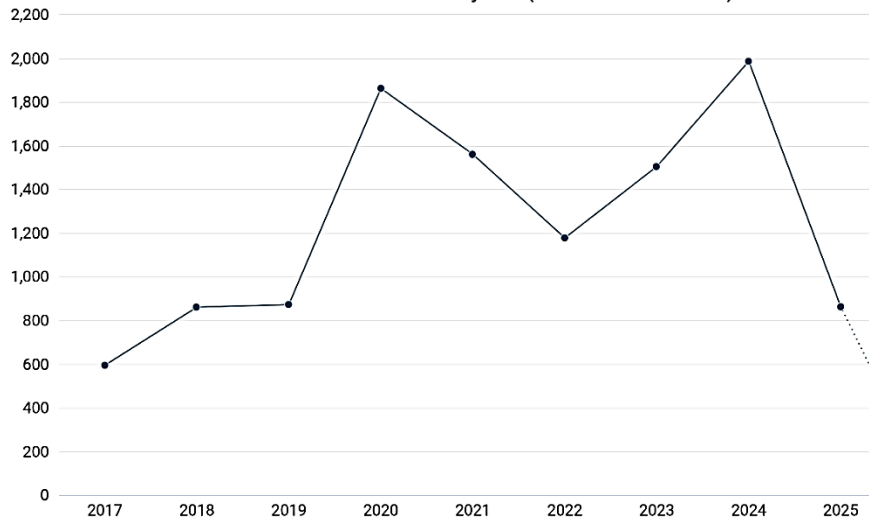
Figure 3.
Time series of publication quantities on the topic of restoration process.



The number of articles published on the topic of restoration process showed an upward trend, reaching its peak in 2024 and declining in 2025. It is interesting to note that, in general, this topic is addressed by a large number of articles over the years. The topic of construction pathology was also analyzed temporally. The graphical results of this analysis are presented in Figure 4.

Figure 4.

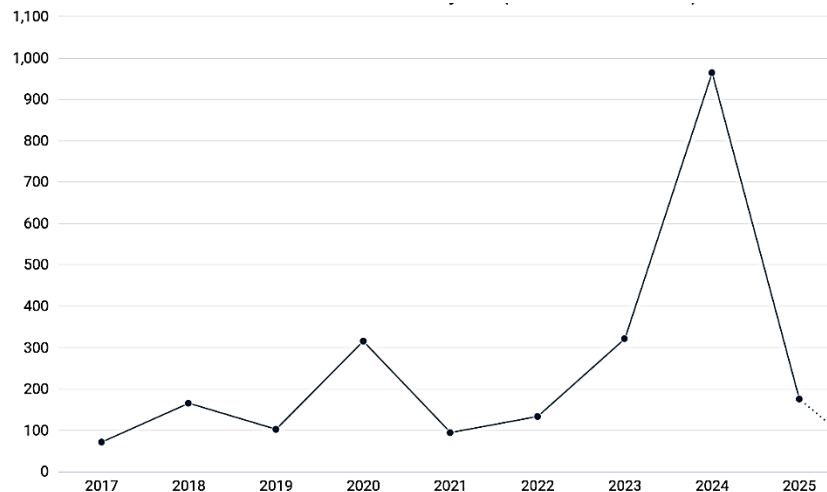
Time series of publication quantities on the topic of Building Pathology.



In the same way, the peak in publications on these topics occurs in the year 2024. Furthermore, two moments of decline in publications draw attention: the years 2022 and 2025. The other topic addressed in this analysis was "Diagnostic engineering in historic buildings." Figure 5 contains the graphical information from this search.

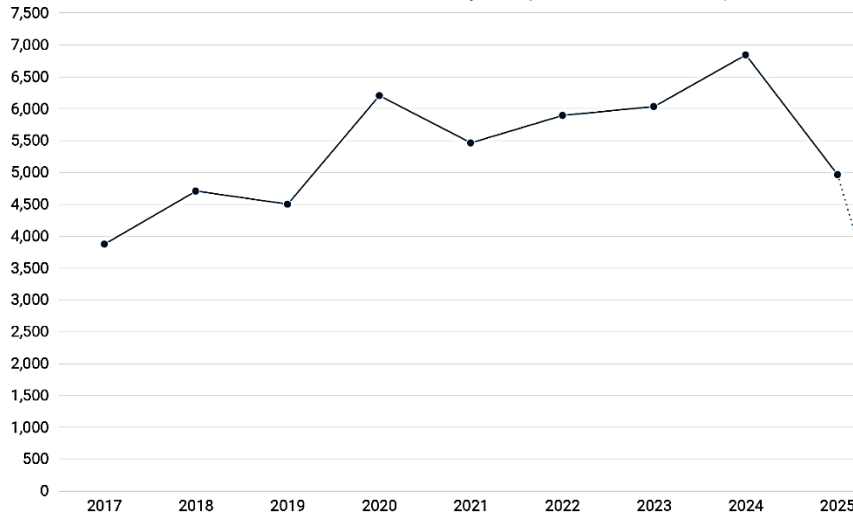
Figure 5.

Time series of publication quantities on the topic of Diagnostic Engineering in Historic Buildings.



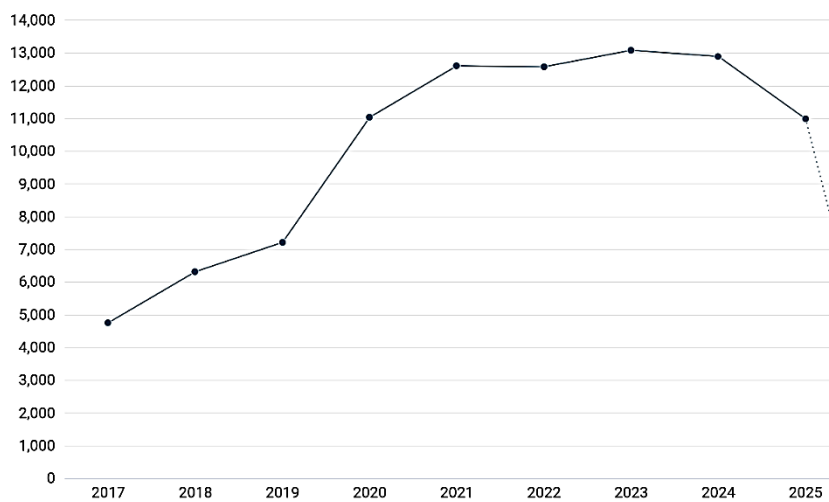
At this stage of the analysis, it is already possible to assume that there is a tendency for the year 2024 to have represented the moment when there was a peak in the number of publications on the topics addressed here. This trend becomes consolidated when Figure 6 is observed.

Figure 6.
Time series of publication volumes on the topic of Damage Map.



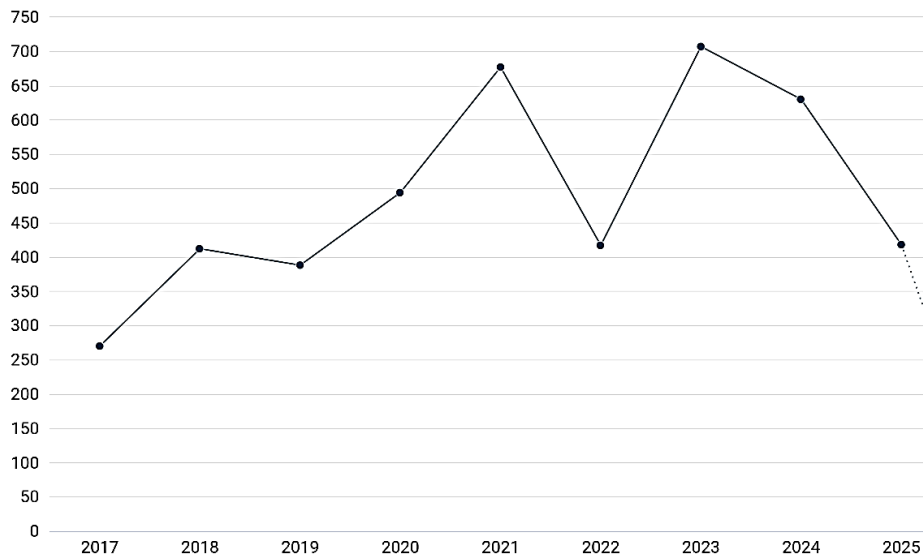
Another topic researched was "Industry 4.0." The graph presented in Figure 7 demonstrates that, among the topics researched, this is the one that has shown the highest number of publications over the years. This fact indicates the importance of this topic.

Figure 7.
Time series of publication volumes on the topic of Industry 4.0.



The last topic addressed was more specific to the field of image processing, namely Semantic Segmentation. Figure 8 presents the results of the time series of publication data for this topic.

Figure 8.
Time series of publication volumes on the topic of Semantic Segmentation.



After analyzing all the search results for the topics addressed here, it was noted that these are relevant topics, as they consistently appear as subjects of study. Furthermore, the year 2024 concentrated peaks in publications. The decline in the number of publications in 2025 for most topics may indicate a decrease in these approaches; however, this assumption can only be made more responsibly when data from future years are included.

In the second part of the results, searches were conducted on the same topics in the following databases: CAPES Journals, SciELO Brasil, and Google Scholar. Initially, results were sought without filters; subsequently, filters were applied, the first through reading the title and the second through reading the abstract, as demonstrated in Table 1.

Table 1.

Search results in databases

Specifications	Database					Total	
	Cape Periodicals	SciELO Brazil	Google Scholar	Scopus	Web of Science		
Keywords Semantic segmentation	20	3	18	2	1	44	
Keywords Semantic segmentation and civil construction	0	0	16	1	1	18	
Total articles found (no filter)	20	3	34	3	2	62	
FILTER	1st Filter – Title reading	7	2	9	1	1	20
	2nd Filter – Abstract reading	5	1	5	1	1	13
Total relevant searches	5	1	5	1	1	13	

After applying the filters, it was possible to list the articles found. Table 2 presents this list of articles.

Table 2.
List of selected articles after applying all filters.

Title	Author and Year	Country	Type / Journal / Event	Main Method/Architecture
Road crack detection using deep convolutional neural networks	Zhang et al. (2016)	USA	Conference– IEEE ICIP 2016	CNN supervised (patch-based classification)
Artificial Neural Networks in Construction Engineering and Management	Waziri et al. (2017)	Nigeria	Article– International Journal of Architecture, Engineering and Construction	Review of ANNs (Backpropagation, hybrids with GA/Fuzzy/PSO)
Concrete Crack Images for Classification (Dataset Mendelej)	Özgenel (2019)	Turkey	Dataset – Mendelej Data	227x227 RGB images; 40k samples (20k with/without cracking)
Segmentação de veias do pulso com uso de redes neurais convolucionais	Cardoso (2020)	Brazil	Dissertation/TCC – PUC Goiás	Comparison of U-Net, SegNet, and DeepLabv3 (SegNet is better)
Convolutional neural networks and image segmentation – a literature review	Cunha (2020)	Brazil	Review/Monograph – UFOP	Review of FCN, CNN and applications
Crack detection using Convolutional Neural Networks	Oliveira et al. (2021)	Brazil	Article– SIBGRAPI Estendido (SBC)	Detectron2 (Mask R-CNN)
Data fusion methodology using deep learning for semantic segmentation of land uses in the Amazon.	Oliveira (2021)	Brazil	Tese (Doutorado) – UFAM (TEDE)	CNN + multiresolution segmentation + merger
Digital image processing for automatic crack detection in ceramic coatings of buildings.	Ruiz et al. (2021)	Brazil	Article– Ambiente Construído	PDI pipeline with UAV/UAV support.
A comparative study of deep learning methods applied to semantic segmentation of obstacles, safe and unsafe zones.	Barbosa & Osório (2021)	Brazil	Conference– Reunião Anual da SBPC (anais)	Comparison of FCN, SegNet and Pix2Pix (GAN)
Deep Semantic Segmentation for Visual Understanding on Construction Sites	Wang et al. (2022)	USA	Dataset + paper (details to be confirmed)	Semantic segmentation models (to be confirmed)
Automated Construction Site Monitoring Based on Improved YOLOv8-seg Instance Segmentation Algorithm	Bai et al. (2023)	China	Article– IEEE Access	Enhanced YOLOv8-seg (FocalNext, EMA, Context Aggregation)
Automated Identification of Pathologies via Semantic Segmentation	Pereira (2023)	Brazil	TCC	CNN/Segmentation (details to be confirmed)
NeRF-to-BIM: Semantic Segmentation for Construction Projects With Neural Radiance Fields	Hachisuka (2018)	USA	Conference – EC3/CIB W78 2023	NeRF + segmentation + conversion to BIM
Semantic Point Cloud Segmentation with Deep-Learning-Based Approaches for the Construction Industry: A Survey	Rauch & Braml (2023)	Germany	Survey – Applied Sciences (MDPI)	Survey
Semantic Segmentation of Building Components for Automated QA	2023	Canada	Conference– CSCE 2022 (publicado 2023) / LNCE	CNN for semantic segmentation (synthetic BIM images)

Assessment of the presence of cracks in images of concrete structures using deep neural networks.	Pereira Junior et al. (2024)	Brazil	Article– Revista Matéria	CNN (details to be confirmed)
Content annotation in images from outdoor construction jobsites using YOLOv8 and Swin Transformer	Farahat & Rezaazadeh Azar (2024)	Canada	Article– Smart Construction and Sustainable Cities (details to be confirmed)	YOLOv8 + Swin Transformer
Fine-tuning vision foundation model for crack segmentation in civil infrastructures (CrackSAM)	Ge et al. (2024)	China	Preprint – arXiv (também referido por Elsevier em submissão)	SAM + LoRA/Adapters (CrackSAM)
Innovative Approaches to Semantic Segmentation in Construction Sites	2024	Germany	Dissertation – TUM (Chair of Computational Modeling and Simulation)	Custom dataset + RTMDet-SAM + Grounding DINO (zero-shot)
Semantic Segmentation of Heavy Construction Equipment Based on Point Cloud Data	Park & Kim (2024)	South Korea	Article– Buildings (MDPI)	RandLA-Net, KPConv (rigid/deformable), SCF-Net
Research and Application of YOLOv11-Based Object Segmentation for Intelligent Construction Sites	He et al. (2024)	China	Article– Buildings (MDPI)	YOLOv11-Seg (instance/segmentation)
ConstScene: A Dataset and Model for Advancing Robust Semantic Segmentation in Construction Environment	Salimi, Loni, Afshar, et al. (2025)	Sweden	LNCS ICPRAI Chapter 2024 (2025) / GitHub Repository	Multi-condition dataset + PCSS benchmarks
Robust Few-Shot Semantic Segmentation for Blurred and ... Construction Environments	Salimi, Loni, Cicchetti, et al. (2025)	Sweden	IEEE (details to be confirmed)	Few-shot/Meta-learning for segmentation
Zero-Shot Object Detection And Segmentation For Construction Sites Through Multi-Model Integration	Tarutani & Himuro (2025)	Japan	Conference (details to be confirmed)	Vision-language models (e.g., Grounding DINO / SAM)
Urban Socio-Semantic Segmentation with Vision-Language Reasoning	2026	Brazil	Article	Visual-Language (VLM) / Visual Reasoning

The list of articles presented in Chart 02 shows that various techniques have been used for the identification of pathological manifestations in the civil construction industry. Another observed point is the diversity of publishers/journals interested in the publication and scientific dissemination of this topic, which reinforces its importance.

The results obtained in this systematic review highlight a scenario of growing scientific maturity in the field of built historical heritage preservation, especially when considering the integration between traditional diagnostic processes and advanced digital methods. It was observed that topics such as historical listing, restoration process, construction pathology, diagnostic engineering, damage mapping, and Industry 4.0 maintain a constant presence in contemporary literature, with particular emphasis on the significant increase in publications in the year 2024. This behavior is aligned with the trends identified by Volk et al. (2014), Deng et al. (2021), and Hu et al. (2022), who discuss the digital transformation in the built environment and the central role of emerging technologies in improving documentation, monitoring, and technical intervention processes in buildings.

The relevance of the topic is also reinforced by the guidelines established for the conservation and restoration of listed heritage assets, which require precise diagnosis, adequate documentation, and compatibility of interventions with the original characteristics of the building (IPHAN, 2015). In this regard, diagnostic engineering has been a structuring axis for the understanding of pathological manifestations, as argued by Helene (1981), Souza and Ripper (1998), and Tinoco (2009), who highlight the importance of methodologies capable of identifying degradation mechanisms and guiding repair strategies.

The increase in the number of publications found in this review confirms these observations and demonstrates a growing interest from the scientific community in the application of new technologies to the study of built heritage. The techniques of digital photogrammetry, infrared thermography, 3D laser scanning (TLS), and the use of drones, widely described by Maldague (2001), Bertolini (2010), Melo and Melo (2023), and Alencastro et al. (2019), appear as consolidated tools in the mapping of pathological manifestations. Their adoption has enabled faster, safer, and more precise analyses, contributing to more robust diagnoses aligned with international conservation standards.

Another notable point in the results concerns the growing incorporation of BIM models and, especially, HBIM, as a means of integrating inspection data, construction history, and maintenance records in a unified digital environment. Works such as those of Sacks et al. (2018), Penjor et al. (2024), and Cui et al. (2025) reinforce the importance of these models for the documentation and intelligent management of historic buildings, highlighting challenges of interoperability, standardization, and continuous model updating. The alignment of these technologies with Industry 4.0 enablers, especially remote sensing, massive data analysis, and automation, is widely discussed by Deng et al. (2021) and Hu et al. (2022), which helps to explain the significant growth in publications on this thematic axis.

Despite this promising scenario, the analysis of the results revealed a relevant scientific gap: the scarcity of studies that directly relate semantic segmentation techniques — especially convolutional neural networks and deep learning — to the automatic identification of pathological manifestations on the facades of historic buildings. Although the use of artificial intelligence is widely widespread in other areas of engineering, its specific application to the context of historic buildings still presents limitations, as indicated by Ferreira (2017), Fleck et al. (2016), Vargas, Paes and Vasconcelos (2016), and Juraszek et al. (2014). The low number of relevant articles found after the filters applied in this review confirms that, despite the recognized potential, semantic segmentation has not yet consolidated itself as a widely used tool in the diagnosis of construction pathologies, especially in environments with a high degree of particularity, such as listed heritage.

This gap becomes even more relevant when considering that inspections in historic buildings frequently involve risks, high costs, restricted access, and the need for high precision

— characteristics that make AI techniques especially promising. The scarcity of studies integrating AI, historic heritage, and diagnostic engineering reinforces the need for theoretical and experimental deepening in this area, something also pointed out by recent works on automation and digital twins in construction, such as Baghdadi (2025) and Ma et al. (2025).

Given this panorama, the results of the present review demonstrate that the initial objective — to identify, systematize, and critically analyze the scientific output on the mapping of pathological manifestations on the facades of historic buildings, with a focus on digital technologies — was fully achieved. The analysis of the selected material allowed for the construction of a comprehensive picture of the state of the art, highlighting the significant advancement of digital documentation techniques, the consolidation of traditional diagnostic engineering methodologies, and, above all, the existence of a persistent scientific gap regarding the use of advanced semantic segmentation models and artificial intelligence for the automatic detection of pathologies in listed buildings. This finding reinforces that, although deep learning technologies are widely widespread across various branches of engineering, their adoption in the context of historic heritage remains incipient and requires greater theoretical and experimental deepening.

Furthermore, the synthesis of the analyzed studies shows that the integration between traditional inspection methods and emerging digital tools from Industry 4.0 is not only technically feasible, but is increasingly necessary given contemporary demands for more efficient, safe, reproducible, and data-driven diagnostic processes. The application of techniques such as digital photogrammetry, thermography, 3D laser scanning, UAV platforms, and BIM/HBIM models reveals a consistent movement in the literature toward the digitization of the lifecycle of historic buildings, contributing to more precise documentation and to interventions compatible with conservation guidelines, especially with regard to the traceability and historicity of the adopted solutions.

Thus, this review contributes by critically organizing the current scientific landscape and offering a robust theoretical foundation for researchers, professionals, and institutions working in the field of built heritage conservation. The results demonstrate that there is still ample room for the development of innovative solutions, especially those that bring diagnostic engineering closer to intelligent decision support systems, automation, and predictive models. The findings therefore reinforce the strategic importance of applying digital technologies and AI to the study of historic buildings, pointing to promising paths for the modernization of inspection practices, the strengthening of document management, and the qualified preservation of cultural heritage in a global context of digital transformation.

Final Considerations/Conclusions

The present systematic literature review highlighted an expressive scientific output related to the topics of historical listing, restoration process, construction pathology, diagnostic engineering applied to historic buildings, damage mapping, Industry 4.0, and semantic segmentation. The high number of publications found demonstrates the growing interest of the scientific community in approaches that integrate the preservation of built heritage, technical diagnosis, and the use of advanced technologies in the context of engineering and architecture.

It was also observed that the year 2024 concentrated the highest number of publications, indicating a recent intensification of research in these areas. This increase can be associated with the expanded use of digital tools, automation techniques, artificial intelligence, and innovative methodologies applied to the diagnosis, monitoring, and conservation of historic buildings, especially in the context of Industry 4.0.

Another relevant aspect identified was the diversity of journals and publishers addressing the topic, which highlights the multidisciplinary nature of the subject and its relevance both in the field of civil engineering and in the areas of historic heritage, architecture, materials science, and computational technologies. This variety of sources reinforces the consolidation of the topic in the scientific landscape and demonstrates its potential for application in different academic and professional contexts.

Thus, it is concluded that the analyzed literature confirms the importance and contemporaneity of the topic, while also indicating a fertile field for future research, especially those that integrate traditional analysis methods with advanced digital tools. The consolidation of these studies contributes significantly to the preservation of historical heritage, the improvement of constructive diagnostic processes, and technological advancement in the civil construction sector.

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