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A systematic review of artificial intelligence for capturing real-world structures into building information modelling

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ABSTRACT

The architecture field faces increasing pressure to digitize complex real-world structures, yet traditional Scan-to-Building Information Modelling (Sc2BIM) workflows remain time-consuming and require many resources. This research addresses the challenge of how Artificial Intelligence (AI) can enhance the Sc2BIM process by automating critical tasks such as point cloud segmentation and model generation, which are essential for producing accurate and efficient Building Information Models (BIM). To tackle this problem, we conducted a systematic review following a structured four-stage methodology: we formulated research questions to define the study's scope, applied clear inclusion and exclusion criteria to identify and screen relevant papers from main scientific resources, performed a detailed statistical analysis of selected studies, and synthesized the results to highlight current trends and research gaps. Our findings indicate that PointNet++ is the most frequently used model for 3D point cloud segmentation, while Convolutional Neural Networks (CNNs) remain the dominant architecture overall; hybrid and transformer-based models are getting popular, and some studies demonstrate successful full 3D BIM reconstructions from raw scans. These results underline the growing role of AI in streamlining the Sc2BIM pipeline, potentially reducing manual effort and improving model accuracy. The key research implication is a comprehensive overview of how AI techniques are applied in Sc2BIM, providing valuable insights for researchers and practitioners seeking to advance automation and efficiency in the digitization of the built environment.

1. Introduction

Building restoration through digital means and methods has gained prominence in the past two decades [1], mainly through the combination of computer graphics technology and techniques such as Laser Scanning, 3D Computer-Aided Design (CAD)modelling, and rendering. Restoration also has benefited from many technological and methodological advancements in recent years, as evidenced in the available literature [2–5]. These come mainly from Light Detection And Ranging (LiDAR) surveying [6],

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Photogrammetry, Videogrammetry [7], Virtual Reality [8], and parametric modelling implementation.

These digital processes are thus replacing traditional hand-drawn ink-and-paper methods in producing drawings, 2D images, and 3D models to use. These processes usually start with data collection through LiDAR or Photogrammetric techniques, which issue a point cloud as an output. Then, a team of specialists loads it into a Building Information Modelling [9] software, cleaning and enriching it with semantic metadata. This information ranges from registering used materials and finishing details to building element relationships and annotations [10]. However, these digital methods have limitations as they are often labour-intensive, time-consuming, and reliant on minimally automated processes.

To accelerate this, the Scan to BIM (Sc2BIM) workflow has emerged as a technical approach to streamline these processes digitally. It refers to the process of converting laser-scanned point cloud data into models within BIM platforms, enabling the interpretation and integration of this information into 3D representations of sites or buildings to support development, design, and construction activities, [10]. Even so, the process faces several challenges, including being resource-consuming, error-prone, and lacking automation, which makes it inefficient and highly dependent on manual expertise.

It is at this point that Sc2BIM could benefit from Artificial Intelligence (AI) techniques, which can automate object recognition, enhance accuracy, and optimize workflows, making it faster, more consistent, and scalable. Furthermore, even though there have been some partial successes, a fully automated AI-applied reconstruction workflow for BIM still has some weaknesses. Most of these methods are limited to monitoring, diagnosis, sustainability applications, data management, rule checking, and enhancing clash detection, while the 3D Reconstruction application of Sc2BIM (usually the stage of the workflow that deals with reconstructing the Point Cloud Data tensors into actual XYZ coordinates, points, surfaces and solid-like volumes) remains an unsolved challenge using open source tools because, to the best of our knowledge, it still relies mostly on software packages like Autodesk Revit and its plugins like Dynamo [11]. This proprietary software dependency to achieve 3D Reconstruction introduces several limitations regarding knowledge sharing and other significant constraints, which will be discussed later in section 3.1. Although relying on a BIM authoring software package's 3D engine may be more practical in the short term, allowing the use of the AI application's built-in functionality instead of writing custom code to reconstruct the 3D geometry, it can hinder broader interoperability and reusability.

AI is a field of computer science that investigates the mechanisms underlying intelligent behaviour in humans, to replicate such behaviours in machines, though not necessarily through the same processes, [12]. Among AI subfields, Machine Learning (ML) has demonstrated the most promising advancements. ML enables systems to generalize behaviours by identifying patterns in data obtained from examples and experience, [13], employing a diverse range of methods, with Artificial Neural Networks (ANNs) being particularly significant. Regarding [14,15], ANNs are computational models composed of interconnected neurons, whose behaviour is governed by the topology and weight parameters of their connections. However, traditional ANNs were inefficient until the emergence of Deep Neural Networks (DNNs), which were introduced using [16]hierarchical, multilayered architectures capable of learning increasingly abstract representations of data. The impact of Deep Learning (DL) is evident in its transformative effects on tasks such as image classification and other complex domains. Fig. 1 illustrates the hierarchical relationship between all the techniques discussed above.

It is important to highlight the impact of AI in the last years, which can be considered to start in 2012 when [17] developed AlexNet, it being the first Deep Learning model to win the well-known image recognition challenge called ImageNet. This impact is shown in Fig. 2, which compiles the number of papers indexed in Web of Science (WoS) that include the term "Artificial Intelligence" AND "Scan To BIM". As can be seen, although the number of publications has stabilized, it continues to increase.

As observed in the relevant literature, the existing AI-powered Sc2BIM methods mostly rely on point cloud-based clustering and inferential techniques, also known as Point Cloud Segmentation [18,19] and Classification [20,21] as shown in Fig. 3. However, there are also works that make use of Image Segmentation [22] and Mapping [23] and we will add them as significant methods to study due to their successful segmentation of elements and their adaptation, mainly from pixel data to point-based classification. Lastly, several Mesh Segmentation [24] and Mesh Classification methods exist [25] that deserve our attention due to their unusual approach to pixel and BIM object classification, with several successes in their accounts.

This broad spectrum of possibilities is only beginning to be explored and documented in scientific literature, which remains largely unsystematized. Although several Systematic Reviews (SRs), surveys, and state-of-the-art studies have been published in recent years, their findings suggest that research should explore alternative data sources, extract component attributes alongside geometries, and address retrospective infrastructure modelling, which remains widely unexplored, [27]. Other studies provide an overview of current

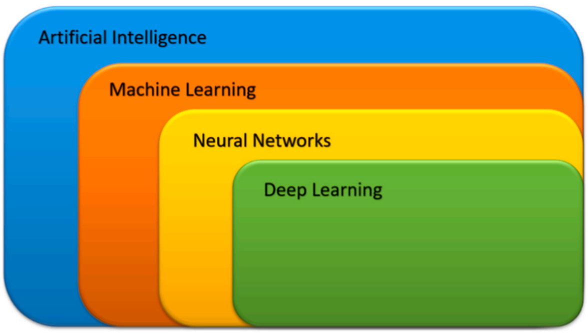

Fig. 1. Hierarchy between artificial intelligence disciplines.

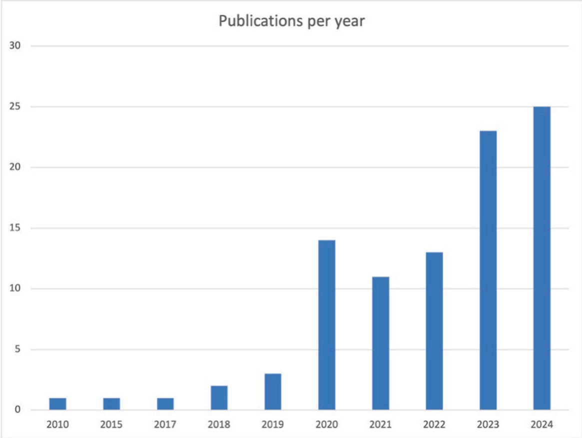

Fig. 2. Distribution by the publication year of the Artificial Intelligence and Scan to BIM papers indexed in Web of Science (WOS) from 2010 to 2024 (n = 94).

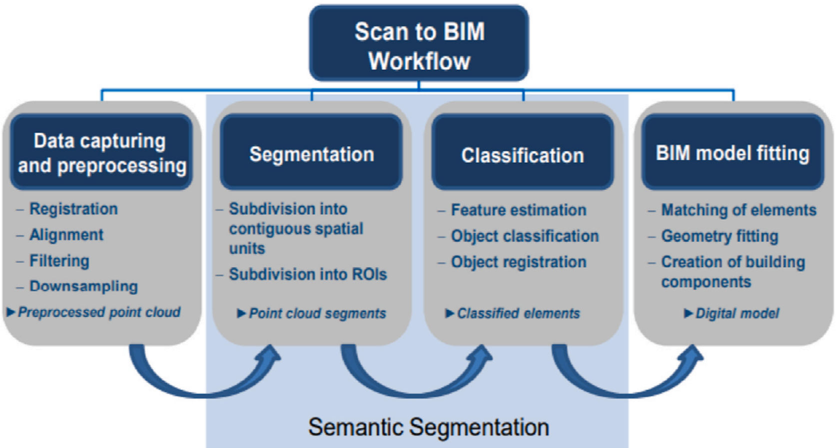

Fig. 3. Scan2BIM steps and where semantic segmentation fits [26].

object recognition and detection strategies in the architecture, engineering, construction, and operation (AECO) domain, specifically examining their potential and limitations based on the richness of semantic information within what is known as the "as-is BIM generation of existing buildings" [28]. Additionally, some studies address the state-of-the-art application of AI techniques in Facility Management (FM) within the BIM context, [29]. Some of these works are general reviews that focus on BIM techniques, and they do not even consider AI techniques or just mention them superficially, for example, Abreu et al. [30] and Pokucinski, S. & Mrozek [31]. Others, such as Wojcik & Zarski [32], assess the applicability of these state-of-the-art BIM and AI methods but are focused on a particular use case, like bridge inspection. In cases where the work is focused on BIM in general, for example, Zabin et al. [33] aim to provide insights only into ML research and not AI in general. Other SRs focused on related fields, such as point cloud processing or computer vision applications in construction, should be considered as follows (Fei et al., 2022). presents a comprehensive survey of DL methods for 3D point cloud completion, compiling cases of occlusion, reflection, or limitations of scanning devices. Also (Kharroubi et al., 2022), review different DL works focused on 3D change detection methods using point clouds, focusing on point-, object-, and voxel-based approaches. Another interesting paper is (Ottoni, Novo, and Costa 2023), which offers an SR of DL applications in computer vision for civil construction within the Construction 4.0 context. Finally [34], conduct a review of computer vision applications in the construction industry, focusing on workspace monitoring. However, there is still a need for an SR that extends beyond FM, encompassing general Sc2BIM. Therefore, this paper primarily aims to report useful insights for researchers, such as identifying successful AI techniques in the field and uncovering unexplored niches. This is necessary to establish a comprehensive reference point for understanding the approaches, techniques, and current state of the art in this critical application of AI within the BIM domain. The paper follows the methodology of an SR to ensure a structured and comprehensive analysis.

The present work is innovative because, as far as we know, this is the first paper that systematically compiles and analyses scientific studies on the application of AI techniques in Sc2BIM with an emphasis on semantic segmentation.

Throughout this work, we contribute by presenting a collection of statistical metrics alongside graphical representations to facilitate data interpretation of the selected papers. It allows for identifying the most used AI techniques for Sc2BIM and assessing their performance across various data types. Understanding effectiveness also highlights potential areas for further experimental research. For professionals in the architectural disciplines and, more specifically, in the restoration and Digital Twinning practices, gaining insights into the studied AI approaches and specific techniques targeted herein is invaluable.

This paper is structured as follows. Section 2 outlines the methodology for paper selection. Section 3 presents an in-depth analysis of the selected studies, discussing their theoretical foundations, contributions, and applications. Finally, Section 4 summarizes the conclusions drawn from this research.

2. Methodology

A Systematic Literature Review (SLR), also known as an SR, is a structured approach used to identify research works relevant to a specific field or research question[35]. Various protocols exist for conducting an SLR, one of the most recognized being the methodology proposed by Ref. [36]. This method follows a series of structured steps to ensure a thorough and unbiased review. The process begins with assessing the necessity of the review, followed by defining precise research questions to guide the study. Second, a detailed search protocol is then developed to ensure a systematic approach to collecting the first set of papers. As the third step to select the most relevant papers, we adhere to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [15] with the following tasks. Inclusion and exclusion criteria are established to refine the selection of studies. Each selected paper undergoes an in-depth analysis of its key features, leading to a well-structured presentation of findings. Finally, we compile and present a comprehensive summary using graphs and statistics about interesting features of the selected papers. This method guarantees rigor, transparency, and replicability, ultimately contributing to the advancement of existing knowledge. The complete process is illustrated in Fig. 4.

2.1. Research questions

As the primary aim of this systematic review is to gather scientific studies applying Sc2BIM and HBIM that have benefited from AI techniques, analysing their characteristics allows us to derive valuable insights. For this SLR, we have defined four research questions that serve as guiding points, helping to delineate the scope of Sc2BIM and identify key areas of interest when using AI. These questions address gaps in the literature, unresolved challenges, and potential opportunities for improvement, shaping the direction of the review.

Research Question 1: Which AI methods have been published in indexed research journals concerning the general Scan to BIM process?

Motivation 1: To have a general overview of all the methods published in indexed, peer-reviewed journals within the Scan to BIM methodology that are AI-powered, and then select according to further specific conditions. This will give a sense of the total landscape of AI-Scan to BIM and allow us to delineate areas of interest within the totality of said territory.

Research Question 2. In these publications, which AI techniques have been developed specifically tailored for Scan to BIM (which is different from remapping and existing models to address a new domain)?

Motivation 2: To identify if any or several AI techniques have been developed specifically for Scan to BIM. This will clarify if Scan to BIM is either a cause or a consequence in the epistemological process concerning AI and Scan to BIM.

Research Question 3. Within these publications, is there or can a fully automated AI-based Scan to HBIM process be identified?

Motivation 3: To locate if there are any or several AI-based, Scan to BIM methods that have automated the whole process. This addresses one of our project leitmotifs, namely the full automation of everything in Architectural BIM workflows. Establishing whether any methods have been fully automated is the conceptual engine of the Scan to BIM research program.

Research Question 4. Would it be possible to replace the "Scan" (i.e., with point clouds for photographs) in both Scan to BIM and Sc2BIM with photos?

Motivation 4: If a method is found that can replace the "Scan" step in Scan to BIM, then it means that both the Scan to BIM workflow and its cognitive approach by Architectural professionals can and is likely to move towards something more lightweight and seamless, hence, promoting a change of input data (and therefore privileging certain techniques over others) from LiDAR to photogrammetry. This also implies that, in the absence of such a method, a new avenue and testing ground emerges for advancing Sc2BIM approaches.

2.2. Search strategies

Various search strategies were employed using keywords from both fields. The search and collection of papers includes everything published in four relevant online databases that were selected to identify literature on Sc2BIM and AI: ACM Digital Library,[2] IEEE Xplore,[3] SCOPUS,[4] and Web of Science[5] (WOS). All queried papers were limited to a specific publication time, from January 1st, 2012, to March 19th, 2025. This decision is based on considering 2012 the beginning of the actual era in AI due to the appearance of AlexNet.

In our case, we used backward citation, starting with the most recent literature (although in the Results section, they are presented

[2] https://dl.acm.org/.
[3] https://ieeexplore.ieee.org/.
[4] https://www.scopus.com/.
[5] https://www.webofscience.com/wos/alldb/basic-search.

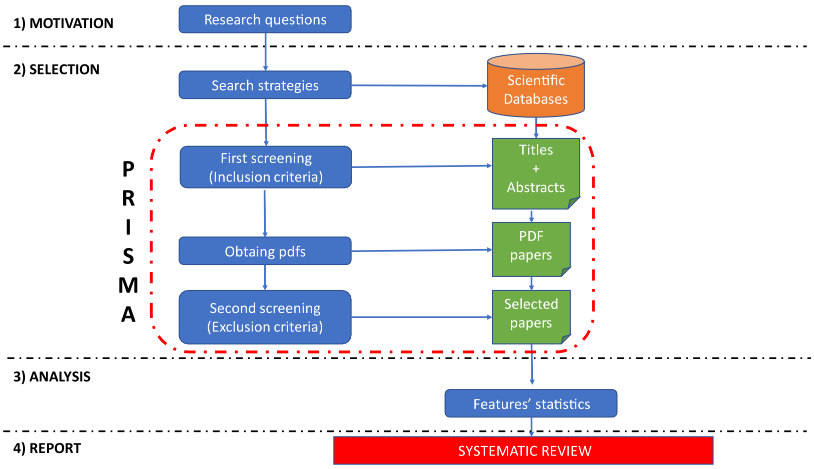

Fig. 4. Workflow followed to achieve the systematic review.

in chronological order). This method was followed to establish connectivity and relevance throughout the screened papers. The search approach follows a structured schema, combining terms from the AI domain with a relevant set of Sc2BIM ones. We carried out this search using 8 keywords filtered via the logical connectors (AND, OR). The queries were introduced in each of the selected databases according to their entry rules and modalities, but the rationale was kept roughly the same, as following*: "semantic" AND "segmentation" AND "bim" OR "scan to bim" OR "scan 2 bim" AND ("artificial intelligence") OR ("deep learning") OR ("machine learning") OR ("neural network")*.

2.3. PRISMA process

This third step includes the screening of papers using the PRISMA methodology. To ensure a collection of high-quality papers, a multidisciplinary team of researchers, including computer scientists, architects, and a researcher who combines both fields in this expertise, has established a set of criteria. In this case, the previous step leads us to only include studies that are published in scientific journals and are not conference papers, retracted papers, editor's notes, books, reviews, or surveys. This way, our review focuses on the most pertinent studies as a search and discard strategy, ensuring high academic quality. This is with only one notable exception in Qi et al. [18,19] due to its status as seminal papers concerning PointNet and PointNet+, which started the point-based point cloud segmentation and the beginning of one of the most used approaches to semantic segmentation in Sc2BIM. We also avoid duplicates that come from searching in different databases.

For the initial screening phase, following the search process, the researcher with a Ph.D. in architecture and a minor in computation and materials science reviewed the titles and abstracts of all retrieved papers due to his knowledge in both fields, architecture and computer science. The goal was to determine whether each study met the inclusion criterion of applying AI for Sc2BIM-related use cases. In cases of disagreement, a second researcher, specialized in computer science with some publications in AI and architecture, made the final decision on whether the paper should advance to the next stage. This approach ensured a balanced evaluation, integrating perspectives from both architecture and computer science.

At this point, we have tried to obtain all the full papers, so a deeper quality analysis could be achieved. The final selection of works has been conducted using more restrictive criteria. Since the methodology for identifying high-quality papers cannot be fully automated, a set of exclusion criteria specific to the fields of computer science and architecture has been established. To ensure that papers are not discarded in this second screening, all the following criteria must be met.

1. The description of input data types is clearly defined to ensure reproducibility. AI models rely on specific types of input data, such as point clouds, sequenced photos, Mesh geometry, or video. Studies that do not use these input types are out of scope, as they are incompatible with the data used in this research. A high-quality paper must explicitly state the data types employed to allow for accurate replication of the methodology. The inclusion of incompatible data types would hinder the comparability of results with existing literature and our datasets.
2. The study must apply AI techniques to obtain results.

Methods that rely solely on manual or non-AI-based processes are outside the scope of this review. The use of AI is essential to align with the research objectives, which focus on automation in Scan to BIM processes. Studies that do not incorporate these techniques are unlikely to contribute to advancements in the field and are rarely found in the relevant literature.

3. The application of AI must be directly related to Scan to BIM or 3D building element reconstruction. Studies that employ AI but do not address Scan to BIM or building element reconstruction fall outside the application domain (BIM) and are therefore out of

scope. This research is focused exclusively on methods that enhance BIM-related workflows. Approaches that deal with other domains, such as CAD, are not relevant to the objectives of this study.

4. The study must present methodological contributions beyond dataset generation. Papers that focus exclusively on dataset creation for AI-based semantic segmentation or Scan to BIM, without presenting techniques for training models or obtaining results, are considered out of scope. While datasets are valuable, studies that do not propose methodologies for utilizing them do not contribute to the advancement of AI applications in Scan to BIM and thus do not align with the focus of this research.

The selection process was carried out systematically, abiding by the PRISMA framework to filter out of scope of interest literature. A flowchart illustrating the PRISMA framework is presented in Fig. 5, summarizing the paper selection process that led to the datasets analysed in this study.

After doing the searches in the scientific databases, a total of 413 papers were included during the selection process collecting as mentioned before. These are only peer-reviewed, non-retracted, non-review, and non-survey articles. Out of all these, we included papers left after filtering duplicates (139), books (12), conference papers (95), editor's notes (1), and other reviews and surveys (36), for a total of 283 filtered out papers and 130 included ones.

From the latter selection, a total of 62 were discarded after reading the title and abstract for not accomplishing the criteria of mentioning AI, Machine Learning, Deep Learning, and Sc2BIM or one of its phases (i.e., Scanning, Semantic Segmentation, Point Cloud Segmentation, 3D Reconstruction, 3D BIM Reconstruction, or a combination of these. While most of the evaluated literature was available, 8 papers remained non-retrievable for evaluation after direct request. This makes a total of 60 papers that were evaluated using the exclusion criteria. After this stage, 0 were considered to not comply with them, obtaining a total of 60 papers that formed the

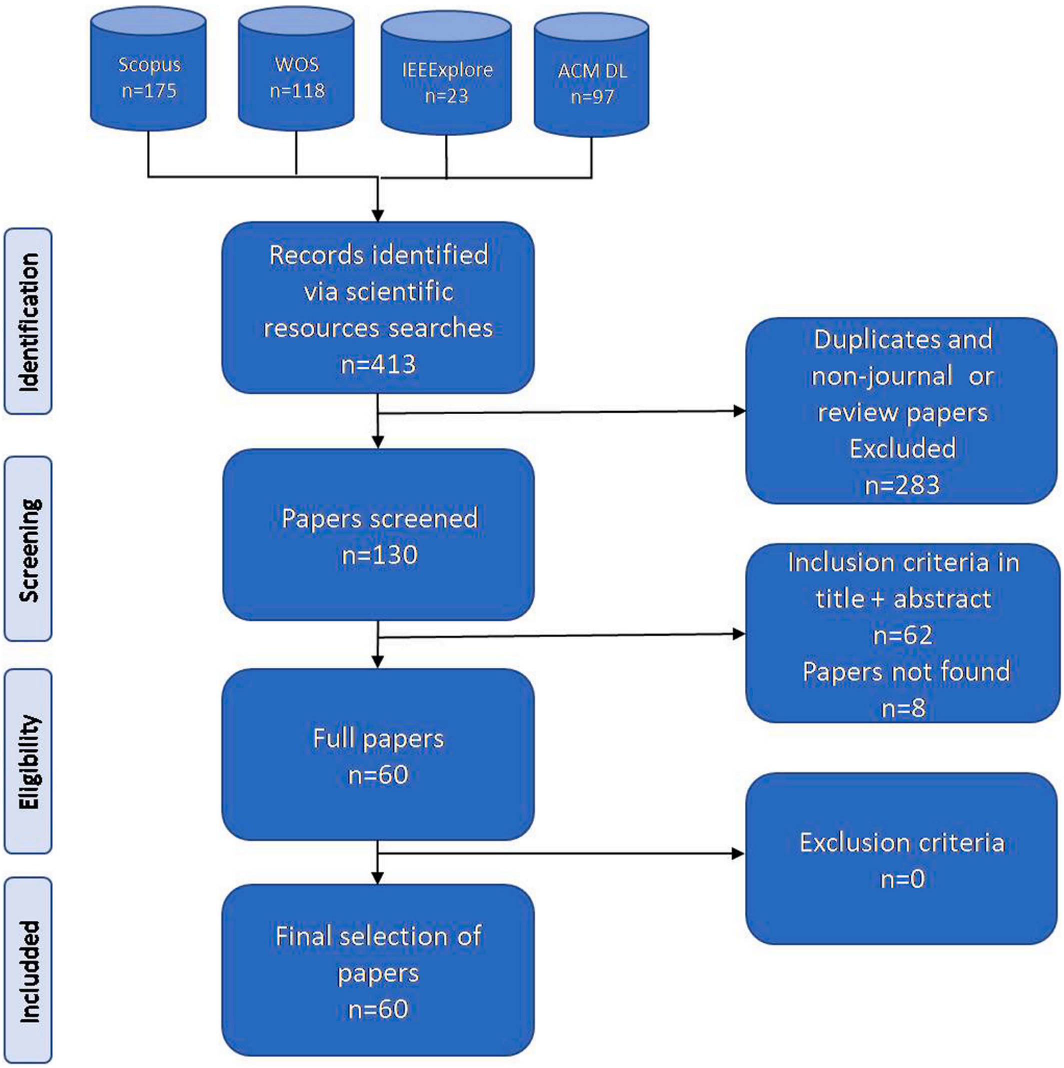

Fig. 5. PRISMA diagram of the systematic review.

final selection.

2.4. Data extraction, classification of studies, and statistical analysis

Once the most relevant papers are identified, key features are extracted to analyse the development of deep learning models in Sc2BIM. This study examines various aspects, including the year of publication, the Deep Learning models applied, performance evaluation metrics, which building or architectural elements are segmented, which application domains imply the research, which BIM format has been used, how the data was collected, and whether it implies synthetic data and the geometric precision.

3. Results

Statistics were collected based on the previously described characteristics of the papers. This data was processed using custom Python scripts and visualized through charts generated with the Matplotlib library by Ref. [37].

3.1. Summary of papers

Based on the type of data used in Sc2BIM, the selected papers were categorized according to their use of Point Cloud Data (PCD), images, or Meshes as shown in the first three ss of Appendix A. Papers that employed a combination of these data types were classified as hybrid approaches, as summarized in the fourth Table of Appendix A. Tables summarize the selected papers, detailing key characteristics such as the paper title, AI model, evaluation metrics, application domain, input file standard, Sc2BIM phases accomplished, data collection techniques, whether the data is synthetic, software dependency, and year of publication.

3.2. Statistics and analysis of the selected papers

One of the most interesting aspects examined in this review is the variety of AI models/algorithms applied across different studies. To illustrate this, we created a pie chart displaying the usage percentages, as shown in Fig. 6. This Figure is relevant as it highlights the models that have been most effective in addressing Sc2BIM problems, making them potential reference solutions for practitioners. Additionally, the less frequently used models remain of interest to researchers as promising candidates for further exploration and development.

Related to this, some well-known Deep Learning models have been mentioned above: PointNet and PointNet++. In Fig. 7, we show a diagram of bars with the number of times these models have been used in the works of the SR. This is relevant because while PointNet serves as a foundational model for directly processing unordered point sets, PointNet++ extends its capabilities by incorporating local neighbourhood information through hierarchical feature learning, making it more suitable for complex and large-scale 3D data, and is considered a de facto standard.

The performance of the previous models can be evaluated using various metrics depending on the type of problem. For

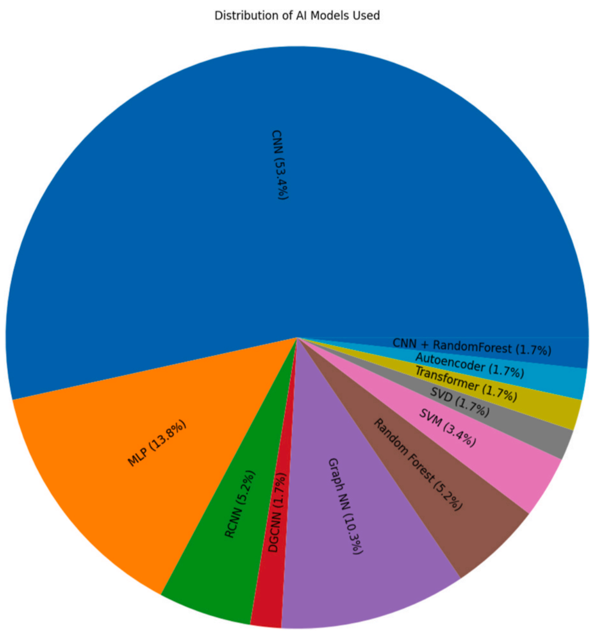

Fig. 6. Use of AI algorithm/models.

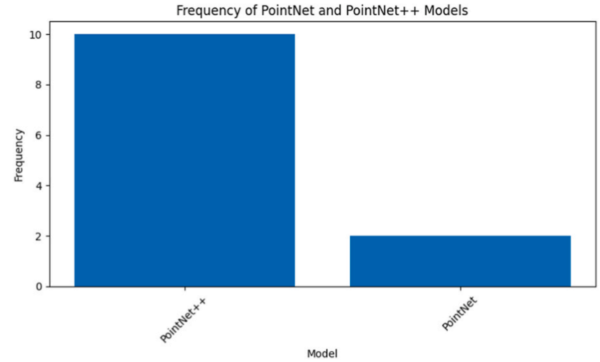

Fig. 7. Use of PointNet models.

classification problems, common metrics include accuracy, precision, specificity, or F1-score, while regression problems often use error metrics such as Mean Squared Error (MSE) and its variants. Fig. 8 presents a pie chart showing the distribution in percentage of these metrics across the reviewed papers. This information is valuable as it allows users to directly identify which metrics are most appropriate for addressing different types of problems.

Related to the metrics, there is not only an interest in knowing which are the most used. By showing in which ranges of values they are, we can measure how accurate the models are for the field of application. It also provides insights into their variability and robustness, helping researchers assess their suitability for different problem settings. Fig. 9 shows box plots illustrating, for the most outstanding metrics, the distribution of their values across different works. Some metrics have been used only sporadically or are not well-known, so they have been excluded from the graphs.

Other interesting features are related to the architecture field, analysing things related to the datasets, the process of Sc2BIM, or the architectural applications. First of all, we are studying the datasets, and in Fig. 10, the use of synthetic and real data is shown. This gives us a glimpse into the nature of the data sources, their distribution, and combination.

Another interesting point is to know which file formats are the most used in the Sc2BIM process, as there are many options that professionals could be interested in. Fig. 11 shows another diagram of bars that depicts the distribution of the used dataset among different standard file formats. Format choice is important as it can cause problems if converting between formats is needed. This is because not all actors use the same software packages and because platform exchange often implies data reduction, simplification, translation, and interpretation, a significant problem while working in real-world construction projects that recent work on neural networks has tried to alleviate [24]. The latter problem can have consequences on project deadlines, lengthening schedules and completion times, not to mention adding difficulty in 3D model element interpretation and confusion amongst teams when they share their models.

Related to that, it is also interesting to study how the use of these formats depends on some specific software. This has some consequences, as, when using specific proprietary software packages, researchers risk platform-specific dependency, which has various sorts of problems concerning forward-sharing their scientific results, future replicability, and copyright issues; not to mention proprietary license costs. Furthermore, using proprietary software formats (i.e. Autodesk Revit, 3ds Max and AutoCAD) opposite open formats (i.e. PLY, OBJ or PCD) not only confines research endeavours, and thus the Sc2BIM field of knowledge, but it also hinders collaboration between architecture, structural engineering, interior design and Mechanical, Electrical and Plumbing (MEP) professional teams in the real world. In this case, we have used a pie chart shown in Fig. 12 that compiles in percentage terms whether this

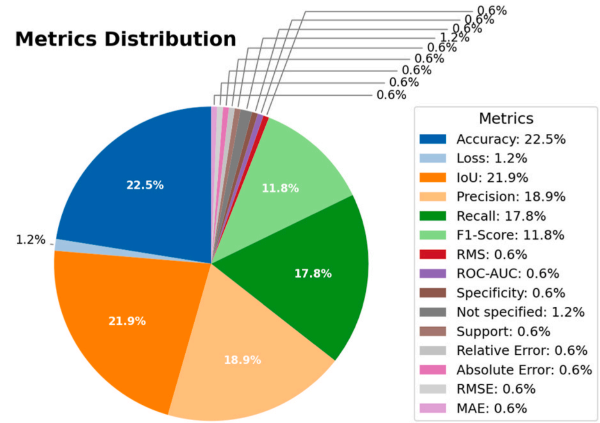

Fig. 8. Percentage distribution of applied metrics.

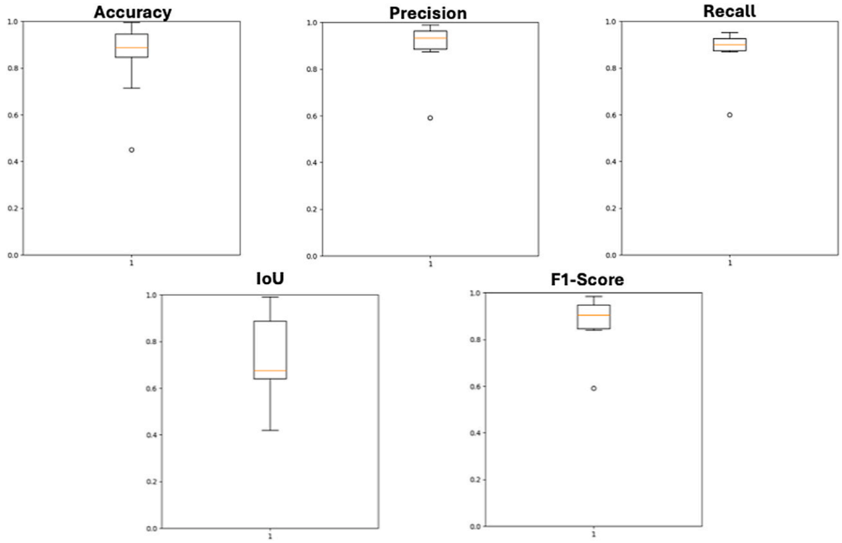

Fig. 9. Metric values and their ranges.

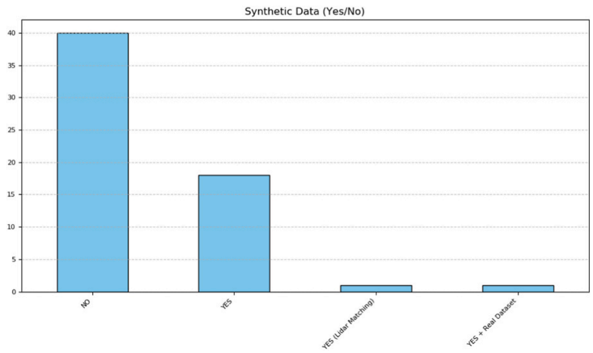

Fig. 10. Distribution of papers by use of real or synthetic data.

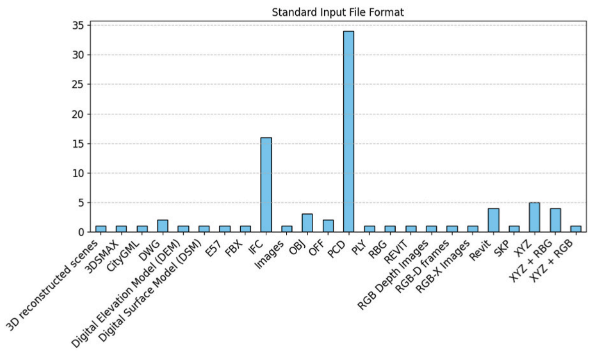

Fig. 11. Distribution of papers by use of standard file formats.

dependency exists and, if so, specifies which software.

This SR also examines which stages of the Sc2BIM process have been addressed, as identifying these stages helps to map the current state of research, highlight gaps in the workflow, and guide future studies toward underexplored areas. Fig. 13 shows the number of stages of the Sc2BIM process in which work has been carried out in each paper. As this Figure is a diagram of bars where each stage is represented, and considering that a work can comprise more than one stage, each work can count in more than 1 bar.

Also, we have delivered a graph related to the application of these works in the architectural field. For this purpose, we have

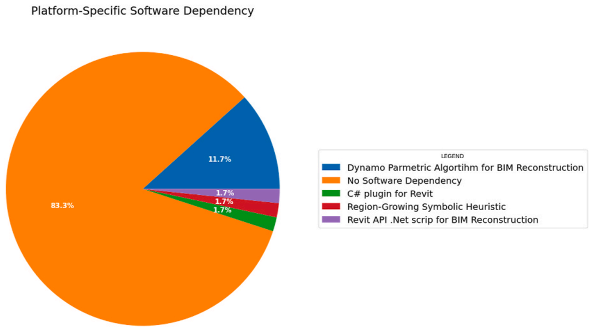

Fig. 12. Percentage of methods dependent on specific software to work.

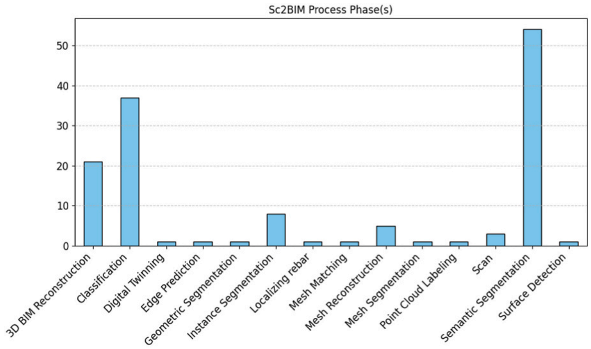

Fig. 13. Distribution of Sc2BIM Phases approached by each study.

grouped the works depending on their application domain. This broad diversity of application fields, as well as the predominance of use in Building Interior, reflects, on the one hand, the construction industry's interest in implementing this technology within design and construction processes. On the other hand, it underscores the need to increase the proportion of activities that foster a more unified vision of the architectural project as a whole. Fig. 14 shows the percentage of works that are focused on different practical fields.

At this point, the last two Figures are related to the Sc2BIM process stages and their dependency on specific proprietary commercial software packages and platforms (especially the latter phase: 3D or BIM Reconstruction).

In Fig. 15 (e.g., all phases accomplished per study) and Fig. 16 (e.g., each separate phase, independent of the study cited), it is shown that, according to the literature, there is a close overlap between the dependence on parametric software like Revit (be it through Dynamo or the Revit API) and the 3D and BIM reconstruction phases.

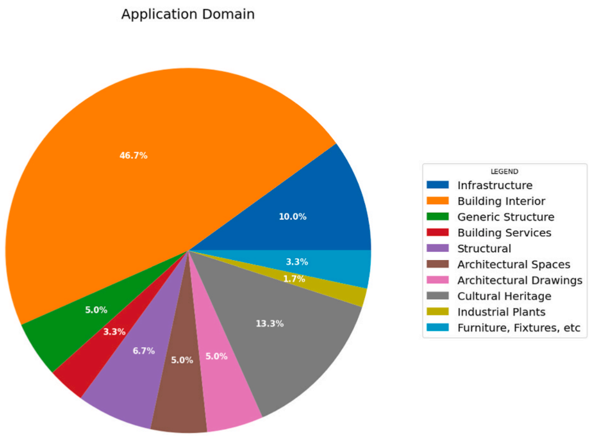

Fig. 14. Percentage of application domains.

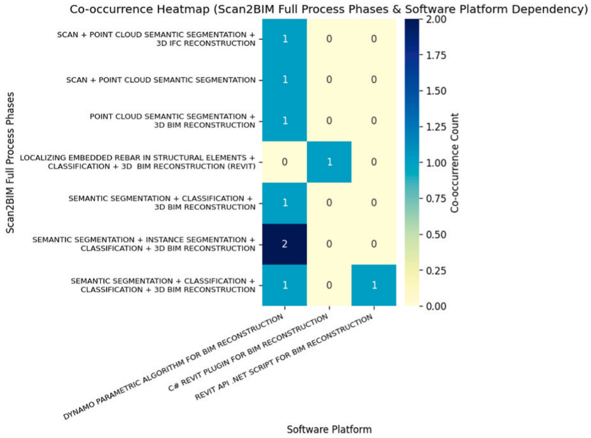

Fig. 15. Relevance of proprietary commercial software packages and the Sc2BIM processes.

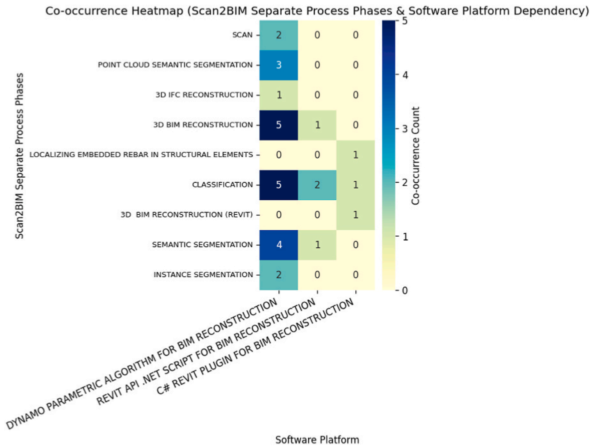

Fig. 16. Relevance of proprietary commercial software packages and the Sc2BIM processes.

4. Discussion

Next, we present the conclusions drawn from the study, offering a comprehensive analysis that brings together trends in annual publications, preferred deep learning models, performance metrics, and other relevant factors.

First, we have different discussions regarding Tables 1–4 that compile all the selected works classified depending on the type of data used: PCDs, images, Mesh, or a mix of two of them. Table A.3 is not discussed because it only contains one paper, so we can conclude that Mesh is still not very relevant and seems like a niche to begin new research lines.

Regarding Table A.1, the frequent use of PCD confirms its essential role as the standard format for representing spatial and geometric information in Sc2BIM workflows. Among the AI models, PointNet++ is the most applied, demonstrating its ability to handle the unstructured characteristics of point clouds. The building interior domain appears as the most explored area, mainly involving semantic segmentation and classification tasks, often using datasets such as S3DIS. In contrast, infrastructure-related cases like bridges and railways are still less represented, opening up the possibility for research in such use cases. The widespread use of LiDAR and TLS methods for data acquisition indicates a preference for high-resolution spatial data. Moreover, some studies include synthetic data to enhance model generalization. Although data formats like IFC and Revit are becoming more standardized, inconsistency remains across different implementations. While many approaches are not tied to a specific software, tools such as Dynamo are occasionally integrated into the workflow.

Based on Table A.2, it is important to note that images still play a relevant role, especially in situations where PCD is not available or is too costly to obtain. Most studies employ CNNs or their extensions, such as RCNN and Mask R-CNN, mainly for semantic segmentation or classification tasks. Data collection methods differ significantly across works, and some researchers include synthetic data to increase training variability and improve model robustness. Standard data formats like IFC, Revit, and CityGML are commonly adopted. In general, software dependency is low, which supports reproducibility and portability, though tools like Dynamo and custom Revit plugins are used in specific cases.

Finally, we have Table A.4 with approaches mixing PCDs with images, except for one paper [24] that uses Mesh with images. This group of studies shows a clear trend toward the use of multimodal data fusion to improve performance in complex modelling tasks. These hybrid approaches are especially common in cultural heritage, where detailed semantic segmentation, classification, and increasingly, 3D reconstruction are essential. A wide range of AI models is applied, suggesting that no single model dominates, but there is a general need to process both geometric and visual data. Despite the added complexity introduced by multimodal inputs, most studies remain software-independent, which helps ensure portability and ease of replication. Interestingly, synthetic data is rarely used, as most works rely on real-world data collected using UAVs, photogrammetry, or TLS.

Regarding the AI techniques used in the studied works (Fig. 6), we can see that DL models are the most used against classical ML algorithms, which are only used in about 10 % of the papers. What is relevant is that the most used Deep Learning models are CNN, which is typically used in computer vision tasks. Next to this, MLPs are also used many times, which makes sense as it is the simplest DL model and very typical when performing segmentation tasks. Apart from that, we also should highlight the use of a hybrid model that benefits from both CNN and Random Forest, and Transformers, one of the most powerful models in recent years.

The former is presented in Moyano et al. [38], where the RF algorithm is employed for point cloud semantic segmentation, enabling the classification of detailed architectural components into nine specific semantic labels. Complementarily, CNNs are implemented for detailed semantic segmentation, allowing the detection of complex geometries and the extraction of fine-grained features. Depending on the segmented label, the accuracy of the RF model ranges from 71.04 % (Abacus) to 98.64 % (Column Shaft). Regarding the CNN, it reports an accuracy of 95.56 %. Overall, the hybrid approach benefits from the interpretability and structured feature handling of RF with the powerful feature learning capabilities of CNNs, offering improved segmentation accuracy and robustness for detailed BIM modelling. However, these benefits come at the cost of increased computational demands, greater workflow complexity, and more intensive data preparation requirements. This demonstrates the room to experiment with hybrid models, a recent tendency in many scientific works in the field of AI.

Transformer-based model is presented by Cui et al. [39] to address the semantic segmentation stage within the Sc2BIM process. The model, called SegFormer, demonstrates high performance for tunnel component segmentation, achieving a mIoU of 86.26 %. The model's IoU results vary by class, ranging from 66.14 % for joints, the connection points between shield tunnel segments, to 96.19 % for pipes, which are utility conduits running along the tunnel walls or ceiling. Using Transformer-based models for this task offers significant advantages, such as strong global context modelling, improved performance for complex geometries, and flexibility in handling multi-channel input data. However, these benefits come with certain limitations, including higher computational demands, larger memory requirements, and the need for extensive annotated training data to fully exploit their capacity.

As part of the analysis of used models, Fig. 7 shows the importance of applying PointNet architectures. This is mainly due to the specificity of PCD data (XYZ points); high amounts of available LiDAR data have driven the development of PointNet-like architectures, so this data can be exploited and used in many fields (i.e., facility management, building surveying, structural and As-Designed building monitoring, and HBIM). PointNet architectures have paved the way towards AI-automated Point Cloud Segmentation and served as a stepping stone for 3D BIM Reconstruction and surveying, as some of the presented studies attempt to achieve. Regarding the comparison between PointNet and PointNet++, the latter has been used in 10 works against PointNet, which has only been used twice. This makes sense as PointNet's main weakness is its inability to capture local geometric structures, which limits recognition of fine-grained patterns and reduces generalizability to complex scenes, Qi et al. [19]. Apart from that, the importance of these architectures for Point Cloud Segmentation is proved by the different solutions based on these architectures proposed in recent years: PointCNN by Li et al. (2018), PointSIFT by Jiang et al. [40], SAN by Cai et al. [41], PointNext by Qian et al. [42], CA-PointNet++ by Wang et al. [43], SoPointNet++ by Chen & Gu [44], or FastKAN by Tan et al. [45]. However, works like Zoumpekas et al. [46] that compare different Point Cloud Segmentation models show that in some experiments, PointNet++ is still among the best.

The next analysis provides information about the metrics used to measure the performance of the models (Fig. 8). If we analyse the most used metrics, 5 of them stand out above the others: Accuracy, Precision, Recall, F1-Score, and IoU. The use of the first 4 metrics shows that this field comprises a lot of classification problems, such as labelling segmented objects. In this case, these metrics are typically used as complementary, as Accuracy describes the performance of the models, and the others add information about False Positives and False Negatives. This is related to the fact that Accuracy can be misleading when using imbalanced datasets. Another interesting point is that IoU is a typical metric for regression problems such as object segmentation, which is aligned with the aim of this SR. In this way, we can conclude that using these metrics is a good practice when performing tasks of architectural element segmentation. Otherwise, this is not enough in BIM applications where the geometric accuracy is critical. This is supported by the limited use of loss metrics such as MSE or MAE, which indicate that segmentation is not being applied to complex structures where precision errors have a significant impact on their values. Finally, the wide variability of metrics poses a challenge in the field, as it highlights the lack of standardized benchmarks for evaluating model performance, making cross-study comparison nearly impossible.

Regarding the values of the most used metrics, we have this information in Fig. 9. What we can see is that F1-Score, Recall, and Precision are very stable with mean values near 90 or 95 percent and with similar ranges. In the case of Accuracy, we can see that the value of this metric is less stable, as in some cases it drops to a value near 70 % which reinforces that Accuracy should not be used alone. Regarding these metrics, we also should mention that in at least one case, for metric values are considered outliers. If we talk about IoU, we can see that the range of values in the analysed works is very diverse, going from nearly 40 % to 100 % with a mean average lower than 70 %. This diversity in IoU could be a consequence of the variety of segmented elements approached in the different works or the low performance of the models in general when facing this type of task. This variability in IoU supports the previously mentioned issues with geometric precision, which is crucial in BIM applications. Also, the cases of low IoU values still entail manual correction, which is a problem, as the papers compiled in this SR are focused on automating stages of the Sc2BIM process and show its low effectiveness when segmenting fine-grained structures. Therefore, we can conclude that although most works achieve good results in classification tasks such as labelling segmented elements, there is still significant room for improvement in more complex tasks where high values in geometric measures are critical.

The following Figures are related to the used data. In this way, Fig. 10 shows real data sources double the proportion of synthetic data, while LIDAR-matching and real-synthetic data combination remain marginal. In domain applications, such as cultural heritage data, it is scarce, so the use of synthetic datasets is sometimes mandatory. This Figure also shows us the importance of real-world data capture and explains why PCD is the most used data format in the papers reviewed herein. This demonstrates how, for many applications, the collection of data from reality can generate operational datasets for training neural models. In other cases, such as those related to ruined or lost architectural heritage, the use of synthetic models becomes essential. Most research utilizing AI technology focuses primarily on either restoration and reconstruction or facility management and monitoring, with an emphasis on real-world building use cases. In studies involving only synthetic datasets, the objective is to explore how training on synthetic data can be applied when testing on real-world data. Conversely, when both synthetic and real datasets are combined, the goal is to develop and evaluate new AI models or architectures, leveraging the added complexity and richness of the dataset mix, particularly by varying the proportion of each type of data. We can conclude that developing open synthetic datasets for niche domain applications represents an important opportunity to support the scientific community working on Sc2BIM. In the case of cultural heritage, this could also be the unique option, as methods like laser scanning are invasive, necessitating to complement of them with real data to measure the performance in real-world scenarios.

In Fig. 11, the usage of standard formats is shown. In this case, what we can see is that the most used ones are PCD and IFC, then there is a set of diverse standards as XYZ and REVIT formats. In the case of PCD, its status as the de facto standard can be attributed to the dominance of LiDAR in data capture and the fact that most works rely on it. In contrast, IFC serves as the industry exchange format, which justifies its widespread use. What we can conclude here is that many different formats could be used, which could be a problem, complicating reproducibility across studies and increasing the risk of incompatibility when integrating outputs into BIM software. Thus, it is recommended the use PCD and IFC since they are widely used and can avoid data incompatibility or import/export issues when changing between BIM software platforms, which is a well-known problem in the BIM industry. Both formats require the least amount of information capture that is the most useful, and, in the case of IFC, its industry standardisation is clearly an advantage over other less-used formats. This dual dominance illustrates the divide between research needs, which favour flexible raw data formats, and industry requirements, which depend on standardized exchange protocols. Moreover, the reliance on software-specific formats such as Revit introduces bias, as it ties the reproducibility of results to proprietary platforms.

Then, Fig. 12 shows the dependency of this data on the use of specific software. What we can conclude is that most of the works do not have dependencies, which is good for scientific works, as science should remain open, and only one software has been used more than once, Dynamo, a visual programming, parametric algorithmic editor that runs as a plug-in in the Autodesk Revit software package. This is presumably because Dynamo is graphically programmable (and therefore more intuitive and faster than coding 3D from scratch) and already integrated with Revit, a BIM authoring software platform, so it uses the latter's 3D engine to generate and visualize the geometry based on the AI model's output and does not have to build it from scratch. All of this underscores the opportunities afforded by the adoption of open-source software. Such developments not only facilitate broader accessibility and transparency in research but also foster collaborative innovation, reduce implementation costs, and enhance the reproducibility of results. Moreover, open-source frameworks allow for the continuous improvement of tools through community contributions, making them particularly valuable in rapidly evolving fields such as architecture, construction, and heritage preservation.

If we looked at the most approached stages in the Sc2BIM process, collected in Figs. 13 and 3D BIM Reconstruction, Classification, and Semantic Segmentation stand out from the others. Also, we find some works on Instance Segmentation and Mesh Reconstruction. These disproportionate quantities are in line with the core of the Sc2BIM projects and are an indication of the weight that the research and industry sectors put on specific phases and their associated techniques. We can say that the rest of the phases accomplished are secondary in importance, yet they remain open avenues for further directions to explore.

Also, we have obtained a distribution to know the application domains of the studies. What we can conclude by looking at Fig. 14 is that a significant portion of the work (46.7 %) is concentrated in a single domain called Building Interior, indicating a heavily explored and possibly saturated area. In contrast, several other domains exhibit only modest representation (1.7 %-6,7 %), highlighting underexplored areas with strong potential for future research. The preferential domain of application also reveals the areas where this technology is not yet predominant, such as the overall management of the construction project, as opposed to the partial management of interior construction. The moderate representation of certain domains, such as Cultural Heritage and Infrastructure, suggests that these fields of application are established but are a good niche area for work.

In Fig. 15 (i.e., all phases accomplished per study) and 16 (i.e., each separate phase, independent of the study cited), a close dependency of proprietary software packages like Revit and the last phase of 3D BIM Reconstruction is established. Looking more closely, the co-occurrence revealed in Fig. 16 between 3D Reconstruction (5), Classification (5) and Semantic Segmentation (3) draw relationship with the Dynamo Parametric Algorithm development for BIM Reconstruction which places REVIT as the most used platform, and being proprietary, reinforces the point made earlier while commenting Fig. 11 about the generalization of methods due to the diversity of tools. This could be because there is still scientific ground to cover concerning the last phases of Sc2BIM (i.e., 3D BIM Reconstruction), which is narrowly approached in the evaluated studies, meaning it is ripe for research. Therefore, we nonetheless recommend that future work be, among other things, avoidant of this kind of strategy because, while it might be "easier" and "industry-adopted", it is also risky due to copyright issues, its expensive nature, and lastly, also due to potentially closing scientific forward-sharing and other unforeseen liabilities.

In the end, we have analysed the consequences of architectural segmentation. This area of research still has a long way to go towards standardisation and systematization, and while terminology has coalesced around conventionalized naming for task operation types, there is still shallow common ground when it comes to procedural and approach overlapping between methods. This means that an optimal way of carrying out segmentation is still to be found, even though there is a clear gravitation around CCN, PointNet, and PointNet++ AI architectures.

5. Conclusions and future works

This study presents a novel and comprehensive review of AI-based approaches applied to Sc2BIM, with a specific focus on semantic segmentation, an area that has not been systematically analysed until now. The key contribution lies in the structured compilation and statistical analysis of relevant literature, offering quantitative insights into prevailing AI techniques, data types, performance metrics, and application contexts. Through visual and comparative representations, we identify dominant trends, underexplored areas, and gaps in current research. This enables the formulation of informed future research directions and experimental priorities. Moreover, by mapping the intersection of AI, semantic segmentation, and Sc2BIM workflows, our findings serve as a valuable reference for both academic researchers and practitioners. This work thus lays the groundwork for more targeted, efficient, and context-aware AI applications in the built environment domain.

The findings reveal a growing interest in applying DL techniques to automate and enhance various stages of the Sc2BIM pipeline. PCD remains the most widely used data type, though the use of Mesh emerges as a potential niche for further research. A noticeable trend is the increasing use of multimodal data, reflecting the integration of diverse data types to improve model performance.

Regarding the AI models, CNNs and their variants dominate due to their effectiveness in processing spatial and geometric information. However, PointNet++, a specialized architecture for PCD, has also shown strong performance across multiple studies. More recently, hybrid and Transformer-based models have begun to surface, indicating a promising shift toward more flexible and robust multimodal approaches capable of addressing the complexities of real-world scenarios. Regarding domain application areas, such as Cultural Heritage and Infrastructure, remain underexplored and offer opportunities for future research.

Despite this momentum, several challenges persist. There is a scarcity of high-quality, annotated datasets suitable for training and benchmarking DL models. This can be complemented with information in Table A.1, where many papers used synthetic data, probably due to the lack of good enough open datasets. This limitation hinders the reproducibility and generalizability of findings, making it difficult to evaluate and compare approaches. While some studies have explored the use of synthetic data to mitigate this issue, such strategies are still relatively rare and underdeveloped. Moreover, most contributions focus on isolated subtasks rather than proposing integrated end-to-end solutions that reflect the full complexity of real-world Sc2BIM workflows. This fragmentation limits the applicability of current models outside controlled research settings.

Another key observation is the limited attention paid to the integration of DL tools into professional BIM environments. While technical performance remains a central concern, aspects such as interoperability with industry standards (e.g., IFC), alignment with existing BIM authoring tools, and ease of use for non-expert users are rarely addressed. For DL-based methods to gain broader adoption, they must be not only accurate and efficient but also compatible with the needs, tools, and constraints of practitioners in fields such as architecture, construction, heritage conservation, and facility management. As a conclusion, we emphasize that there is still no standard, widely adopted methodology for implementing Sc2BIM. Furthermore, most of the studies achieve 3D BIM Reconstruction (15.7 %), typically with the support of proprietary software. Even fewer engage with Mesh Reconstruction (3.7 %), and Digital Twinning efforts are nearly absent (0.7 %).

In summary, the application of AI to Sc2BIM is a rapidly evolving research frontier with significant potential. Realizing this potential will require not only technical innovation but also greater attention to data availability, methodological standardization, and user-centred system design. By addressing these challenges through interdisciplinary collaboration and practical integration, DL can fundamentally transform how we document, analyse, and engage with the built environment.

The main conclusion of this work, encompassing the application of Deep Learning to Sc2BIM, highlights that, despite the progress made with the AI models, current approaches remain constrained by the type of data they exploit. Most works rely either on PCD or on IFC, which limits the completeness and interoperability of the resulting models. Our analysis suggests that research should prioritize the development of methods that integrate PCD and IFC within a unified open-source framework, thereby combining geometric precision with semantic richness and reducing reliance on proprietary tools, ultimately contributing to the democratization of the technology.

Future research should investigate more advanced deep learning architectures, such as Transformers and GNNs, which offer the capacity to model complex spatial relationships within unstructured 3D data. Additionally, the development of hybrid models appears promising, aligning with the observed trend toward multimodal data integration that combines point clouds, images, and increasingly, Mesh data. To support this evolution, future studies should prioritize the creation of robust and standardized frameworks for multimodal and data fusion. Key challenges to be addressed include precise data alignment and modelling across heterogeneous inputs. Establishing consistent preprocessing pipelines and formalized fusion strategies will be critical for enabling more accurate, reliable, and semantically rich 3D reconstructions.

The lack of large, high-quality, annotated datasets emerged as a problem to solve. Many studies make use of synthetic data, which, while useful, is not yet sufficient to support generalizing the solutions. There is a clear need to build and share open-access, domain-specific datasets, especially in underrepresented areas or areas where scanning tools are problematic, such as Cultural Heritage. Equally critical is the establishment of standardized evaluation metrics and benchmark tasks, which would enable fair and transparent comparison across different approaches. In this way, the use of loss metrics appears critical for developing more precise tools in tasks such as reconstruction.

Another significant gap lies in the fragmentation of current approaches, which often address isolated subtasks rather than offering integrated, end-to-end solutions. Future work should strive to develop complete pipelines that span from raw data acquisition through to BIM generation and integration into existing software ecosystems. Interoperability with industry standards such as IFC and BCF is particularly important to ensure adoption in professional workflows. Modular and open-source systems could also accelerate development and customization for various use cases.

The review also identifies application-specific opportunities, particularly in domains such as cultural heritage. Future work should consider the development of domain-specific semantic ontologies, as well as low-intrusion scanning and modeling approaches suited for fragile or protected sites.

Equally important is the integration of AI tools into existing BIM authoring environments. Most current research overlooks the practical aspects of deploying these tools in real-world design and facility management workflows. To be effective, future systems must prioritize not only technical performance but also usability, compatibility with industry platforms.

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CRediT authorship contribution statement

Nelson Montás-Laracuente: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Emilio Delgado-Martos:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Carlos Pesqueira-Calvo:** Writing – review & editing, Validation, Formal analysis. **Giovanni Intra Sidola:** Writing – review & editing, Validation. **Ana M. Maitín:** Writing – review & editing, Conceptualization. **Álvaro J. García-Tejedor:** Resources, Project administration, Conceptualization. **Alberto Nogales:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A.1
Summary of studies using PCDs[a].

Paper	AI Model	Metric	Domain Application	Standard Format	Sc2BIM Phase(s)	Data collection technique (s)	Synthetic Data (Yes/No)	Software Dependency	Year
[47]	PointNet++	Accuracy, Loss, IoU	Infrastructure	IFC	Sc + SSeg + 3DBRec	LiDAR	NO	Dynamo	2023
[48]	MLP	Accuracy, Loss, IoU	Building Interior	IFC	Sc + SSeg	TLS	NO	Dynamo	2023
[49]	PointNet++	Precision, Recall, F1-Score	Building Services	IFC	SSeg + 3DBRec	LiDAR	YES	NO	2023
[50]	PointNet++	IoU, Accuracy, Precision, Recall, F1-Score	Building Interior	PCD	SSeg + 3DBRec	3D scanner (Nav-Vis M6)	YES	Dynamo	2024
[51].	RANSAC	IoU, Precision, Recall, F1-Score	Building Interior	XYZ, RGB	SSeg	3D Models from TLS	YES	NO	2022
[52]	PointNet++	Precision, Recall, RMSE	Architectural Drawings	IFC	SSeg + 3DBRec	Various Public Datasets	NO	NO	2022
[53]	PointNet++	ROC-AUC, Accuracy,	Architectural Drawings	PCD	SurfDetec + EdgePred	S3DIS Dataset	NO	NO	2024

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Table A.1 (*continued*)

Paper	AI Model	Metric	Domain Application	Standard Format	Sc2BIM Phase(s)	Data collection technique (s)	Synthetic Data (Yes/No)	Software Dependency	Year
		Precision, Recall							
[34]	CNN	Precision, IoU	Building Interior	XYZ	InSeg + Class	S3DIS Dataset	NO	NO	2021
[54].	MLP	Accuracy, IoU	Building Interior	PCD	SSeg + Class + MeshRec	S3DIS Dataset	NO	NO	2019
[55]	DGCNN	Precision, Recall, F1-Score, IoU, Accuracy	Infrastructure	PCD	SSeg + Class + MeshRec	3D Scanner	NO	NO	2024
[56].	CNN	Accuracy, IoU	Building Interior	OFF	SSeg + Class	ModelNet40 Dataset, S3DIS Dataset	YES	NO	2019
[57].	MLP	Precision, Recall, Accuracy	Structural	OFF, PCD	GSeg + SSeg	Laser Scanner	YES	NO	2023
[58]	KPConv	Precision, Recall, F1-Score, IoU	Industrial Plants	FBX, DWG, IFC, OBJ	SSeg	TLS-LiDAR	NO	NO	2024
[59]	Random Forest	Accuracy, Precision, Recall, F1-Score	Generic Structure	XYZ	SSeg + Class	TLS-LiDAR	NO	NO	2022
[60]	MLP	Accuracy, IoU	Structural	PCD	SSeg + Class + 3DBRec	LiDAR	YES	NO	2024
[61]	CNN, PointNet++	Accuracy, IoU	Architectural Drawings	PCD	SSeg + Class	LiDAR	NO	NO	2023
[26]	SVM	Precision, Recall, Accuracy, IoU	Infrastructure	IFC	SSeg + Class	Laser Scanner	NO	NO	2024
[62]	MLP	Accuracy, Precision, Recall, F1-Score	Structural	PCD	PCLabel + SSeg	Mixed-Reality Headset, Revit Models	YES	NO	2024
[63]	KPConv	Accuracy	Building Services	PCD	Class	ModelNet40ModelNet40 Dataset	YES	NO	2022b
[64]	CNN	Accuracy	Building Interior	Revit	SSeg	TLS-LiDAR	YES	NO	2022
[65]	PointNet++	IoU	Building Interior	PCD, Revit	SSeg	TLS, 3D Revit BIM Models	YES	NO	2023
[66].	PointNet++	IoU	Building Interior	PCD	SSeg + MeshRec	S3DIS Dataset, Redwood Dataset, VLX Sensors	NO	NO	2023
[67]	SVM	Accuracy, Precision, Recall	Building Interior	PCD	SSeg + Class	TLS	NO	NO	2021
[68]	GNN	Accuracy, Precision, Recall, IoU	Infrastructure	PCD	SSeg	TLS	NO	NO	2021
[69]	MLP	Precision, Recall, IoU	Building Interior	PCD, DWG, RVT, SKP	SSeg	S3DIS Dataset, Laser Scanner	YES	NO	2020
[70]	Random Forest	Accuracy, Precision, Recall, F1-Score	Cultural Heritage	PCD, Revit	SSeg + Class + 3DBRec	TLS	NO	NO	2023
[71]	GNN	IoU, Accuracy	Building Interior	PCD	SSeg + Class + 3DBRec	S3DIS Dataset, ScanNet Dataset	NO	NO	2022
[72]	CNN, Attention	Relative Error, Absolute Error	Furniture, Fixtures, etc	PCD	SSeg + InSeg + Class + MeshRec	Robot Dataset, Furniture Dataset	YES	NO	2022
[73]	KPConv	IoU, Accuracy	Infrastructure	IFC	SSeg + Class	S3DIS Dataset, Karman Dataset, Infrastructure-MLS	NO	NO	2024

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Table A.1 (*continued*)

Paper	AI Model	Metric	Domain Application	Standard Format	Sc2BIM Phase(s)	Data collection technique (s)	Synthetic Data (Yes/No)	Software Dependency	Year
						Dataset, Bridge TLS Dataset			
[74]	KPConv	Accuracy, F1-Score, Precision, Recall, RMSE	Architectural Spaces	PCD, 3DS	SSeg + InSeg + Class + 3DBRec, MeshMatch	LiDAR	YES	NO	2024
[75]	ResPointNet++	OA, Precision; Recall, F1 score, IoU, mIoU	Building Interior	Revit, IFC, PCD	SSeg + Class	3D BIM Models based on S3DIS Dataset	YES	NO	2024
[76]	AttTransNet	Precision, mIoU	Building Interior	PCD	SSeg + Class	S3DIS Dataset, CRASLAB Dataset	NO	NO	2024
[77].	U-Net + SoftGroup	Average Precision; IoU	Building Interior	PCD	SSeg + InSeg + Class + 3DBRec	S3DIS Dataset	NO	Dynamo	2024
[78]	DHANet	Precision, Recall, F1 score, IoU	Building Interior	PCD	SSeg + Class + 3DBRec	S3DIS Dataset	NO	NO	2024
[38]	Random Forest, CNN	Accuracy, Precision, Recall, F1-score	Cultural Heritage	PCD	SSeg + Class	TLS	NO	NO	2024
[79]	PointNet++, Residual	IoU, Accuracy, Precision, Recall, F1-Score	NO	XYZ	SSeg	TLS, LiDAR	NO	NO	2021
[10]	MLP	IoU, Accuracy	NO	XYZ	SSeg + Class + 3DBRec	S3DIS Dataset	NO	YES	2022

[a] Abbreviations in Tables A.1, A.2, A.3 and A.4: Terrestrial Laser Scanner (TLS), Ground-Penetrating Radar (GPR), Unmanned Aerial Vehicles (UAV),Scanning (Sc), Semantic Segmentation (SSeg), Instance Segmentation (InSeg) Geometric Segmentation (GSeg),Point Cloud Labelling (PCLabel), 3D BIM Reconstruction (3DBRec), Mesh Reconstruction (MeshRec), Mesh Segmentation (MeshSeg), Mesh Matching (MeshMatch) Surface Detection (SurfDetec), Edge Prediction (EdgePred), Intersection over Union (IoU), Root Mean Square Error (RMS), Overall Mean Average Precision (mAP), Mean Accuracy (mAcc).

Table A.2
Summary of studies using Images.

Paper	AI Model	Metric	Domain Application	Standard Format	Sc2BIM Phase(s)	Data collection technique(s)	Synthetic Data (Yes/ No)	Software Dependency	Year
[80]	CNN	Precision, Recall, IoU	NO	IFC	SSeg + 3DBRec	RGB cameras, NavVis	YES	NO	2023
[23]	CNN	Precision, Recall, F1-Score	NO	RGB	Localizing rebar + Class + 3DBRec	2D Ground-Penetrating Radar (GPR)	NO	C# plugin for Revit	2021
[81]	CNN	IoU	NO	Revit	SSeg	RGB-D videos (iPad)	NO	NO	2020
[82]	CMX, DeepLabV3	IoU, Recall, Precision	NO	Images, DEM, DSM	SSeg + Class + 3DBRec	Tianjin Dataset training, The Urban 3D Dataset	NO	Dynamo	2024
[83]	CNN	Accuracy	NO	CityGML	SSeg	LiDAR GPS, KITTI Dataset Replicas	YES	NO	2022
[84]	RCNN	–	NO	IFC	SSeg + Class	Drone Photos, Agisoft Metashape	NO	NO	2020
[85]	Mask R-CNN	Overall mAP	NO	IFC, PCD, Images	SSeg + InSeg + Class + 3DBRec	UAV, 360° Cameras, Fisheye Cameras	YES	NO	2024
[86].	CNN	IoU	NO	IFC	SSeg + 3DBRec	Drawing Plans	NO	NO	2022

Table A.3
Summary of studies using Mesh.

Paper	AI Model	Metric	Domain Application	Standard Format	Sc2BIM Phase(s)	Data collection technique(s)	Synthetic Data (Yes/No)	Software Dependency	Year
[24]	CNN	Accuracy, Precision, Recall, F1-Score	NO	IFC	SSeg + InSeg + Class	IFCNet Dataset	YES	NO	2022

Table A.4
Summary of studies with hybrid approaches.

Paper	AI Model	Metric	Domain Application	Standard Format	Sc2BIM Phase(s)	Data collection technique(s)	Synthetic Data (Yes/No)	Software Dependency	Year
[87]	RCNN	Precision, Recall, IoU, Accuracy	Building Interior	PCD	SSeg + Class	MS COCO Dataset	NO	NO	2023
[88]	KPConv	IoU, Accuracy	Cultural Heritage	PCD	Sc + Class + 3DBReco + DTwin	UAV DP	NO	NO	2024
[89]	Random Forest	Precision, Recall, Accuracy, F1-Score	Cultural Heritage	PCD	SSeg + Class+ 3DBRec	TLS, Drones, Photogrammetry	NO	NO	2023
[90]	GNN	Precision, Recall, F1-Score, IoU	Cultural Heritage	OBJ	SSeg	3D Models, TLS, Photogrammetry	YES	NO	2020
[91]	GNN	Accuracy, Precision, Recall, F1-Score, Support, IoU	Cultural Heritage	PCD	SSeg	ArCH Dataset	NO	NO	2020
[92]	CNN	Accuracy	Building Interior	PCD, PLY	SSeg + Class + 3DBRec	Smartphone Photogrammetry, Google Tango	NO	NO	2019
[93]	GNN	F1-Score, Accuracy	Cultural Heritage	PCD	SSeg + Class	ArCH Dataset, Laser Scanner, Photogrammetry	NO	NO	2021
[63]	CNN	Precision, Recall	Building Interior	PCD, Depth Images	SSeg + InSeg + Class + 3DBRec	LiDAR, + RGB Depth Images	NO	Dynamo	2022a
[94]	AlexNet, GoogleNet	mean IoU, Average Class Accuracy, Overall Accuracy, IoU	Building Interior	PCD	SSeg + Class	MINC Dataset, S3DIS Dataset	NO	NO	2024
[39]	PSPNet, HRNet, DeepLabv3, OCRNet, SegFormer	mAcc, mIoU	Infrastructure	PCD	SSeg + Class	STSD Dataset	NO	NO	2024

Data availability

No data was used for the research described in the article.

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