



## **Recognizing as-built building materials: a systematic mapping study**

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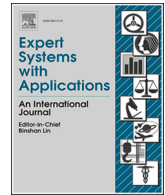
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## Review

## Recognizing as-built building materials: a systematic mapping study

Josie Harrison \*, Yinan Yu , Alexander Hollberg 

Chalmers University of Technology, Gothenburg, Sweden

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## ABSTRACT

Recognising materials in existing, as-built buildings is essential for analysing safety, energy performance, material reclamation, amongst many other use cases. As-built building material recognition is challenging because building materials often mimic others, and controlled laboratory conditions are not practical. This systematic mapping study is the first to focus on as-built building material recognition, consolidating fragmented research across disciplines to reveal data modalities, recognition techniques, research gaps, and key future directions. After reviewing over 20,000 documents, several key insights were identified: 1) many studies lack contextual information necessary to assess generalization; 2) visible light, hyperspectral, infrared, radiowave, tactile, audio, electric field, and text are potential data modalities; 3) studies are needed beyond the neighborhood scale; 4) experiments optimized for ease-of-use pair images with foundation models; 5) highly cited experiments use multi-modal data with foundation models. Additionally, a structured overview of public datasets is provided. This study supports researchers by establishing effective and scalable methods for as-built building material recognition applicable in many use cases.

## 1. Introduction

The growing accessibility of artificial intelligence (AI)—driven by reduced costs, easier access to large models, and user-friendly interfaces—has expanded AI's role in everyday life. While large language models (LLMs) excel at processing text, they are limited compared to the vast amount of data humans gather from interactions with the physical world. Most human knowledge, particularly in early life, comes from sensory experiences, not language (Korteling et al., 2021). AI models that rely solely on text miss the opportunity to develop a richer 'world understanding' by incorporating other data modalities. Recognizing this, a new field of interest focused on 'spatially intelligent AI' has recently emerged that can "model the world and reason about" places in 3D space and time (Hello, World Labs, 2024a). As a major component of the physical environment, buildings and the materials from which they are assembled are of growing interest across many academic fields. Studying as-built material recognition (rather than materials in their pre-construction or post-demolition states) is crucial because it captures the actual condition of materials during a building's operational life. Designing recognition systems specifically for as-built conditions ensures reliable performance in real-world settings, avoiding the inaccuracies that arise when models trained on isolated materials are expected to generalize to complex, weathered, and modified building contexts. As-built material recognition underpins a wide range of cross-domain applications, including assessing whether existing building stock requires

intervention (e.g., energy efficiency Xu et al., 2023, hazard detection Bonifazi et al., 2018, climate mitigation Li et al., 2021), enabling intelligent interaction with buildings (e.g., autonomous navigation Bell et al., 2015 and adaptive network sensor communication Kocevskaja et al., 2022), and supporting long-term material management (e.g., cultural heritage preservation and material reclamation Raghu et al., 2023).

Material recognition refers broadly to automated methods to classify, identify, or detect a specific material, which is typically performed through classification or semantic segmentation (see Section 2.4 for an in-depth description). These automated material recognition methods have traditionally used first principles techniques (mathematical models derived from fundamental physical laws rather than empirical data); however, in the past couple of decades, it has become common to use machine learning (ML) techniques (see Section 2.5 for an in-depth description). As-built building material recognition is specific to materials that buildings are constructed from and recognizes the materials in their assembled state, which differs from the recognition that is performed either before the materials are assembled or after deconstruction. Lastly, 'buildings'—in this context—refer to the structures that humans occupy, which differs from the 'built environment' that refers to any man-made structure such as bridges, cemeteries, or levies.

A few key characteristics of as-built building material recognition make the task non-trivial for any agent (human or non-human) to perform recognition. Firstly, many building materials mimic other materials, especially in indoor environments. Take, for example, wood floor-

\* Corresponding author.

E-mail addresses: [josie@chalmers.se](mailto:josie@chalmers.se) (J. Harrison), [yinan@chalmers.se](mailto:yinan@chalmers.se) (Y. Yu), [hollberg@chalmers.se](mailto:hollberg@chalmers.se) (A. Hollberg).<https://doi.org/10.1016/j.eswa.2026.132376>

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ing. Traditional construction practices used solid wood flooring but substitutes such as vinyl or wood composite flooring have become common in recent years to reduce costs and offer increased durability. To accurately recognize this as solid wood (or perhaps the specific type of wood) would require a data modality that goes beyond regular vision perception. Additionally, material recognition methods with superior accuracy, efficiency, and effectiveness have traditionally required destructive testing and controlled laboratory conditions, which would be unfeasible to adapt to a mobile use case. For some use cases, such as heritage conservation, studies that recognize materials with destructive or laboratory techniques are not applicable because it's often not possible to sacrifice a sample of material. Additionally, material recognition methods that work on as-built buildings are more likely to extend to the built environment but not vice versa because buildings are more likely to contain imitating materials. To ensure this systematic mapping study focused on studies that acknowledged the complexity of as-built building material recognition, the scope was narrowed to approaches that leveraged advanced techniques rather than assuming the task was straightforward.

Several academic fields actively study this specific topic of recognizing as-built building materials. There are often specific use cases attached to each academic field; for example, civil engineering discourse is often interested in material reclamation (Raghu et al., 2023; Sun et al., 2024; Zbiral & Nežerka, 2023), while geomatics discourse is often interested in climate resiliency (Ilehag et al., 2019; Wyard et al., 2023; Zahiri et al., 2022). However, academic fields come to develop their own preferred data modalities and methods to perform material recognition, which leaves little opportunity for interdisciplinary research (see Section 4.1 for further discussion on this point). Because of these silos, and to the best of the authors' knowledge, there is currently no overview of the gaps in application, no comprehensive overview of all the methods and data modalities most appropriate for as-built material recognition, and no collection of resources available for experimentation. Academic silos can lead to researchers repeating the same experiments, overlooking promising methods and data modalities, missing opportunities to focus on the most effective approaches, and failing to build upon previous work and public datasets (Camero & Alba, 2019).

Several review articles have previously collected experiments that recognize materials; however, these articles often concentrate on a single data modality and do not specifically address as-built building materials, limiting their applicability to the distinct challenges of real-world building material recognition. To address the fragmentation of research related to building material recognition, a systematic mapping study can offer a more comprehensive view of the topic by encompassing diverse research areas, methodologies, and data modalities across multiple disciplines. Systematic mapping studies originated in medical research as a method to provide a broad overview of research landscapes, identifying trends, gaps, and patterns across diverse studies, offering a more comprehensive understanding than traditional literature reviews (Petersen et al., 2008). While a literature review would typically include a quality filter to exclude low-quality papers, systematic mapping studies allow all primary studies to be included in the final matrix and they often only extract information from the meta-data and abstract of the primary studies. By bringing together disparate research, systematic mapping studies reduce the likelihood of redundant studies by offering a comprehensive overview of existing work. Additionally, they help uncover trends in research focus and methods, enabling researchers to stay informed about emerging practices. These studies can promote interdisciplinary knowledge sharing, fostering collaboration across fields like architecture, computer science, and environmental studies.

In general, this systematic mapping study aims to address the problem of academic silos and provide a guide for readers to understand the broad landscape of research related to recognition of as-built building materials. To achieve this, the study formulates key research questions that explore the relationships between data modalities, recognition methods, contextual factors, and research gaps.

- Context
  - RQ1: Where do silos exist in academic fields studying building material recognition?
  - RQ2: What are the variety of phrases used to describe the task of recognizing building materials?
- Application
  - RQ3: Which building materials have previous studies focused on?
  - RQ4: Which scales have been studied?
- Data
  - RQ5: What are the characteristics of dataset types?
  - RQ6: What public datasets are available?
- Methods
  - RQ7: Which methods offer resources for potential users to implement them effectively in their specific use case?
  - RQ8: Which methods have the highest influence in academic literature, as evidenced by citation frequency?
  - RQ9: What are the emerging methods for as-built building material recognition?

Building on these research questions, this study presents several contributions that enhance the understanding of as-built building material recognition, offering insights into data modalities, recognition methods, and existing research gaps:

- First systematic mapping study focusing on the recognition of as-built building materials
- Consolidation of data modalities collected with mobile hardware appropriate for recognizing as-built building materials
- Identification of future areas of studies in terms of specific materials, geographic range and scale, and public datasets
- Identification of current research tendencies and emerging practices of data modalities, data formats, model types, and task categories
- Consolidation of public datasets and key phrases specific to the recognition of building materials

This study supports readers new to the topic of building material recognition that have ambitions to avoid redundant primary research, decide on which public datasets to leverage, perform an experiment using methods that have a high amount of support, and choose gaps in the literature that align with their research interest. Researchers both new and familiar with the topic will find value in the consolidation of all data modalities applicable to building material recognition, a collection of public datasets and search phrases, and the observation of recent trends in methods.

The remainder of this paper is organized as follows: Section 2 provides background on prior review articles on material recognition and introduces the conceptual framework used in this study, including the categorization of recognition elements such as building layers, data modalities, task types, and model types. Section 3 describes the review framework. Section 4 presents the results of the study, following the research questions introduced earlier and organized by context, application, and methods. Section 5 discusses the interpretation of these findings, identifying gaps in the existing literature and synthesizing guidelines for method selection. Finally, Section 6 concludes by summarizing the key contributions of the study and outlining promising directions for future research in as-built building material recognition.

## 2. Background

### 2.1. Previous review articles

Several prior review articles have explored the task of recognizing as-built building materials; however, these efforts tend to focus on only one dimension of the problem (such as building materials, recognition methods, or data modalities) without consolidating all three. Among reviews that address building materials, the scope is typically restricted to a single sensing modality. For example, Alaloul et al. (2021) conducted

a short structured review of ML material classification for construction monitoring, but their focus was limited to pre-as-built materials and relied solely on image and point cloud data. Similarly, Balogun et al. (2024) presented a systematic review of AI applications for building deconstruction, including a subsection on material identification; however, this work was likewise limited to image and LiDAR data.

Beyond building-specific reviews, several articles have examined single modality material recognition methods without targeting building materials. Zocco et al. (2022) reviewed computer vision approaches for material stock databases in support of the circular economy; however, this material recognition encompassed all potential waste material, not specifically building waste. Tremeau et al. (2020) provided a comprehensive overview of image-based deep learning for material recognition and highlighted important distinctions between laboratory datasets and “in-the-wild” datasets; nevertheless, the review did not address the unique constraints of the built environment.

In parallel, other reviews have focused on non-visual sensing modalities, again without a building-specific lens. Ho (2018) surveyed the physical, perceptual, and cognitive foundations of thermal-based material recognition, with applications spanning haptic and tactile sensing, but did not consider building materials explicitly. Lutz et al. (2021) offered the broadest coverage of sensing modalities among the reviewed literature (including surface images, force and torque, vibration, tactile, multispectral, fluorescence, electric impedance, and temperature data) yet similarly stopped short of addressing as-built building materials as a distinct category.

Taken together, existing review articles are fragmented across application domains, recognition methods, and data modalities, with most studies concentrating on a single modality. This fragmentation limits their relevance for the unique challenges of recognizing building materials in real-world, operational environments.

## 2.2. Building layers

A key aspect of the systematic mapping study involves fitting data from the selected articles into predefined frameworks, enabling a structured analysis. Building layers were categorized using the Shearing Layers of Change (Brand, 1994) framework because of its straightforward breakdown of the distinct systems of a building, and are subsequently referred to as ‘building layers’. Originally developed by building material reclamation researchers, Shearing Layers of Change stipulates the site (soil type, pavers), the structure (beams, columns), the skin (cladding, gutter systems), the services (plumbing, electrical wiring), the space plan (drywall, flooring), and the stuff (furniture, appliances) (Wöhler et al., 2024). For the purposes of this study, the ‘site’ and ‘stuff’ layers were excluded. Utilizing the Shearing Layers of Change framework provided a clear structure for analyzing the topic in relation to the various layers of buildings.

## 2.3. An overview of data modalities for recognizing building materials

The built environment continuously emits and reflects a wide range of signals that can be leveraged for building material recognition, and a central focus of this study was to gather and organize evidence on the data modalities most indicative of as-built materials. This emphasis is important because material recognition performance is strongly influenced by how well a given modality captures the underlying physical properties of a material. In this section, each data modality is therefore described in terms of the physical principles it measures, typical sensing configurations, key strengths and limitations, and its suitability for different recognition tasks and building contexts. The following subsections provide a theoretical overview of these modalities, establishing the foundation for the later analysis of trends, gaps, and methodological guidelines across modalities.

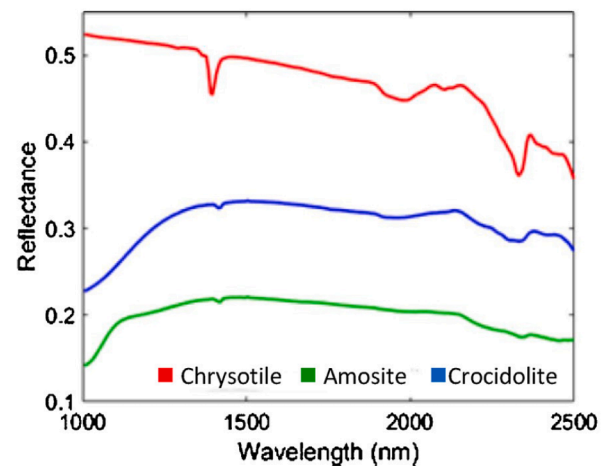


Fig. 1. Example of infrared data from Bonifazi et al. (2018) showing three types of asbestos materials.

### 2.3.1. Visible light

Visible light data is mostly captured in a pixel format using RGB channels, though alternatives like laser-reflected signals have also been explored (Olgun & Turkoglu, 2022). In the electromagnetic spectrum, visible light wavelengths range from 380 to 700 nanometers (Aeronautics, 2010). This data modality typically includes standard images of components made from specific materials, but the content can vary widely, ranging from speckle patterns of lasers (Salem et al., 2023) to light-fields (Wang et al., 2016) or linear-polarization images taken at different angles (Mei et al., 2022). However, for most of the studies, it is often unclear whether annotations in these datasets are based on the visual appearance of the material or the material composition verified by the manufacturers. Visible light data is highly sensitive to environmental conditions, such as lighting and weather, which can significantly influence the predictions. Additionally, geometry plays a role in recognition, leading to the terminology “stuff” (background materials) and “things” (discrete objects), which is a common distinction in computer science studies (Caesar et al., 2018).

### 2.3.2. Hyperspectral

Hyperspectral data comes formatted as a hypercube, similar to an image but with far more channels than RGB, capturing a broader range of the electromagnetic spectrum. In the electromagnetic spectrum, it’s possible for hyperspectral imagery wavelengths to range from 0.4 to 1000  $\mu\text{m}$  (Aeronautics, 2010). While it could technically be grouped with infrared data, hyperspectral imaging is typically considered a distinct and highly specialized field, particularly well-developed in geomatics and geography. The data is typically captured with specialized hyperspectral cameras (Al-Khafaji et al., 2022; Habili et al., 2023; Zahiri et al., 2022) that are often not consumer-ready products. This data modality excels in natural lighting conditions and can be captured from a distance, making it highly versatile for remote sensing applications. However, hyperspectral data is sensitive to artificial lighting and environmental factors like dampness, which can affect its accuracy.

### 2.3.3. Infrared

Infrared data can be captured in either waveform (Fig. 1) or hypercube format, focusing on the part of the electromagnetic spectrum just beyond the visible light range. In the electromagnetic spectrum, the infrared wavelength range is 0.4 to 1000  $\mu\text{m}$  (Aeronautics, 2010). It is collected using spectrometers, which are often designed for industrial applications (Bonifazi et al., 2018; Cho et al., 2018; Maristany et al., 1993), though some consumer-ready products are making this device more accessible, such as the LinkSquare spectrometer and several products from Teledyne FLIR. Similar to hyperspectral data, infrared data

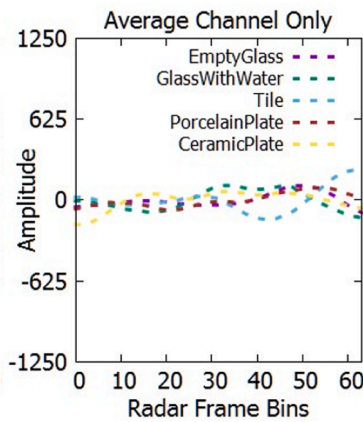


Fig. 2. Example of radiowave data from Yeo et al. (2016) showing five different types of objects.

excels in natural lighting conditions; however, its performance tends to decrease under artificial lighting or when environmental irregularities, such as dampness, are present.

#### 2.3.4. Radiowave

Radiowave data is captured in waveform format (Fig. 2) and occupies the higher end of the electromagnetic spectrum, just beyond the infrared range at frequencies of 3 GHz to 30 kHz (Aeronautics, 2010). This data is typically gathered using radar devices, which have a wide range of applications. For example, Google's Pixel 4 smartphone used "Soli" hardware for gesture recognition (Yeo et al., 2016), and consumer-grade radar devices, such as Walabot, are now available as stud detectors (Agresti & Milani, 2019). Some benefits of radiowave data are its ability to penetrate through non-metallic materials, its non-invasiveness, and its invariance to environmental conditions that affect other data modalities, such as poor lighting or weather. It also offers an extended range, though higher-end hardware is required for longer distances. Despite these advantages, radiowave data can be sensitive to interference, such as disruptions caused by a hand holding the device during measurement.

#### 2.3.5. Tactile

Tactile data, formatted as a waveform, is commonly used in robotics applications where the goal is to enable robots to autonomously navigate spaces or grasp objects. This data is captured using a bionic finger (Song et al., 2012) or similar device that applies a specific amount of force to a material and measures the resistance. There was once a consumer-grade device called BioTac available; however, there are currently no consumer-grade devices available for this type of data collection. A key limitation is that tactile data requires direct contact with the material to make a prediction, but it has the advantage of being unaffected by environmental conditions or interference, making it a reliable method.

#### 2.3.6. Audio

Audio data is formatted as a waveform (Fig. 3) and can capture either the reflectance of sound off a material (Tan et al., 2011) or the reverberation of sound through a material resulting from an impact (Kannan et al., 2020). However, the replicability of using audio for as-built building material recognition is questionable; while audio material classification is feasible through reverberating the entire component, achieving this for larger structures, such as entire walls, requires very strong reverberation (Shanbhag et al., 2023). Additionally, when conducted within a room, isolating the desired audio signal from reflections produced by other objects becomes crucial for accurate analysis. These challenges highlight the complexities involved in utilizing audio for effective material recognition in real-world settings.

#### 2.3.7. Electric field

Electric field data is recorded in waveform format and measures capacitance response, which can be utilized for material recognition by assessing how various materials influence the capacitance of a sensor when subjected to an applied electric field. This emerging area of study (Niu et al., 2024) is intriguing due to its potential applications, but it is typically confined to laboratory conditions and small components.

#### 2.3.8. Text

Text data, such as written descriptions of a building's geometry and cadastral (zoning and property) information, can be a valuable resource for as-built building material recognition. The logic behind this is that certain materials might be used in specific regions or time periods, allowing for inferences about the building's construction (Zhou & Chang, 2021). However, these inferences are highly dependent on local building practices, which can vary widely over time and across regions, making text-based predictions less reliable in areas where diverse building methods are prevalent. Additionally, cities structure their cadastral data based on local regulations, priorities, and historical factors. There is typically little pressure to standardize these data structures across municipalities, making data integration and comparison challenging. Despite these challenges, text data offers a non-invasive approach that can complement other recognition methods by providing context for material identification.

### 2.4. Categorization of tasks

The articles included in this study primarily employed one of two tasks for building material recognition: classification and semantic segmentation. Classification involves assigning a (single or multiple) label to an entire sample, identifying the material as a type, such as wood or metal. This task type can be used for any data format. Semantic segmentation—on the other hand—can only be applied to image or hypercube data and involves labeling each pixel or mask within an image with a material category. This allows for a more granular understanding of the material composition in complex scenes. Both tasks serve different purposes but are essential for advancing as-built building material recognition.

### 2.5. An overview of models

All the articles included in this study used some type of model to extract meaningful information from data; these models were broadly categorized into either "first principles" or "machine learning" models. First principles models are based on fundamental physical laws and theories, directly applying knowledge of material properties to predict labels. Since it requires a deep understanding of the material properties, this model type is often not as user-friendly as ML models. In contrast, ML models rely on data-driven approaches with an emphasis on the predictive power of a model. These ML models were further divided into sub-categories: "traditional machine learning", "deep learning", and "foundation" models. Traditional ML models use hand-crafted features and simpler algorithms, while deep learning models automatically learn features from data using complex neural networks. Foundation models, a more recent development, are similar to deep learning models but are pre-trained on large datasets and can be fine-tuned on feature sets tailored to a use case, offering flexibility across a wide range of applications. While ML models are adaptive and scalable, first principles models are not data-hungry and are typically not as computationally expensive as ML models.

## 3. Search method

The search method generally followed the methodological framework for systematic mapping studies as suggested by Petersen et al. (2015), which recommends to

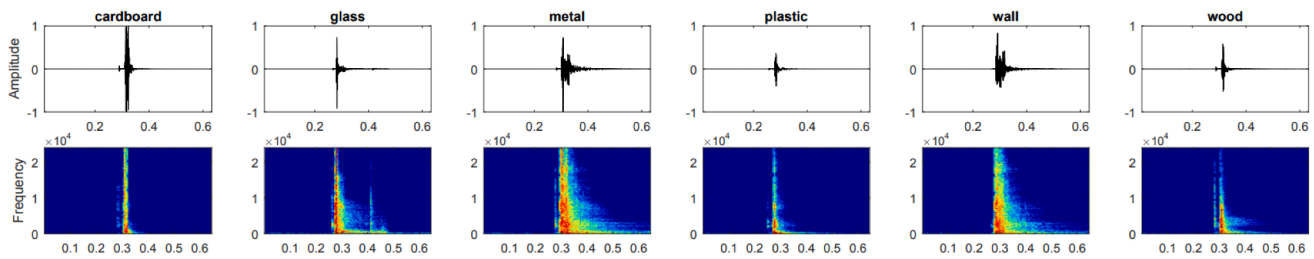


Fig. 3. Example of audio data from Kannan et al. (2020) showing the audio recording (top) for five materials and their Fourier transform representation (bottom).

- identify the research question,
- search for relevant studies,
- select studies,
- extract the data, and
- analyze and classify the results.

This guideline was tailored specifically to software engineering because of the field’s rapid technological evolution, diverse methodologies, and complex subdomains, which requires a structured approach to categorize, analyze, and map its vast and varied research landscape. Since material recognition often uses computer science techniques and has similar characteristics as software engineering, Petersen’s methodology was appropriate for this study.

After identifying the research questions, PICO (population, intervention, comparison, and outcomes) was used to develop keywords and formulate search strings from the research questions. This led to the search query located in Appendix A. This search query proved to be difficult because the word ‘material’ can have many different meanings and is often used as a synonym for ‘artifact’; for example, ‘learning material’, ‘genetic material’, or ‘materials and methods’. Therefore, it was necessary to include many negations in the search query, which was calibrated against 10 key articles found previously. If a negation was included that resulted in missing several of the key articles then that negation was taken out of the query. This process was repeated several times until a reasonably sized search result was returned with 7/10 of the key articles included.

This study identified and retrieved empirical articles from the SCOPUS and Web of Science databases in December 2026. A filter limited the results to English-language studies published between 2014 and May 2025 because earlier investigations showed that activity on this topic started to gain traction around 10 years ago, and ML methods used prior to 2014 are likely to be outdated. Before data was extracted from the articles, a list of exclusion and inclusion criteria was applied to the search results. The following criteria was used:

- Inclusion
  - Any use case where as-built recognition of building materials is desired, or a study with data collected from ‘mobile’ devices. Either the study clearly focuses on as-built material recognition, or it uses mobile sensors that can easily capture materials from multiple angles and are therefore relevant to as-built settings. Mobile is defined as a device that:
    - \* Has its own power source, or can draw power from a smartphone or laptop.
    - \* Does not require the user or the device to hold, grip, or grasp the object being studied.
    - \* Can record data from multiple angles.
    - \* Works as a single unit, without needing a separate ‘sender’ and ‘receiver’ device.
  - Qualitative or quantitative evaluation.
  - Description of the dataset used for the model that includes labels of materials commonly found in buildings.
- Exclusion
  - Recognition of materials that occurred pre-construction, after demolition, or materials in a ‘container’.

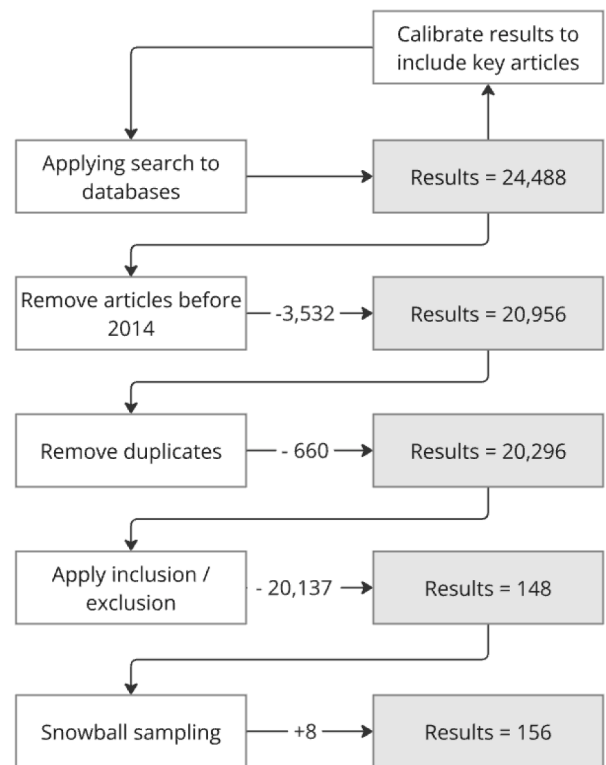


Fig. 4. PRISMA diagram of number of results from each step in systematic mapping study process.

- Detection of quantities of materials.
- Literature reviews, systematic mapping studies, and surveys.
- Image datasets that focus on materials unrelated to buildings (e.g., everyday items, natural scenery, animals, or other “things” and “stuff”).
- Studies that include only a single building-relevant material class. Recognition in such cases could likely be driven by irrelevant characteristics rather than by generalizable differences between multiple building materials.
- Studies that are based on satellite datasets. The resolution of satellite datasets is typically around 1.3m/pixel, which has a high chance of aggregating multiple building (and non-building) materials, making its relevance to detailed material recognition limited.

The PRISMA diagram shown in Fig. 4 outlines the result size after each step of the search method. From the remaining 156 articles, data was extracted following a template designed to answer the research questions established at the beginning of the review process. This template’s fields included: paper title, link to paper, number of citations, year published, country studied, phrase used to describe method, authors, use case, field of study of first author, dataset source, scale of

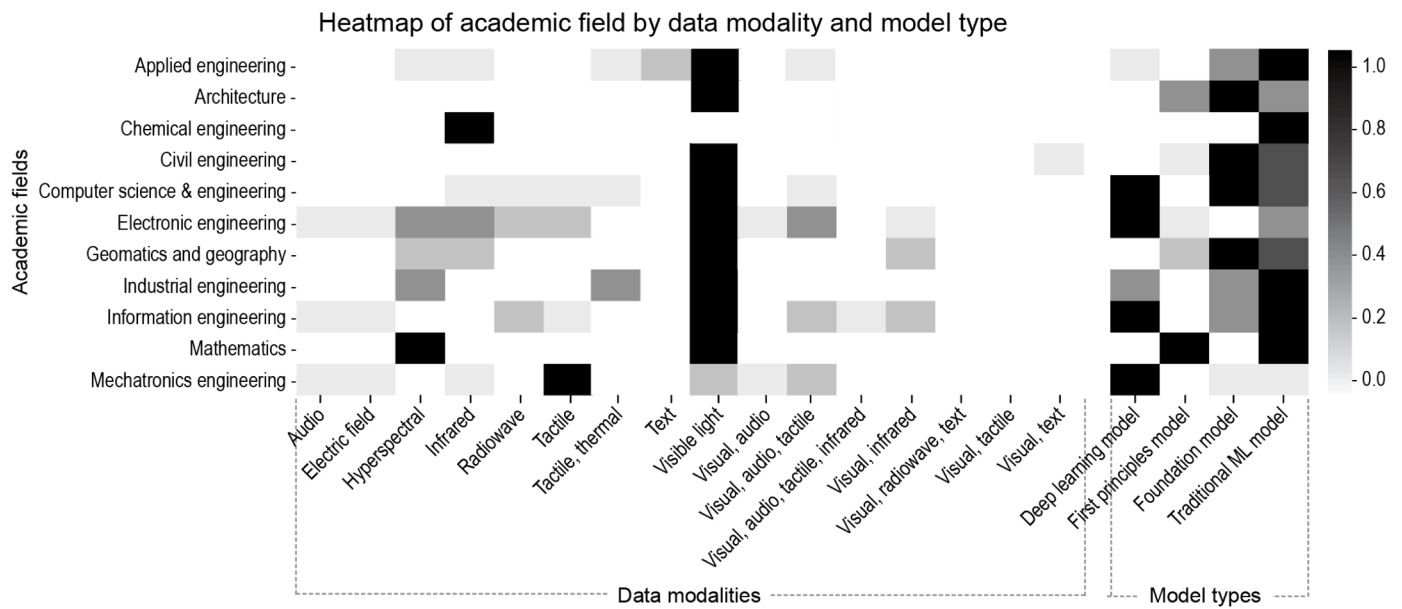


Fig. 5. RQ1 heatmap showing academic fields on the y-axis with data modalities and model types on the x-axis.

use case, building type, building layer, data format, data modality, data description, programming language, labels specific to building materials, task category, best downstream model, general model category, computer hardware, evaluation metrics, hardware for data collection, publication name, and public datasets used or referenced. The full data extraction is available at [Zenodo, DOI:10.5281/zenodo.18141935](https://zenodo.org/doi/10.5281/zenodo.18141935). After the data was extracted, the matrix was numerically analyzed and converted into data visualizations.

#### 4. Results

##### 4.1. Context | RQ1: Where do silos exist in academic fields studying building material recognition?

The academic fields were recorded for each distinct author in the study and categorized according to Wikipedia’s entry for engineering branches ([List of engineering branches, 2024b](#)), which has the most universally applicable grouping of academic engineering disciplines. This resulted in the heatmap graph shown in Fig. 5 that plots the number of studies from each first author’s academic field that has studied a specific data modality and a specific model type. The heatmaps were normalized using min-max normalization across the x-axis to better demonstrate the difference in the number of studies within a field. A value of 1.0 means that is the highest count of studies for that particular academic field. Distinct patterns emerged for certain data modalities, with hyperspectral data predominately studied in mathematics, infrared data explored mainly in chemical engineering, tactile studied in mechatronics engineering, and visible light data receiving attention from applied engineering, architecture, civil engineering, computer science & engineering, electronic engineering, geomatics & geography, industrial engineering, information engineering, and mathematics. Notably, electronic engineering has the most spread between all the possible data modalities, and mathematics is evenly split between hyperspectral and visible light.

A similar trend was observed for model types across different fields. Deep learning models were commonly used in computer science & engineering, electronic, information, and mechatronics engineering, whereas traditional ML models were prevalent in applied engineering, chemical, industrial, information engineering, and mathematics. Foundation models were commonly used in architecture, civil engineering, computer science & engineering, and geomatics & geography. Computer

science did not show a preference for a specific model type but was instead spread out between three different types of models.

The evidence of silos in Fig. 5 justifies the need for a systematic mapping study, helps uncover redundant efforts, facilitates knowledge sharing of diverse methodologies and insights across disciplines, encourages collaboration, and can bring self-awareness to academic fields to open up the possibility of experimenting with a wider variety of methods.

##### 4.2. Context | RQ2: What are the variety of phrases used to describe the task of recognizing building materials?

Table 1 provides a collection of key phrases used in the titles or abstracts of articles to describe the objective of material recognition. The variety of key phrases used in material recognition studies arise largely due to the existence of disciplinary silos between different academic departments, as observed in section 4.1. Each field—whether it be civil engineering, computer science, or mechatronics engineering—approaches the problem of material recognition from a unique perspective, using discipline-specific terminology. For example, within computer science literature, there is a clear distinction between “things” and “stuff” in material and object recognition ([Bell et al., 2015](#)). “Things” refer to discrete, countable objects with well-defined boundaries, such as chairs, buildings, or beams. These objects can be individually identified and separated from their surroundings. In contrast, “stuff” refers to amorphous, continuous regions of materials without clear boundaries, such as facades, floors, walls, or ceilings. These materials are spread across an area and do not have specific instances that can be counted or isolated, requiring different recognition techniques like semantic segmentation. Within studies utilizing hyperspectral data, it seems to be common to refer to semantic segmentation as ‘pixel-wise classification’, which is possibly why ‘classification’ is used more than one would expect to refer to segmentation tasks. Another possible reason for the variation in phrasing is that researchers often simply do not explore all possible phrasing for a task and instead rely on the established vocabulary common to their field. The result of these silos is a fragmented body of literature where comparable studies may be overlooked because they use different terminology, underscoring the need for more interdisciplinary collaboration to unify and streamline research efforts.

This table can serve as a resource for optimizing search strategies in literature reviews, helping researchers locate relevant studies more

**Table 1**  
RQ2 table showing the variety of phrases used for both classification and semantic segmentation tasks. Note: citations limited to maximum of three.

Task category	Task wording	Phrases used to describe objective in title or abstract
Classification	Classification	'classification of building structures' (Zhou & Chang, 2021; Zhou et al., 2023a), 'classification of different materials' (Shao et al., 2020), 'classification of near infrared spectra' (Belmerhnia et al., 2021), 'classification of roof materials' (Alchapar et al., 2020), 'materials image classification' (Fortuna-Cervantes et al., 2022), 'material and object classification' (Yeo et al., 2016), 'material classification' (Erickson et al., 2020; Ilehag et al., 2019; Weis & Santra, 2019), 'material image classification' (Bunrit et al., 2020), 'texture classification' (Benco et al., 2020; Porebski et al., 2022; Wang et al., 2023)
	Sensing	'hyperspectral remote sensing' (Pandey & Tiwari, 2021), 'tactile sensing' (Ali et al., 2022)
	Prediction	'predicting indoor materials' (Kocevska et al., 2022)
	Recognition	'material recognition' (Alfarrarjeh et al., 2019; Dimitrov & Golparvar-Fard, 2014; Sun & Gu, 2022), 'material type recognition' (Cho et al., 2018), 'recognition of construction and demolition waste materials' (Zbrál & Nežerka, 2023), 'tactile object recognition' (Doherty et al., 2023), 'texture recognition' (Ali et al., 2022), 'wood recognition' (Huang et al., 2021)
	Perception	'material and surface shape perception' (Niu et al., 2024), 'texture perception' (Strese et al., 2017)
	Analysis	'texture analysis' (Peeples et al., 2022)
	Detection	'contrast target detection' (Singh, 2024), 'material detection' (Benco et al., 2020; Bunrit et al., 2020)
	Library	'hyperspectral library' (Lantzanakis et al., 2023)
	Identification	'material identification' (Abriha et al., 2018; Agresti & Milani, 2019; Harrsion et al., 2020)
	Semantic Segmentation	Classification
Detection		'detect specific building characteristics' (Gosling-Goldsmith et al., 2024), 'material detection' (Al-Alimi et al., 2022), 'materials detection' (Bonifazi et al., 2018)
Recognition		'building structural type recognition' (Zhou et al., 2023b), 'material and texture recognition' (Zhang et al., 2017), 'material recognition' (Bell et al., 2015; DeGol et al., 2016; Wang et al., 2016), 'recognition and separation of diverse materials' (Zeljkić et al., 2023)
Perception		'material perception' (Mao et al., 2022)
	Segmentation	'building facade segmentation' (Habibi et al., 2023), 'construction instance segmentation' (Yan et al., 2023b), 'glass segmentation' (Mei et al., 2022), 'material segmentation' (Cai et al., 2024; Heng et al., 2023; Upchurch & Niu, 2022), 'semantic segmentation for material recycling' (Ariram et al., 2021), 'semantic segmentation method on stuff and thing classes' (Caesar et al., 2018), 'semantic segmentation to identify façade materials' (Xu et al., 2023)

efficiently by using the full variety of possible keywords for a specific task. Going back to the PICO method described earlier, the table above could be used to redefine the first two letters: population and intervention. Additionally, it would be strategic to use a proximity operator for the population term since it is not guaranteed that the population and intervention terms appear in a specific order. For example, the search query could be phrased as TITLE-ABS-KEY( ("material\*" OR "surface\*" OR "texture\*" OR "urban" OR "façade") W/4 "segmentation" ). This approach not only streamlines the search process but also enhances the precision of literature reviews by leveraging targeted keywords and search operators to identify studies that are most relevant to the research focus.

4.3. Application | RQ3: Which building materials have previous studies focused on?

The histogram in Fig. 6 plots the number of articles that experimented with a particular building material with the material label on the x-axis and the number of studies on the y-axis; the legend groups each bar according to the building layers. The material labels from the articles were lightly edited by removing component descriptions and converting them into singular form. Since the full list of labels was quite long, the histogram was filtered to only show labels with at least five or more studies. Wood is the predominant material studied with identified building layers split between space plan and skin layers. Besides this, most studies focus on a limited set of materials (wood, metal, stone, brick, glass) and mainly on façades, which may not align with specific use cases, highlighting a gap in research on methods appropriate for diverse materials and building layers.

4.4. Application | RQ4: Which scales have been studied?

Plotting the scale of a study and the data format can show tendencies of scalability and whether the data format influences the scalability. The histogram in Fig. 7 shows the scale of a study on the x-axis and the number of studies on the y-axis while the bars are divided by the data format for each scale. It can be seen that many studies fail to mention a specific location, and there are no studies at the scale of a country. Pixel data can be seen across a range of scales (city, multi-city, and multi-national). Additionally, many studies mentioned that their experiment would have benefited from access to more data (Ariram et al., 2021; Bonifazi et al., 2018; Doherty et al., 2023). Most building material recognition studies overlook mentioning the study's scale, which makes it difficult to assess model generalizability and applicability in real-world scenarios. This is especially true when dealing with complex data modalities like hypercube data or regional variations in material appearance. This result underscores the need for broader, context-aware research.

4.5. Data | RQ5: What are the characteristics of dataset types?

Fig. 8 shows the count of studies focusing on manually collected or public datasets, broken down by data format while Fig. 9 shows the count of public datasets with the data format on the x-axis, broken down by the data modality. When a manually collected dataset is made public as a research outcome of an article, the first instance was classified as manually collected with future studies that reference it marked as utilizing a public dataset. Most studies rely on manually collected datasets. Interestingly, public waveform datasets were cited only four times, despite being the second most common public dataset. This raises ques-

### Histogram of material labels studied by Shearing layer

Shearing layer    ● Not specified    ● Skin    ● Space plan

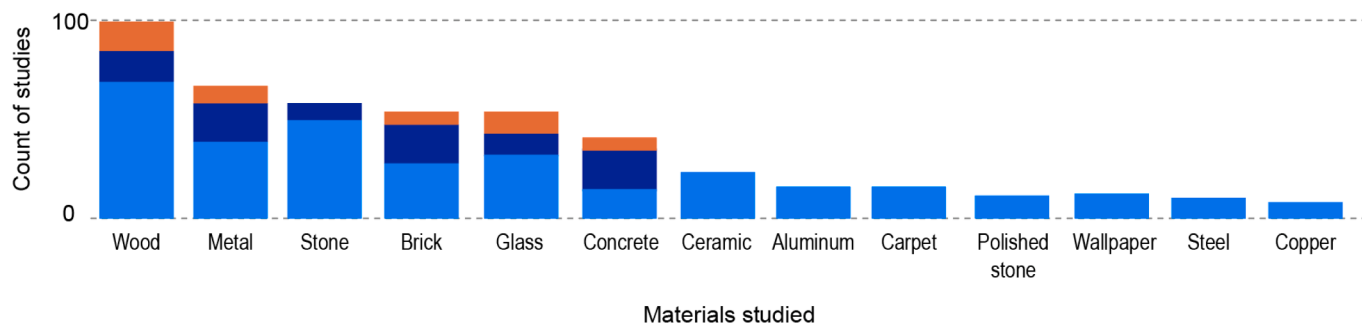


Fig. 6. RQ3 histogram showing the count of material labels studied, broken down by building layer.

### Histogram of study scaled by data format

Data format    ● Hypercube    ● Multi-modal    ● Pixel    ● Tabular    ● Waveform

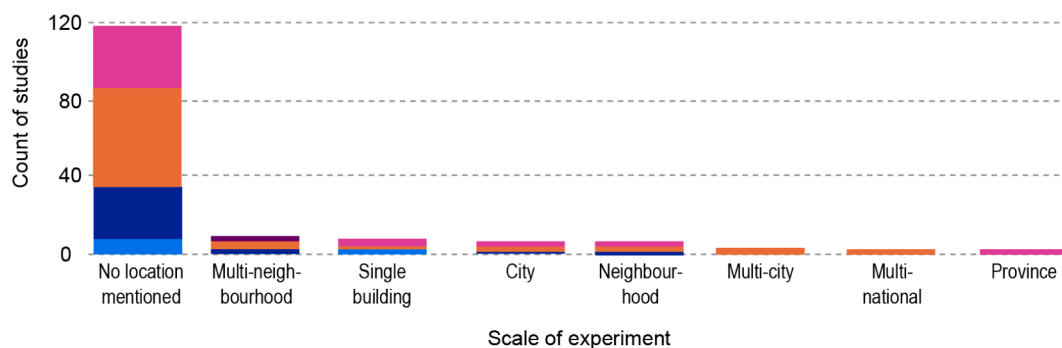


Fig. 7. RQ4 histogram showing the count of scales studied, broken down by data format.

### Histogram of dataset sources studied by data format

Data format    ● Hypercube    ● Multi-modal    ● Pixel    ● Tabular    ● Waveform

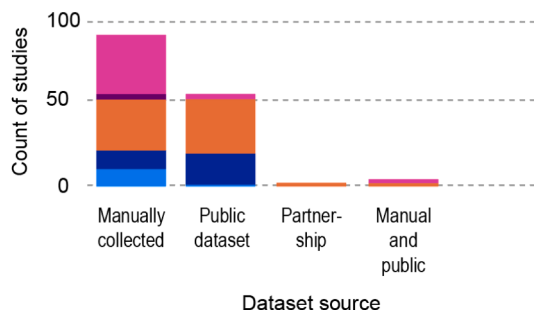


Fig. 8. RQ5 (a) histogram showing the count of dataset sources studied, broken down by data format.

### Histogram of public datasets available by data format

Data modality    ● Hyperspectral    ● Infrared    ● Radiowave    ● Tacile    ● Visible light    ● Visual, audio, tactile    ● Visual, infrared

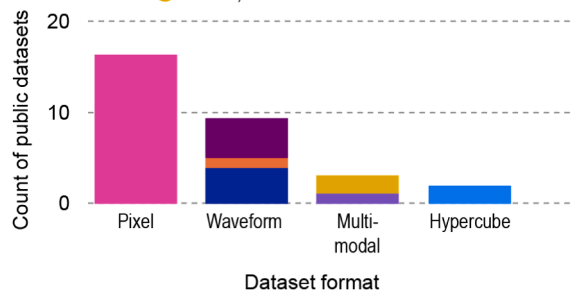


Fig. 9. RQ5 (b) histogram showing the count of public datasets by dataset format, broken down by data modality.

tions about why these datasets are not more frequently referenced and why so many studies prefer to manually collect their own data. Public datasets are essential for ML model development, yet these results show that most building material recognition studies rely on manually collected data, due to existing public datasets not capturing aspects needed for research. Manually collecting custom datasets adds time and complexity to research efforts for a majority of experiments.

#### 4.6. Data | RQ6: What public datasets are available?

Aggregating diverse public material recognition datasets offers researchers a more extensive and varied foundation for research and experimentation. Tables 2-3 identifies key characteristics for each dataset: the data modality, the size of the dataset, and the specific material label; this information is also offered online on [Zenodo, DOI:10.5281/zenodo.18141924](https://zenodo.org/doi/10.5281/zenodo.18141924). The size varies for each data modality; for example, infrared datasets range from 26 to 181 spectra with a mean of 80, while visible light datasets range from 32 to 164,000 images with a mean of 31,604. This collection of public datasets enables quick identification

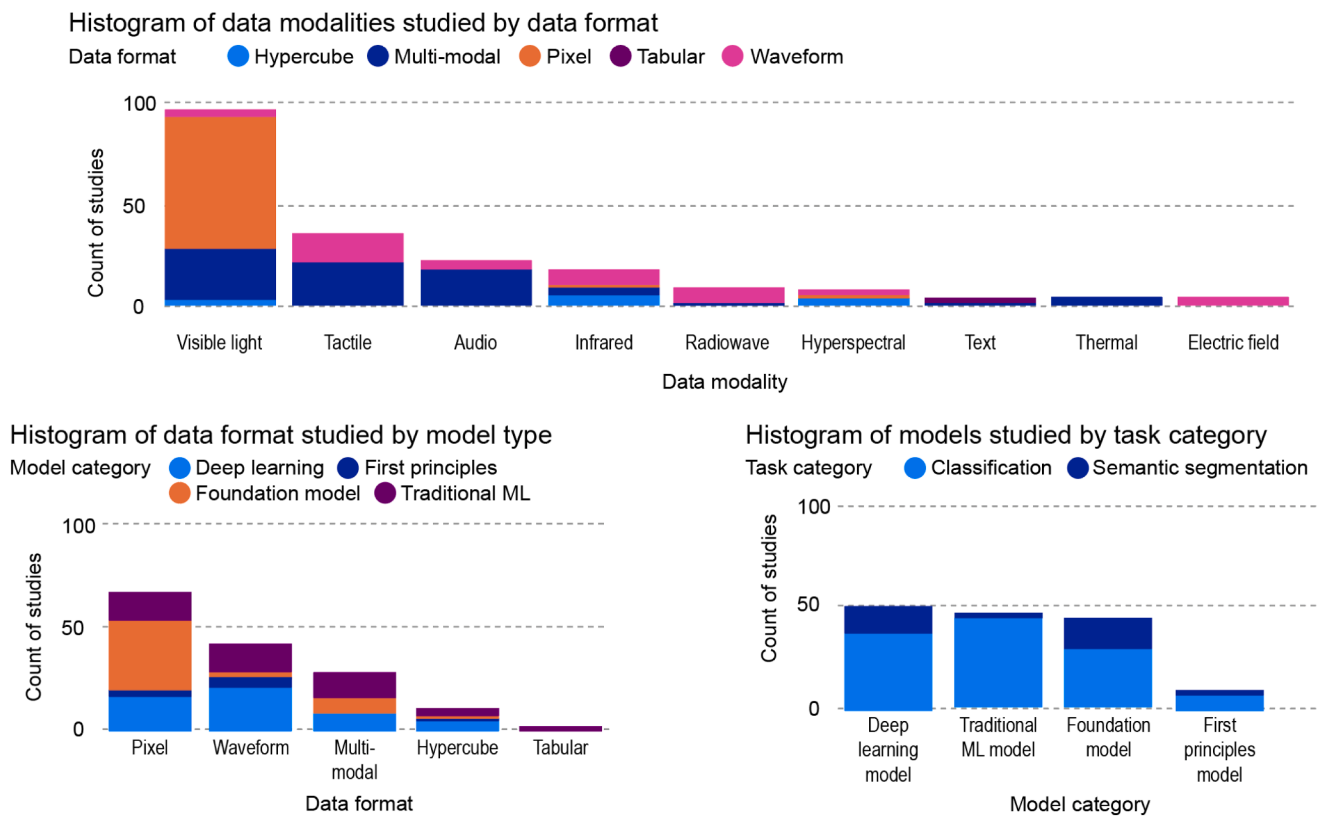


Fig. 10. RQ7 histogram showing the count of data modalities, data formats, and model categories studied.

of datasets that meet specific criteria, such as those focusing on certain material types or those offering particular data modalities. The inclusion of size helps the reader gauge whether a dataset is sufficiently large for training ML models. By organizing this information in a structured format, readers can easily compare datasets and select the most appropriate resource for their research objectives.

4.7. Methods | RQ7: Which methods offer resources for potential users to implement them effectively in their specific use case?

Fig. 10 identify the data modalities, data formats, model categories, and task categories that have high support for usage. This assumes that a specific method will have more documentation if many studies have implemented the method. A high amount of documentation ensures that many tutorials, forum discussions, and articles would likely exist to provide guidance for researchers interested in using the methods. The graphs in Fig. 10 indicate an experiment using visible light in pixel format trained with a foundation model for classification is likely to have a higher amount of documentation available. Similarly, it would likely be difficult to find resources for certain combinations, such as waveform, hypercube, or tabular data with foundation models. It should be noted that these results are in the context of as-built building material recognition. It is generally known that there are many resources available for deep learning models trained on pixel data; however, foundation models are likely to have more up-to-date resources for this particular task.

4.8. Methods | RQ8: Which methods have the highest influence in academic literature, as evidenced by citation frequency?

The previous question identified methods with the highest support; however, this does not indicate whether the methods have the highest impact. The citation metric for the Fig. 11 was calculated by normalizing the total citations to the number of citations per year and aggregating

each bar category to the median value. Additionally, articles from 2025 were excluded since they have not had enough time to accumulate citations. The histograms are not intended to claim that certain methods are correlated with higher citations since the sample size was not large enough for this; instead, it is solely presented to provide some indication of the impact the method had on academic discourse. While extracting insights from citation counts can be criticized—such as citations not necessarily reflecting a specific aspect of a paper or differences in citation patterns across academic fields—it still serves as a useful metric. Citations normalized by year provides a potential indicator of a paper’s impact on academic discourse, despite variations in how quickly or frequently certain fields accrue citations.

A histogram comparing the median citations per year against the data format, model type, and task category can indicate the impact that methods have on the academic community, shown in Fig. 11. The numbers above the bars indicate the number of studies for each category. Notably, studies that incorporate multiple modalities tend to receive the highest citations. In terms of model category, foundation models appear to be cited more frequently than the other three types. Additionally, semantic segmentation studies generally receive more citations than classification studies. These findings contrast with the earlier analysis of commonly used methods, which is expected—highly cited methods are not necessarily the most frequently employed.

4.9. Methods | RQ9: What are the emerging methods for as-built building material recognition?

RQ8 and 9 observed the amount of current support and impact of particular methods; however, this is unlikely to be static and it is equally important to observe the emerging trends to capture which methods could have more support and impact in the near future. Fig. 12 plots the number of studies along the y-axis with the year published on the x-axis; each quadrant splits the studies up into the data format type and the

**Table 2**

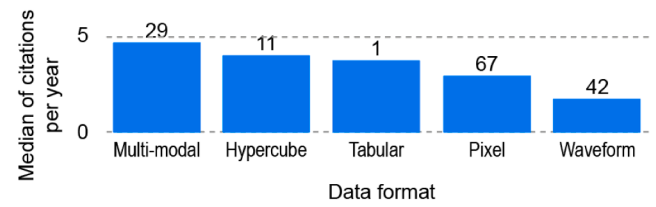
RQ6 table showing a collection of public datasets related to building material recognition Note: citations limited to maximum of ten.

Dataset name	Modality	Size	Classes related to building materials	Link to homepage	Cited by
LIB-HSI	Hyperspectral	513 images	“glass window”, “brick”, “concrete”, “blocks”, “metal”, “door”, “timber”	<a href="https://data.csiro.au/collection/csiro:55630">https://data.csiro.au/collection/csiro:55630</a>	(Habibi et al., 2023)
DeepTherm	Infrared	41,444 images	“MDF”, “MFC table tops”, “concrete wall”, “wood surface”, “brick wall”, “metal shutter door”, “marble tiles”	<a href="https://youngjuncho.com/datasets/">https://youngjuncho.com/datasets/</a>	(Cho et al., 2018)
ECOSTRESS (formerly ASTER)	Infrared		“white marble”, “red brick”, “oxidized galvanized steel metal”, “black tar paper”, “asphalt shingle”, “copper”, “weathered red brick”, “reddish asphalt shingle”, “concrete”, “terra cotta”, “pine wood”, “glass”, “red smooth-faced brick”, “aluminum”, “slate stone shingle”	<a href="https://speclib.jpl.nasa.gov/library">https://speclib.jpl.nasa.gov/library</a>	(De Silva et al., 2013; Heiden et al., 2007; Ilehag et al., 2019; Lantzanakis et al., 2023; Wyard et al., 2023)
KLUM	Infrared	181 spectra	“brick”, “mortar”, “ceramic”, “concrete”, “granite”, “limestone”, “metal”, “plaster”, “sandstone”, “wood”	<a href="https://github.com/rebeccailehag/KLUM_library">https://github.com/rebeccailehag/KLUM_library</a>	(Lantzanakis et al., 2023; Wyard et al., 2023)
LUMA-SLUM	Infrared	74 spectra	“quartzite”, “stone”, “granite”, “cement/concrete”, “brick”, “roofing shingle”, “roofing tile”, “metal”, “PVC”	<a href="https://urban-meteorology-reading.github.io/SLUM.html">https://urban-meteorology-reading.github.io/SLUM.html</a>	(Ilehag et al., 2019; Wyard et al., 2023)
WaRM	Infrared	26 spectra	“metal”, “slate”, “membrane”, “tile”, “PVC”, “corrugated cement sheet”, “solar panel”	<a href="https://zenodo.org/records/7414740">https://zenodo.org/records/7414740</a>	(Wyard et al., 2023)
Zambrano-Prado et al.	Infrared	39 spectra	“ceramic”, “concrete”, “cement”, “metal”, “stone”, “wood”	<a href="https://www.tandfonline.com/doi/figure/10.1080/01431161.2020.1798548?scroll=top&amp;needAccess=true">https://www.tandfonline.com/doi/figure/10.1080/01431161.2020.1798548?scroll=top&amp;needAccess=true</a>	(Wyard et al., 2023)
Walabot	Radiowave	100 samples	“polystyrene”, “cement blocks”, “leccese stone”, “stab. cement”, “wood1”, “wood2”, “glass”	<a href="https://lstm.dei.unipd.it/paper_data/Walabot_material_classification/#dat">https://lstm.dei.unipd.it/paper_data/Walabot_material_classification/#dat</a>	(Agresti & Milani, 2019)
HapMat	Tactile	30000 samples	“wood”, “metal”	<a href="https://github.com/henryyantq/haptic-kinematics">https://github.com/henryyantq/haptic-kinematics</a>	(Yan et al., 2023a)
4D Light Field	Visible light	100 images	“glass”, “metal”, “stone”, “wood”	<a href="https://cseweb.ucsd.edu/~sim\$viscomp/projects/LF/">https://cseweb.ucsd.edu/~sim\$viscomp/projects/LF/</a>	(Zhang et al., 2017)
COCO-Stuff	Visible light	164,000 images	“ceiling-tile”, “floor-marble”, “floor-stone”, “floor-tile”, “floor-wood”, “wall-brick”, “wall-concrete”, “wall-panel”, “wall-stone”, “wall-tile”, “wall-wood”	<a href="https://github.com/nightrome/cocostuff">https://github.com/nightrome/cocostuff</a>	(Schwartz & Nishino, 2020; Yan et al., 2023b)
CUReT	Visible light	5,612 images	“frosted glass”, “plaster”, “roof shingle”, “rough tile”, “quarry tile”, “insulation”, “slate”, “limestone”, “brick”, “concrete”, “stones”, “wood”	<a href="https://www.cs.columbia.edu/CAVE/software/curet/">https://www.cs.columbia.edu/CAVE/software/curet/</a>	(Bell et al., 2015; DeGol et al., 2016; Leung & Malik, 2001; Liu et al., 2011; Varma & Zisserman, 2002; Xu et al., 2023)
Flickr Material	Visible light	5,612 images	“stone”, “glass”, “wood”, “metal”	<a href="https://people.csail.mit.edu/lavanya/fmd.html">https://people.csail.mit.edu/lavanya/fmd.html</a> (Alvarez-Gonzalez et al., 2021; Bell et al., 2015; DeGol et al., 2016; Fortuna-Cervantes et al., 2022; Mao et al., 2022; Schwartz & Nishino, 2020; Wang et al., 2023; Zhang et al., 2017)	
KITTI	Visible light	203 images	“concrete”, “metal”, “glass”, “plaster”, “ceramic”, “brick”, “wood”	<a href="https://github.com/kyotovision-public/RGB-Road-Scene-Material-Segmentation">https://github.com/kyotovision-public/RGB-Road-Scene-Material-Segmentation</a>	(Caesar et al., 2018; Cai et al., 2024)
Local Material	Visible light	5,845 images	“ceramic”, “concrete”, “glass”, “metal”, “plaster”, “stone”, “wood”	<a href="https://vision.ist.i.kyoto-u.ac.jp/codeanddata/localmatdb/">https://vision.ist.i.kyoto-u.ac.jp/codeanddata/localmatdb/</a>	(Heng et al., 2023)
MINC	Visible light	105,076 images	“carpet”, “polished stone”, “brick”, “wallpaper”, “tile”, “ceramic”, “stone”, “wood”, “glass”, “metal”, “mirror”	<a href="http://opensurfaces.cs.cornell.edu">http://opensurfaces.cs.cornell.edu</a>	(Armeni et al., 2019; DeGol et al., 2016; Heng et al., 2023; Mao et al., 2022; Peeples et al., 2022; Upchurch & Niu, 2022; Xu et al., 2023; Zhang et al., 2017; Zhou et al., 2022)
Sensicut	Visible light	38,232 images	“natural hardwood”, “engineered wood”, “bamboo”, “laminated MDF”, “styrene”, “aluminum”, “stainless steel”	<a href="https://hcie.csail.mit.edu/research/sensicut/sensicut.html">https://hcie.csail.mit.edu/research/sensicut/sensicut.html</a>	(Salem et al., 2023)

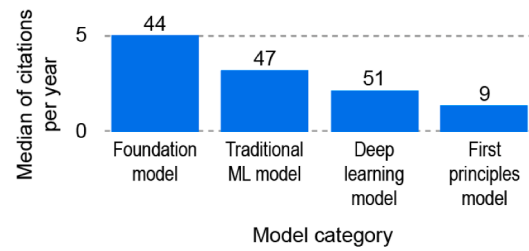
**Table 3**  
RQ6 table continued showing a collection of public datasets related to building material recognition Note: citations limited to maximum of ten.

Dataset name	Modality	Size	Classes related to building materials	Link to homepage	Cited by
URCR	Visible light	971 images	"brick", "stucco", "rustication", "siding", "wood", "metal"	<a href="https://github.com/raghudeepika/urban-resource-cadastr-repository">https://github.com/raghudeepika/urban-resource-cadastr-repository</a>	(Harrison et al., 2024)
Vistex (MIT)	Visible light	32 images	"brick", "metal", "stone", "tile", "wood"	<a href="https://vistex.media.mit.edu/vistexmod/imagery/VisionTexture/vistex.html">https://vistex.media.mit.edu/vistexmod/imagery/VisionTexture/vistex.html</a>	(Benco et al., 2020)
LMT Haptic	Visual, audio, tactile	184 samples	"stones", "glossy surfaces", "wooden surfaces", "foams"	<a href="https://zeus.lmt.ei.tum.de/downloads/texture/">https://zeus.lmt.ei.tum.de/downloads/texture/</a>	(JooLee et al., 2022; Liu et al., 2021; Zhou et al., 2024; Zhu et al., 2023)
Penn Haptic	Visual, tactile	480 samples	"aluminum", "brick", "concrete", "glass", "steel"	<a href="https://edmond.mpg.de/dataset.xhtml?persistentId=doi:10.17617/3.0C79KW">https://edmond.mpg.de/dataset.xhtml?persistentId=doi:10.17617/3.0C79KW</a>	(Doherty et al., 2023)
SpectroVision	Visual, infrared	14,400 samples	"ceramic", "glass", "metal", "wood"	<a href="https://github.com/Healthcare-Robotics/spectrovision">https://github.com/Healthcare-Robotics/spectrovision</a>	(Erickson et al., 2020)

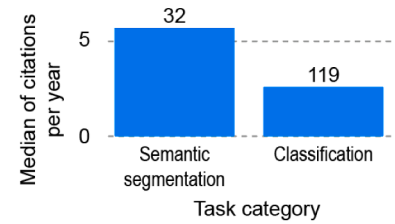
Bar graph showing median citations per year by data format



Bar graph showing median citations per year by model category



Bar graph showing median citations per year by task category



**Fig. 11.** RQ8 bar graph showing median citations per year by data format, model type, and task type. Numbers above each bar indicate the count of studies.

legend shows the type of model used. For hypercube data, it seems that deep learning has become the standard model since 2021. This contrasts with pixel data, which has rarely implemented deep learning models since 2014 in favor of foundation models; however, it is likely that deep learning models were commonly used before the time window of this study. Equally contrasting is the unlikelihood of waveform studies to implement foundation models (besides a few studies in 2019). Since waveform data is not as common as pixel data, it's likely that a large public dataset needed to train a foundations model on waveform data simply does not exist. Lastly, multi-modal data has historically been a rare data format with some experimentation in 2018 and 2020, but the slight uptick since 2021 with foundation models indicates that this data format is an emerging area of study. These results highlight the emerging trend of using multi-modal data, though it also reveals limitations for waveform data like infrared, where pre-trained foundation models are scarce.

## 5. Discussion

### 5.1. Gaps in the literature

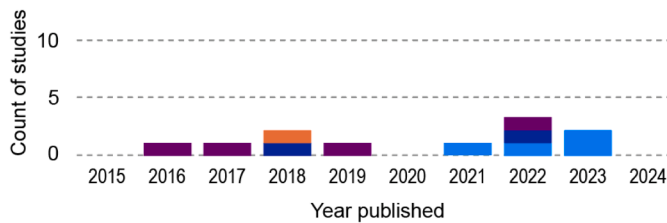
#### 5.1.1. Missing contextual information

As observed in RQ3 and RQ4, most building material recognition studies tend to focus on technical methods and model performance, often neglecting important contextual characteristics such as the study's scale, the study's location, the specific building layer being analyzed, the type of building, and the intended use case. This omission makes it difficult to assess the generalizability of the datasets and models to different environments or conditions, and leaves it unclear which data

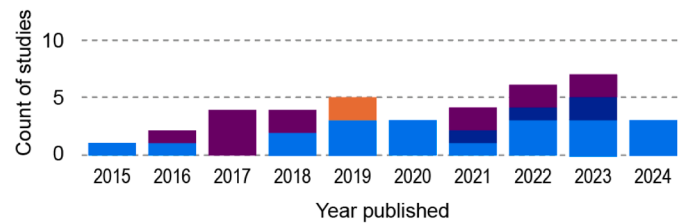
## Trends in material recognition studies across data formats

Model category ● Deep learning ● First principles ● Foundation model ● Traditional ML

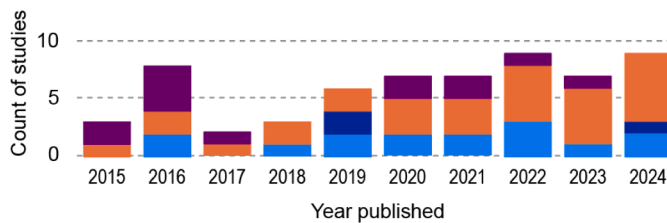
Histogram of hypercube studies timeline by model type



Histogram of waveform studies timeline by model type



Histogram of pixel studies timeline by model type



Histogram of multi-modal studies timeline by model type

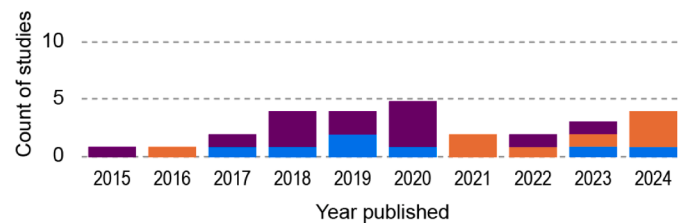


Fig. 12. RQ9 timeline plots showing the count of studies for the top 4 most common data formats. Each plot is broken down further into model category.

modalities are best at recognizing specific building layers. For example, radiowave data might be successful at recognizing materials in the structural layer of a building, but only one study made this combination of data modality and building layer explicit (Singh, 2024). Furthermore, many studies fail to specify whether the materials were annotated based on their actual physical properties or simply based on their visual appearance. This lack of clarity in the annotation process can lead to significant challenges when attempting to apply these models to real-world scenarios, as materials that look similar can have very different properties. Without understanding both the context of the dataset and the reliability of the material annotations, it is hard to gauge the true applicability and robustness of the models, limiting their usefulness in diverse and practical settings.

While potential explanations for the omission of contextual information could be hypothesized, we found it difficult to do so in a rigorous and well-supported manner. To our knowledge, there is currently no literature that systematically examines why such contextual details are commonly omitted in material recognition studies. When specific reasons do apply, they are rarely explicitly stated in the reviewed articles. Given this, we chose to avoid speculative explanations and instead focused on documenting the observed reporting gaps and their implications for reproducibility and comparability. We believe this approach maintains methodological rigor while highlighting an important area for future research.

### 5.1.2. Limited range of scales studied

Previous studies on building material recognition limited their analysis to relatively small scales, such as a single building, a neighborhood, or a city, as seen in RQ4. Since construction practices vary widely from one country to the next, it is worthwhile to consider whether methods applied to the countries studied would generalize to countries that haven't yet been studied. This limited scope can lead to unforeseen complications when attempting to implement these methods in real-world, large-scale scenarios. For instance, as highlighted in RQ4, most studies applying hypercube data—a data modality characterized by its high dimensionality and large storage requirements—have been conducted at the single building scale. Hypercube data is tricky to handle for sev-

eral reasons: the volume of data can often exceed 1 terabyte and samples can have over 400 features corresponding to each channel (Nelson et al., 2022). Given the size and complexity of hypercube data, scaling beyond a single building is likely to pose significant challenges in terms of data storage and computational cost (Shao et al., 2020), making it impractical for broader applications. Moreover, building material appearance can vary greatly across regions and countries, as they are often sourced locally. For example, brick and wood can differ significantly in color and texture depending on the geographic area they are extracted from. Such regional variations mean that recognition methods developed in one location may not perform well in another, highlighting the need for broader, context-aware research to ensure effective material recognition across diverse global environments.

### 5.1.3. Lack of public datasets

Public datasets are crucial for the development of ML models, as they provide standardized data that allows researchers to train, validate, and compare their methods effectively. However, RQ5 reveals that while most studies cite public datasets, there is still a large number of studies that resort to collecting their own datasets for experimentation, especially those working with audio data, since no public dataset currently exists for this modality. This lack of available data adds significant time and complexity to research, as the process of manually collecting data is both time-consuming and sometimes cost-prohibitive. RQ5 also showed that waveform public datasets were the least cited even though they are the public common type of public dataset. A possible reason for this could be a lack of awareness of available public datasets, which RQ6 aims to solve. Additionally, RQ9 highlighted multi-modal data as an emerging trend, yet multi-modal public datasets—those that include more than one modality of data—remain the smallest category, limiting opportunities for research that integrates diverse data sources. Furthermore, no multi-modal public datasets include hyperspectral or radiowave data, which are valuable for capturing detailed material properties. This lack of comprehensive, diverse public datasets creates significant barriers to advancing ML research in building material recognition.

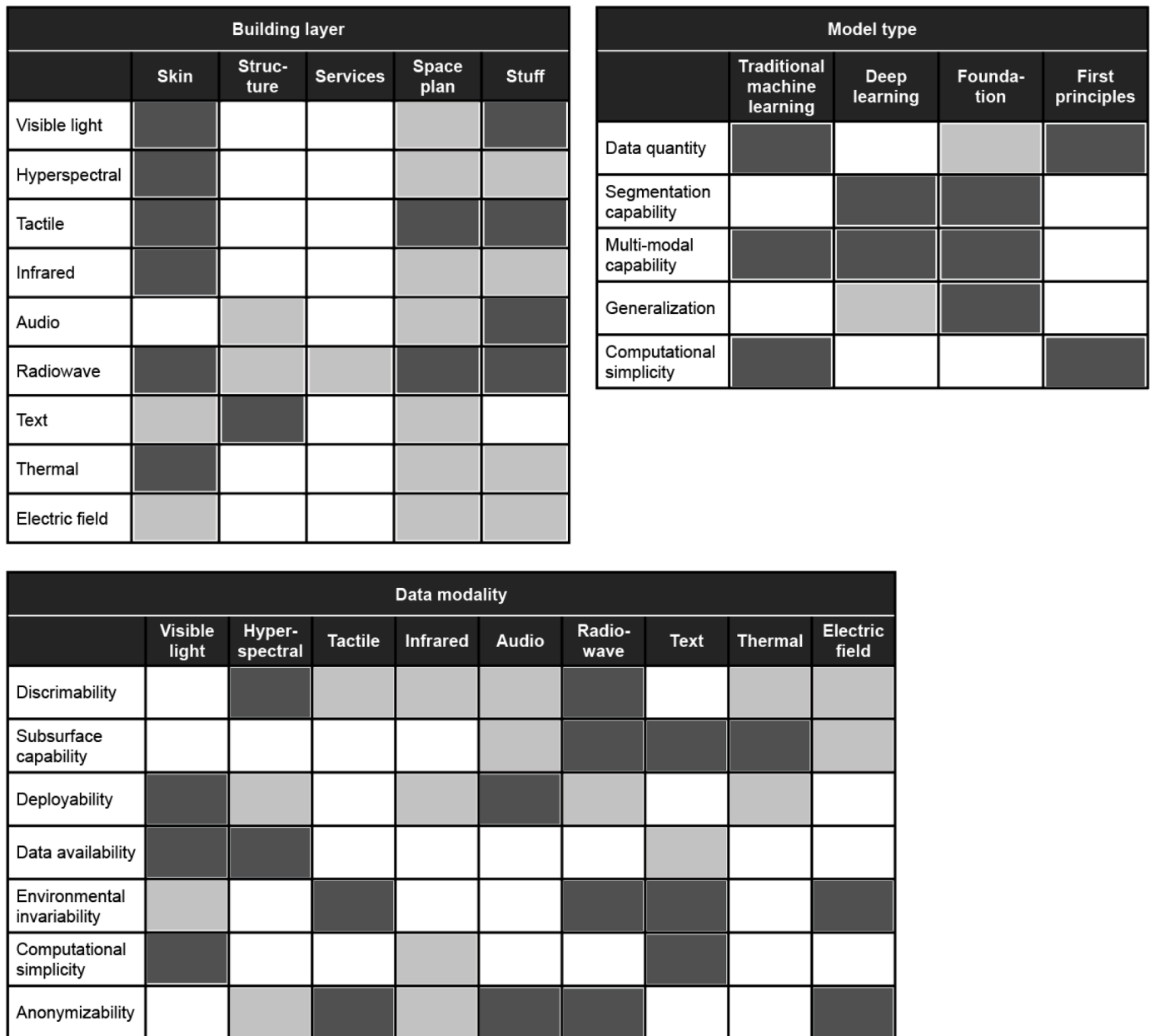


Fig. 13. Overview of key factors in deciding on parts of a material recognition pipeline: building layer, data modality, and model type. A dark box indicates a match, white box indicates a bad match, while a grey box indicates a match with some limitations.

5.2. Guidelines on methods

While the previous section identified gaps in the current application of as-built building material recognition research, this section shifts focus toward the accumulation of evidence for specific methods. Based on the reviewed literature, this section provides practical guidelines for selecting appropriate methods at different stages of the recognition pipeline (such as data modality and model type) as well as end-to-end pipeline configurations aligned with specific research objectives. These full pipeline recommendations are discussed in further detail in Section 5.2.2.

As-built material recognition enables a variety of applications, from evaluating the need for interventions in existing building stock (such as energy performance, hazard assessment, and climate resilience) to supporting intelligent interaction with the built environment (including autonomous navigation and adaptive sensor networks), as well as in-

forming long-term material management (such as cultural heritage conservation and resource management). In material reclamation efforts, automated material identification would enable the creation of material resource cadastres, reducing waste and promoting circular economy practices. For hazardous material mapping, accurate detection of potentially harmful substances could ensure safer demolition and renovation projects. In storm runoff analysis, identifying materials that impact water absorption and flow could improve urban planning to mitigate flooding. Building energy efficiency analysis could benefit by determining insulation properties, enabling tailored retrofitting solutions. Asset management could see improvements through precise tracking of material conditions and lifecycles, enhancing maintenance and replacement decisions. In climate mitigation and resilience, understanding material characteristics is crucial for identifying materials that are unlikely to survive major weather events, allowing for the selection of more durable and sustainable alternatives and the development of adaptive

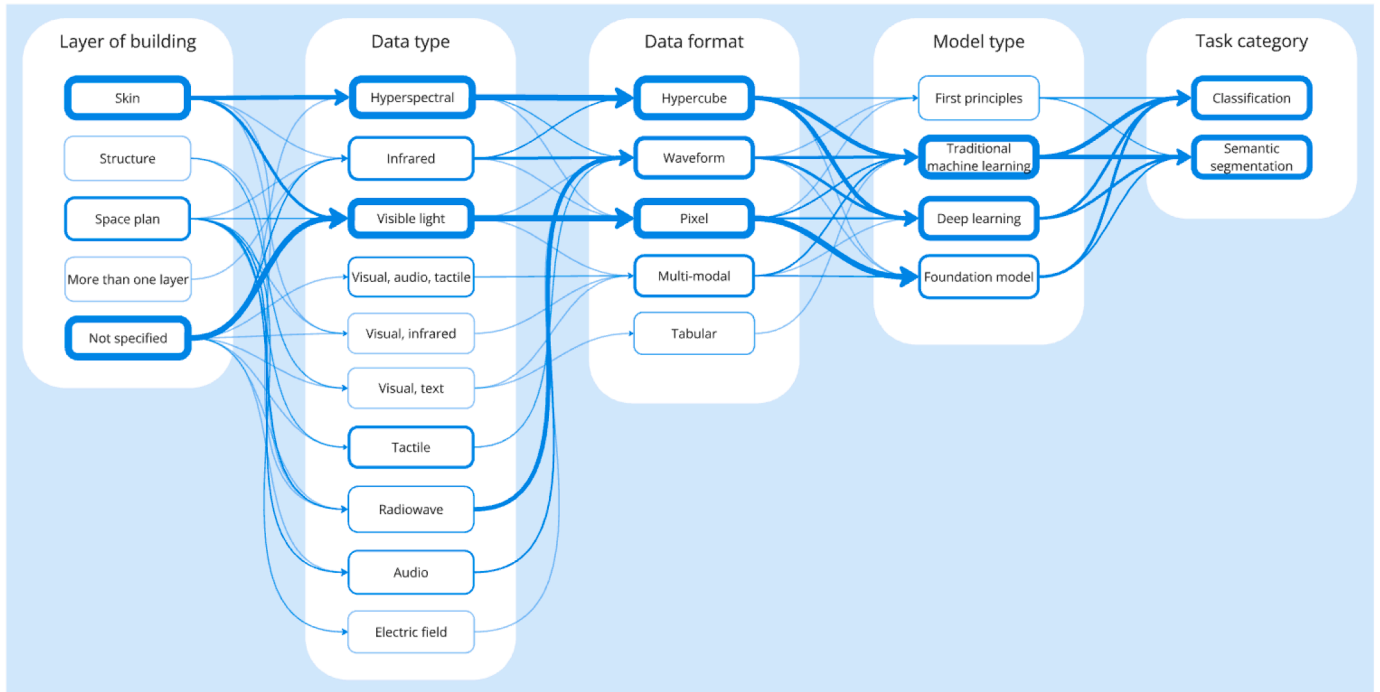


Fig. 14. Overview of the five step process to perform as-built building material recognition and the variety of options for each step. A thicker line indicates a higher number of studies as discussed in Section 5.3.1.

building strategies. Cultural heritage preservation could be enhanced by identifying and cataloging historic materials, aiding restoration efforts. For autonomous robots, material recognition could enable efficient navigation and manipulation in complex indoor environments. Lastly, environment-aware communications, could use material data to explore how sensor networks can adapt to and leverage real-time awareness of indoor environmental factors—such as obstacles, building materials, and spatial layouts—to optimize signal transmission, reduce energy consumption, and enhance wireless communication efficiency.

5.2.1. Factors influencing data modality and model type

The factors influencing individual method selection across the pipeline are summarized in Fig. 13, which maps the suitability of different data modalities and model types. In the figure, a dark box indicates a strong methodological match, grey box indicates a match with limitations, and white box indicates an unsuitable match. This visualization is intended as a decision-support tool rather than a prescriptive framework.

The choice of data modality is strongly influenced by the building layer of interest: most existing studies focus on the skin layer due to its accessibility and documentation, while the structure and services layers remain the least studied and most challenging because they are often difficult to access. Visible-light imaging performs best under adequate lighting conditions, primarily for the skin and occasionally space plan layer, especially when material composition can be inferred from geometric cues in the stuff layer. Hyperspectral, infrared, and thermal modalities benefit from natural daylighting, offering improved discrimination of surface-level materials. In contrast, tactile sensing and radiowave modalities are largely invariant to environmental conditions and can be used both indoors and outdoors, with radiowave sensing having the potential to detect internal layers of a building. Audio-based methods typically require controlled acoustic environments and have been studied almost exclusively at the furniture scale. The effectiveness of text data depends on the availability of well-defined material archetypes, however it could be applied to any layer that has been documented. Electric field sensing is an underexplored modality; however,

preliminary evidence suggests potential for surface-level material recognition.

Beyond building layer, the choice of data modality is also shaped by modality-specific characteristics related to discriminability, subsurface capability, deployability, data availability, environmental invariability, computational simplicity, and anonymizability. Visible light sensing is the most practical to deploy due to the widespread availability of cameras, the abundance of public datasets, and the maturity of models that enable low-latency inference; however, it is limited to recognizing surface appearance rather than intrinsic material properties and carries a risk of capturing personally identifiable information. Hyperspectral, infrared, and thermal modalities offer increased discriminability compared to visible light by capturing additional electromagnetic responses, but their adoption is constrained by higher equipment costs, greater sensitivity to environmental conditions, and increased computational complexity. While large-scale hyperspectral satellite datasets exist, they are restricted to identifying only roof materials. Tactile, radiowave, and electric field modalities are comparatively invariant to environmental conditions and pose no risk of containing personal information. Among these modalities, radiowave sensing exhibits the strongest overall potential, combining high discriminability with the unique ability to detect hidden or internal layers, robustness to environmental conditions, and inherent privacy preservation, positioning it as one of the most promising modalities in terms of inherent characteristics.

Model selection is similarly influenced by characteristic trade-offs related to data requirements, segmentation capability, multi-modal capability, generalization, and computational simplicity. Traditional machine learning and first-principles models require the least amount of training data and are computationally lightweight, making them attractive in data-scarce or resource-constrained settings. Foundation models, when trained from scratch, can be just as (or even more) data-intensive as deep learning models; however, this requirement is reduced when fine-tuning pre-trained models. Although segmentation is technically feasible with traditional machine learning models, deep learning and foundation models have outperformed other model types for segmentation. First-principles models are generally limited to single-modality

experiments, whereas multi-modal learning with traditional machine learning is possible but relies on sophisticated feature engineering and late-fusion strategies. In contrast, deep learning and foundation models have more support for end-to-end multi-modal learning. Finally, pre-trained foundation models exhibit the strongest potential for generalization to unseen data, benefiting from large-scale pre-training that captures transferable representations.

### 5.2.2. Pipeline optimized for ease-of-use

The various elements involved in as-built building material recognition have been organized into five steps—building layers, data modalities, data formats, models, and task categories—and summarized in a Sankey diagram (Fig. 14). This diagram visually represents all the available options at each step, providing a clear and detailed overview of the entire as-built building material recognition process. Starting with building layers, the diagram shows options according to building layers, each connected to multiple data modalities that can be used to capture relevant information. The data modalities include visible light like images, radiowave data for radar signatures, and acoustic data for sound-based material characteristics. Moving to data formats, the diagram illustrates the different forms these data can take, such as pixel-based, waveform-based, or multi-modal, emphasizing the flexibility in how materials can be recorded. The flow continues to show models—ranging from traditional ML techniques to foundation models—indicating the variety of approaches for analyzing the collected data. Finally, task categories such as classification and semantic segmentation are depicted, showing how each model can be applied to achieve specific goals in material recognition. The diagram's visual structure highlights the interconnected pathways and choices at each step, illustrating the multitude of options available for effectively identifying building materials in real-world conditions.

The data modalities, model types, and task categories that have been studied the most, as shown in Fig. 14, will likely have the greatest amount of resources available for researchers who want to conduct their own experiments. RQ7 provides statistics on which specific methods are likely to be easily implemented, suggesting that using visible light in pixel format, with a foundation model performing image classification would likely offer high ease of use. A few of the most studied foundation models included VGG16, Mask R-CNN with ResNet50, and DenseNet. RQ5 further supports these findings by showing that pixel/visible light datasets are the most common type of public dataset, while RQ6 indicates that the mean size of these public datasets is 31,604 images. These results can guide decisions on data modality, format, model type, and classification task; however, it is important to note that this guidance merely indicates that there is more support for this particular combination of methods.

Section 5.2 provides rough guidelines for methods for a novice user to start their own experiment, offering some indication of which approaches might lead to a successful outcome. Literature reviews that critically synthesize specific methods (such as the many literature reviews available for models trained on images Garcia-Garcia et al., 2018) are an excellent resource for more advanced discussion on specific techniques. However, there is a lack of literature reviews focused on models for other data modalities. This presents an opportunity for future studies by readers to fill this gap, potentially establishing best practices for less common data formats.

### 5.3. Limitations

Systematic mapping studies are inherently vulnerable to threats to validity due to potential biases in study selection, data extraction, and the subjective interpretation of findings, which can compromise the comprehensiveness and accuracy of the review. In this study, the initial screening and application of the inclusion and exclusion criteria were conducted by one author. To reduce the risk of false positives, the second and third authors independently reviewed the first round of selected

results. Because the goal of this study was to map the existing evidence as a foundation for future in-depth reviews, any remaining risk of false negatives was considered less critical than it would be in a traditional systematic review. Additionally, some results used citations per year as an indicator of impact, though it's acknowledged that citations are typically normalized by year and field, as some disciplines receive more citations than others. Consequently, citation metrics based on a small number of articles may not be fully generalizable across all academic fields included in the study, but they were still considered valuable for indicating trends rather than definitive measures of influence.

The guidelines provided in the discussion offer a basis for experiments; however, for more thoroughly studied and robust techniques, conducting or consulting a literature review would provide a better foundation. Literature reviews have the potential to guide decisions on a narrow aspect of either data modalities and model types, offering holistic insights drawn from a critical analysis of existing research. For example, when deciding on which methods to use, it is also important to consider various trade-offs, such as computational efficiency, interpretability, scalability, and resource requirements, as these factors can significantly impact the feasibility and effectiveness of the chosen approach for different use cases.

## 6. Conclusion

Given that a wide variety of academic fields incorporate material recognition into their work, it is unsurprising that methods applicable to recognizing as-built building materials are fragmented, with certain approaches being prevalent in specific academic fields but not in others. The finding from this study that waveform format data is the second most common type of public dataset yet the most manually collected, is one example demonstrating the need for a systematic mapping study to foster interdisciplinary collaboration and streamline research efforts.

The primary goal of this study was to consolidate fragmented research across disciplines into a comprehensive reference that reveals data modalities, recognition techniques, research gaps, emerging trends, and key future directions. Research from the past decade highlights gaps in as-built material recognition, including missing contextual information, limited material diversity and specificity, and a shortage of public datasets. While foundation models dominate highly cited work, they remain scarce for niche modalities such as radiowave or hyperspectral. Additionally, many of the articles found in this systematic mapping study revealed key resources that have not been previously collated, including public datasets and search terminology, which are a valuable reference for guiding future research.

Overall, this study makes several key contributions: 1) it represents the first systematic mapping study focusing on the recognition of as-built building materials, 2) it consolidates data modalities collected with mobile hardware suitable for as-built materials, 3) it identifies future research directions based on the gaps found in the literature, 4) it identifies current research tendencies and emerging practices related to data modalities, formats, model types, and task categories, and 5) it provides a consolidated list of public datasets and search phrases relevant to as-built building material recognition. These contributions aim to unify fragmented research efforts and guide future work on this topic. These contributions are particularly valuable to researchers new to the field, offering them a structured overview of methods, tools, and current research trends to guide their experiments effectively. For experienced researchers, the consolidation of data modalities, public datasets, and emerging practices provides an efficient way to identify gaps, select appropriate methods, and expand upon existing research, fostering a more unified and comprehensive approach to as-built building material recognition.

The results and discussion of this systematic mapping study highlight several promising directions for future research in as-built building material recognition. These include the need for critical literature reviews that extend beyond image-based approaches to other data modalities,

as well as opportunities to transfer and adapt methods proven in one domain to new use cases. Future experiments would benefit from involving a broader and more fine-grained range of materials than the commonly studied categories of wood, metal, stone, brick, and glass, and from datasets that explicitly encode contextual information such as scale, location, building layer, building type, and intended application. There is also a clear need for publicly available multi-modal datasets that better match the practical needs of material recognition research, particularly by annotating data based on known material properties rather than visual appearance alone. Additionally, more thorough investigation of radiowave data across all building layers is needed to fully understand and realize the potential of this modality. With its potential to advance sustainability, safety, and urban planning, as-built building material recognition is well positioned to play a transformative role in enabling smarter, more adaptive, and more sustainable use and maintenance of material resources in the built environment.

### CRedit authorship contribution statement

**Josie Harrison:** Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft; **Yinan Yu:** Conceptualization, Validation, Writing – review & editing; **Alexander Hollberg:** Conceptualization, Validation, Funding acquisition, Project administration, Supervision.

### Data availability

The dataset used in this study is publicly available and can be accessed at [Zenodo, DOI:10.5281/zenodo.18141935](https://zenodo.org/doi/10.5281/zenodo.18141935). The dataset includes all the raw data necessary to replicate the findings presented in this article. For any additional information or inquiries regarding the dataset, please contact the corresponding author.

### 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. Scopus search query

Search query used in Scopus: (TITLE-ABS-KEY ( material\* AND NOT ( soil OR genes OR biogas OR liquid OR subsurface OR "course material\*" OR "training material\*" OR microscopy OR "electrode material\*" OR "material property" OR "material\* and method\*" OR "material compound\*" OR "materials science" OR "cyber-attacks" OR "functional materials" OR semiconductor\* OR radioactive OR interatomic OR chemical\* OR optical OR geomorphological OR genetic\* OR plant OR "experimental materials" OR "performing material\*" OR "original material" OR "volumes of material" OR osteoradionecrosis OR sleep OR radiomics OR Taxonomy OR "risk factor" OR Healthcare OR "drug analysis" OR "nerve cell network" OR neurorehabilitation OR "quantum mechanics" OR Dysbiosis OR pharmaceuticals OR "space object\*" OR "Biocompatible Materials" OR moisture OR Genomics OR Organic OR damage OR defect\* OR batteries OR "Tool wear" OR simulation OR "Projective Mapping" OR gear

OR adsorption OR wear OR fuzzy OR dosimeter OR crack OR Fatigue OR beneficiation OR volatilization OR crime\* OR "Requirements engineering" OR leakage OR strength OR agronomic OR fluids OR drug OR clinic\* OR water OR dust OR topology OR film OR enamel OR river OR dance OR "particle size" OR stability OR scrap OR degradation OR Triboelectric OR Plasma OR diaphragms OR continents OR elastic OR peridynamics OR Circuit\* OR leaf OR brain OR superalloys OR nanopowders OR catalysis OR animal\* OR bone OR phosphor\* OR corrosion OR extrusion OR "lived experience" OR subzero OR Pyrolysis OR physiological OR maturity OR "electron diffraction" OR medical OR tourmaline OR "air quality" OR "Magnetic fields" OR aircraft OR gas OR rainwater OR "material performance" OR biomedical OR dentist\* OR supernova OR "Waste Sorting" OR cyberbullying OR Psychology OR Atom\* OR ore OR Atmosphere OR Mechanical OR machining OR underwater OR osteoarthritis OR "Granular materials" OR "Grained materials" OR "Stress-strain curves" OR dosimetry OR spam OR "Eye movement" OR volatility OR "Materials Processing" OR MNIST OR "Convex hull" OR Malignant OR "Dark Matter" OR pedagogical OR Fluorescent OR gamification OR curricula OR "Web Material" OR "Rate of change" OR Neutrons OR exfoliated OR Groundwater OR "policy maker\*" OR "plate impact" OR plasticity OR pronoun OR police OR music OR speech OR "Lévi-Strauss" OR "patron use" OR Stars OR psychological OR hospital\* OR "impact loading" OR "waste processing" OR "Adhesive joints" OR "media noise" OR tissue OR "structural diagram\*" OR "DNA Sequencing" OR "protective devices" OR fracture\* OR "company location" OR "verbal learning" OR "Framing effect\*" OR attenuation OR Galaxies OR molecu\* OR "thermal decomposition" OR genotype OR "hydrated sulphates" OR Oceanography OR Magnetic OR vegetation OR geological OR herbarium OR Health OR glacial OR "trace element" OR "sound propagation" OR Diagnosis OR laboratory OR "product market" OR "pore-chart analysis" OR ionization OR aerospace OR evolutionary OR USMARC OR sputtering OR Aviation OR Electromagnet\* OR purchasing OR Bilingual OR "price index" OR survey OR freezing OR Cartoons OR fire OR deformation OR fault OR Amphibians OR biosensor OR "technical ceramic\*" OR weapon\* OR photons OR planets OR sapphire OR powder OR shear OR "fake news" OR knitted OR nebular OR biometrics OR pottery OR food OR video OR pavement OR textile\* OR blood OR Disabil\* OR gravity OR social OR "credit/lending" OR children OR adult OR transportation OR "past events" OR biolog\* OR Retroreflective OR Excavator OR Pleistocene OR policy OR refining OR superconduct\* OR dielectric OR microorganism OR bacteri\* OR crystals OR religion OR wetland OR sedimentary OR dinosaur OR female OR embryo OR luminescence OR disease OR resin OR "grain kernel" OR "cell wall" OR protein OR explosive OR specimen OR "clay mineral" OR theatrical OR "information retrieval" OR naval OR nuclear OR lake ) ) AND TITLE-ABS-KEY ( "machine learning" OR classification OR detection OR "computer vision" OR recognition OR "in the wild" AND NOT ( regression OR "natural language processing" OR "Defect detection" OR "Damage detection" OR "Change detection" OR "anomaly detection" OR "pose estimation" OR "Zone Detection" OR "yield prediction" OR "bibliometric analysis" OR forecasting OR "predictive maintenance" OR "comment detection" OR "Issue classification" OR optimization OR "systematic mapping study" OR "gradation detection" OR "lightning detection" OR "fault detection" OR "flaw detection" OR "Text Recognition" OR "Posture recognition" OR "Air Classification" ) ) AND DOCTYPE( ar OR cp ) AND PUBYEAR > 2014) AND ( LIMIT-TO ( LANGUAGE,"English" ) )

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