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A Contactless Multi-Modal Sensing Approach for Material Assessment and Recovery in Building Deconstruction

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Abstract: As material scarcity and environmental concerns grow, material reuse and waste reduction are gaining attention based on their potential to reduce carbon emissions and promote net-zero buildings. This study develops an innovative approach that combines multi-modal sensing technologies with machine learning to enable contactless assessment of in situ building materials for reuse potential. By integrating thermal imaging, red, green, and blue (RGB) cameras, as well as depth sensors, the system analyzes material conditions and reveals hidden geometries within existing buildings. This approach enhances material understanding by analyzing existing materials, including their compositions, histories, and assemblies. A case study on drywall deconstruction demonstrates that these technologies can effectively guide the deconstruction process, potentially reducing material costs and carbon emissions significantly. The findings highlight feasible scenarios for drywall reuse and offer insights into improving existing deconstruction techniques through automated feedback and visualization of cut lines and fastener positions. This research indicates that contactless assessment and automated deconstruction methods are technically viable, economically advantageous, and environmentally beneficial. Serving as an initial step toward novel methods to view and classify existing building materials, this study lays a foundation for future research, promoting sustainable construction practices that optimize material reuse and reduce negative environmental impact.

Keywords: deconstruction; material reuse; multi-modal sensing; artificial intelligence; machine learning; drywall; circular economy; sustainable construction; automated assessment; building materials

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1. Introduction

The construction industry, a significant consumer of natural resources, is urgently in need of sustainable solutions. It accounts for approximately 40% of global energy use [1], contributing to 35% of worldwide CO_2 emissions and generating between 45% and 65% of the waste accumulated in landfills [2]. This massive environmental footprint necessitates the adoption of circular economic principles, which prioritize material reuse and resource efficiency over traditional linear approaches to extraction. Unlike conventional methods where construction and demolition (C&D) waste is discarded, circularity seeks to minimize waste and maximize resource efficiency, thereby reducing overall environmental impacts [3].

Despite the growing emphasis on circular economic principles, significant challenges remain in their practical implementation. This research addresses three critical challenges in construction sustainability: (1) the lack of efficient methods for assessing material reuse potential in existing buildings; (2) the absence of standardized approaches for non-destructive material recovery; and (3) the need for data-driven decision support tools in deconstruction planning.

To illustrate the application of circular economic principles, this study focuses on gypsum wallboard (drywall), representing a significant opportunity for waste reduction in the construction industry. In traditional linear construction practices, drywall assemblies are often modified or demolished in ways that damage the drywall, making it unsuitable for reuse [4]. Each year, the United States generates 13 million tons of gypsum wallboard debris, with 85% ending up in landfills [5]. This presents a significant environmental challenge, as gypsum can produce hazardous gases such as hydrogen sulfide when it decomposes near biodegradable materials [6].

Addressing these challenges requires innovative assessment methods for material recovery. Advanced sensing technologies have been successfully used in other material reuse studies to assess the condition of wood and metal, providing valuable data to guide reuse decisions [7–10]. However, their application to drywall assessment remains underexplored. In the context of drywall, these technologies are beneficial for identifying undamaged sections suitable for reuse, even when hidden behind surface finishes or affected by age-related deterioration.

This research investigates the reuse potential of gypsum wallboards in renovation projects. The key research question guiding this study is: "How can drywall be deconstructed and reused to minimize environmental impact while maintaining material integrity for future use"?

To address this question, this investigation was structured around the following research objectives:

1. Develop and validate a contactless assessment methodology for evaluating material reuse potential.
2. Create an integrated framework combining multi-modal sensing technologies with machine learning for material analysis.
3. Demonstrate the practical application and benefits of the proposed approach through a drywall deconstruction case study.
4. Provide recommendations for industrial implementation of the contactless material assessment method.

Machine-learning algorithms are integrated into this process to analyze the data collected from the sensors and predict the suitability of materials for reuse. By comparing historical data on material properties with real-time sensor inputs, machine learning enhances the precision and efficiency of the assessment process. This combination of sensing and machine learning represents a novel contribution to the study of drywall reuse in construction, offering a more data-driven, scalable approach to material recovery and reuse.

In summary, this study addresses the technical, environmental, and economic challenges of drywall reuse by developing a guided, contactless deconstruction process. By applying advanced sensing techniques, machine learning, and circular economy principles, the research aims to provide a framework for more sustainable drywall deconstruction practices, potentially informing future construction policies and standards. The findings contribute to the theoretical understanding and practical implementation of circular economic principles in construction, particularly in material assessment and recovery.

2. Advanced Technologies and Methods for Material Assessment in Construction

This section examines specific technological developments in automated material assessment, focusing on sensing technologies, detection algorithms, and implementation frameworks that inform the proposed methodology. The analysis specifically addresses the technical capabilities and limitations of current approaches to guide subsequent system development.

2.1. Advanced Sensing Technologies in Building Assessment

In recent years, significant advancements in construction monitoring have been witnessed through multi-modal sensing systems. These systems integrate Light Detection and Ranging (LiDAR), Internet of Things (IoT) devices, thermal imaging, hyperspectral imaging, advanced RGB cameras, and Radio-Frequency Identification (RFID) to enhance assessment capabilities and reduce costs [11,12]. Implementing artificial intelligence, coupled with machine-learning approaches, enables continuous structural integrity, environmental conditions, and material properties [13].

The fusion of multiple sensing modalities addresses the limitations of single-modal approaches. For example, combining RGB and thermal imaging through early, intermediate, and late fusion techniques has improved defect detection accuracy in exterior wall inspections [14]. This multi-modal approach expands sensing capabilities across different dimensions—thermal and multispectral cameras in the spectral dimension and LiDAR and depth cameras in the spatial dimension [15]. Recent applications demonstrate success in thermal behavior simulation using passive airborne multi-modal sensor data [16] and on-site construction safety management through Building Information Modeling (BIM) integration [17].

Notably, façade deterioration detection achieved 86.5% mean average precision through the fusion of infrared and visible imagery [18]. The integration of RGB, depth, and thermal imaging has proven effective for precise indoor sensing applications [19]. While these technologies demonstrate significant potential for building assessment, their application specifically to material reuse evaluation creates new opportunities for innovation. The challenge lies in adapting these technologies to assess current conditions and potential for future material recovery and reuse.

2.2. Machine Learning Applications in Material Assessment

Machine-learning algorithms have significantly enhanced the capability to process and analyze multi-modal sensor data in construction applications. Recent implementations demonstrate success in automated defect detection, material classification, and condition assessment, with deep-learning models trained on thermal-visible image pairs achieving detection rates that significantly outperform manual inspection methods for common structural defects [20,21]. The combination of thermal and visible imaging modalities has proven particularly powerful, as multi-view thermal-visible datasets have achieved high accuracy in cross-spectral matching across building infrastructure [22]. Neural networks have proven especially effective in correlating surface measurements with material conditions, attaining coefficient of determination values higher than 0.96 [23].

Applying machine learning to sensor fusion has enabled more sophisticated analysis capabilities, where advanced algorithms can analyze multiple data streams simultaneously to create comprehensive material assessments [24]. Such systems integrate thermal signatures, visual features, and depth information to identify suitable deconstruction methods, optimize disassembly sequences, and estimate material recovery rates [20,21]. Incorporating machine-learning-driven sensor fusion into construction operations enhances accuracy and reliability, improving decision-making processes and resource utilization, as shown in recent efforts to optimize material recovery by fusing diverse sensing modalities [25].

Real-time processing capabilities have advanced through the implementation of edge computing and optimized neural network architectures, allowing for rapid analysis of sensor data streams and immediate feedback for deconstruction operations [22,25]. Machine-learning models—including neural networks, random forests, and support vector machines—have effectively matched thermal-visible image pairs and predicted hazardous material presence with accuracy rates exceeding 74% [25]. Moreover, these technologies can forecast material deterioration patterns, enabling proactive maintenance and recovery planning [23].

2.3. Automated Assessment and Recovery Systems

Building on the advancements in assessment technologies, computational optimization has led to systematic approaches to deconstruction planning. Genetic algorithms have demonstrated success in sequencing deconstruction activities while maintaining structural stability [20]. These algorithms account for structural interdependencies, safety constraints, and material recovery objectives, generating optimized deconstruction sequences that maximize material salvage potential.

Multi-objective optimization models balance competing factors such as cost, time, and environmental impact [26]. These models incorporate various constraints, including structural stability, workspace accessibility, and material handling requirements. Advanced planning systems utilize real-time sensor feedback to adjust deconstruction sequences based on actual site conditions.

BIM integration enhances planning precision by providing detailed spatial and material information [27–29]. It enables virtual planning and simulation of deconstruction sequences, allowing for optimization before physical work begins. Recent developments in 4D BIM incorporate temporal aspects of deconstruction planning, enabling better coordination of recovery activities.

Automated recovery systems have evolved to include robotic implementations with sophisticated control systems [20]. These systems combine sensor feedback with precise mechanical control to execute complex deconstruction tasks. Advanced robotic assembly systems can use Computer-Aided Design (CAD)-informed path planning to optimize part manipulation and insertion trajectories [30]. This can be adapted to minimize damage during material recovery and deconstruction.

2.4. Current Technical Limitations

Several technical challenges affect automated material assessment systems, requiring careful consideration in system design and implementation. The limited detection capabilities for subsurface conditions without invasive methods [31] present a significant challenge, particularly in structures with multiple material layers or complex assemblies. Traditional building assessment methods rely on invasive inspections that are time-consuming and disruptive, leading to an incomplete understanding of available materials and hindering effective planning [32].

Environmental factors significantly impact sensing system performance. Temperature variations, humidity levels, and ambient lighting conditions can affect sensor accuracy and reliability. While thermal imaging systems are generally effective for detecting subsurface features, their performance diminishes when temperature differentials are minimal, as subtle thermal variations and low-contrast anomalies tend to be lost amidst the background noise of the thermal image [33]. RGB-based systems face challenges with varying lighting conditions and surface reflectivity, while depth sensors must account for occlusions and complex geometries [34].

Integration difficulties between sensing systems and automated recovery equipment pose additional challenges [13]. Real-time processing of multi-modal sensor data requires significant computational resources [13], and synchronization between different sensor types remains complex [35]. Current systems often struggle with latency issues when processing multiple data streams simultaneously, potentially affecting the precision of automated recovery operations [36].

The economics of automated assessment and deconstruction present another technical barrier. Compared to standard demolition, automated deconstruction requires more sophisticated equipment, specialized sensors, and advanced processing capabilities [37]. Building assembly complexity and uncertainty around material recovery rates further contribute to these technical challenges [38]. Market uncertainties also impede adoption, as variable quality standards and unstable demand create risks for implementing advanced technical solutions [39,40].

2.5. Drywall Assessment and Recovery Challenges

The composition and widespread use of gypsum wallboard present significant opportunities for material recovery in construction. Traditional gypsum boards, comprising approximately 90% calcium sulfate dihydrate and 10% paper by weight [41], maintain consistent material properties that could enable reuse applications. However, current assessment methods face several technical limitations that complicate recovery efforts. Traditional finishing methods eliminate the modular nature of panels through taping, joint compound, and paint, making it difficult to remove intact panels later [5].

Current on-site assessment relies primarily on visual inspection, which fails to detect internal deterioration or hidden moisture damage that could compromise reuse potential [42]. While drywall samples can be thoroughly evaluated through laboratory testing [43,44], this process typically requires several days and destructive sampling methods. This time-consuming and destructive nature of comprehensive material assessment presents a significant barrier to efficient and widespread reuse implementation.

The technical challenges extend to the identification of hazardous materials. Although drywall is technically recyclable, the presence of contaminants such as asbestos, lead, and joint compounds often renders drywall waste from demolition and renovation activities unsuitable for recycling [45]. Standard practices treat drywall as waste material, defaulting to recycling or disposal [4], mainly due to technical difficulties in assessing and maintaining material integrity during removal.

Recent research presents contrasting views on drywall reuse potential. While damage from removal is repairable using existing methods, the labor-intensive nature of careful deconstruction presents technical challenges under current practices [46]. Two potential technical approaches have emerged: carefully removing individual panels for reuse or preserving entire prefabricated wall sections with panels still attached to frames. While successful reuse has been demonstrated through systematic deconstruction approaches [46], current industry practices lack standardized methods for evaluating material conditions without compromising panel integrity.

Environmental monitoring during storage and transportation poses additional technical challenges. Limited storage facilities and transportation logistics affect material quality maintenance between deconstruction and reuse [47,48]. Temperature and humidity control during storage, protection from physical damage during transport, and maintenance of material traceability all require technical solutions for successful implementation.

These technical limitations and assessment challenges inform the development of new material evaluation and recovery methodologies, highlighting the need for innovative solutions that simultaneously address multiple aspects of the assessment and recovery process.

2.6. Research Gaps and Proposed Approach

While existing research has highlighted the potential of contactless building assessment technologies and automated deconstruction planning, gaps remain in developing comprehensive, integrated systems for material assessment and recovery. Current approaches often address individual aspects of the deconstruction process rather than providing holistic solutions that bridge material evaluation, analysis, and recovery optimization.

The literature review has identified several critical gaps:

1. Limited integration of sensing technologies: While individual sensing technologies have proven effective for building assessment, their integration, specifically for material reuse evaluation, remains underexplored. Current methods typically rely on single-modal approaches, limiting the comprehensiveness of material assessment.
2. Lack of nondestructive evaluation methods: Traditional material assessment often requires destructive testing or visual inspection, which can damage the material or lead to incomplete evaluation. Nondestructive methods for predicting material reusability are largely underdeveloped.
3. Absence of standardized protocols: Current practices lack standardized approaches for assessing material recovery potential, resulting in inconsistent evaluation methods and variable recovery outcomes.
4. Limited automation in decision support: Existing deconstruction planning relies heavily on manual assessment and experience-based decisions and lacks data-driven support systems for material recovery optimization.

This research addresses these gaps through several innovative approaches:

1. Multi-modal sensing integration: The proposed methodology combines thermal imaging, RGB, and depth data in a novel way to create comprehensive material profiles. This integration enables the detection of hidden geometries, material conditions, and potential defects without physical intervention.
2. Automated material analysis: This research advances beyond simple condition assessment to predict material reusability and optimal recovery methods by developing machine-learning algorithms specifically for material reuse classification.
3. Systematic assessment framework: The research establishes a standardized approach to material evaluation through contactless methods, providing a repeatable and reliable assessment protocol for industry adoption.
4. Data-driven decision support: The integration of sensor data with automated analysis provides evidence-based recommendations for deconstruction planning, optimizing both the recovery process and material reuse potential.

The drywall case study validates these approaches, demonstrating practical implementation while addressing industry-specific challenges in material recovery. This research thus bridges the gap between theoretical possibilities and practical implementation, advancing the field toward more sustainable construction practices.

3. Materials and Methods

This investigation employed advanced non-contact sensing technologies, primarily focusing on thermal infrared imaging as a foundational platform for exploring multi-modal material assessment systems. The primary objective was to develop a robust methodology for the non-destructive identification of structural elements within drywall assemblies, explicitly focusing on stud detection and positioning. This approach presented significant advantages over conventional handheld detection methods, offering enhanced spatial coverage and temporal efficiency through automated scanning protocols. Furthermore, this methodology established a framework for the future integration of complementary sensing modalities, including near-infrared (NIR) spectroscopy and hyperspectral imaging, to enhance detection capabilities across diverse material compositions and environmental parameters.

3.1. Core Methodology Objectives

The thermal imaging investigation focused on several key objectives:

1. Validation of the reliability of thermal imaging for stud detection using quantitative methods.
2. Optimization of environmental parameters and methodological protocols for maximum detection accuracy.
3. Development of robust algorithmic frameworks for interpreting thermal data and localizing structural elements.
4. Cross-validation of system performance across various wall assembly configurations and environmental conditions.

In parallel, the research explored the integration of advanced computer vision technologies and machine-learning-based object detection algorithms. This multi-modal approach enabled simultaneous evaluation of subsurface structural elements and surface conditions, significantly enhancing the efficiency of material salvage assessment. Specific computer vision objectives included:

1. Implementation of automated rapid assessment protocols for material condition evaluation.
2. Development of machine-learning-based damage detection and classification systems.
3. Establishment of standardized quantitative metrics for material quality assessment and reuse potential.

By combining thermal imaging for subsurface analysis with computer vision for surface assessment, the goal was to develop a comprehensive, efficient, and non-invasive system for evaluating existing building materials. This dual approach addressed the hidden structural context of materials and their visible surface conditions, providing a more complete picture for salvage and reuse decisions. The research focused on developing and integrating these technologies into practical workflows for the construction and demolition industries. In the future, advanced sensing technologies are expected to become standard tools in sustainable building practices. This will make material reuse easier and more effective, contributing to a more circular economy in construction.

3.2. Methodological Framework

3.2.1. Material Context Analysis

The initial phase involved comprehensive identification and characterization of the material within its architectural context. This study specifically focused on gypsum wallboard used in interior partition wall assemblies. Successful salvage and material recovery required a thorough understanding of the material's properties and attachment systems, elements that were either fastened to or depended on the selected material. In the case of drywall, a critical contextual element was the stud. Consequently, stud placement and identification became essential components of the investigation.

3.2.2. Multi-Parameter Material Assessment

The second step involved implementing multi-dimensional material characterization protocols to identify the properties, conditions, and qualities of the materials to be salvaged. Recognizing that simplistic data were insufficient for analyzing materials that had undergone various histories and environmental changes, it was crucial to enrich material information because each material possessed a unique profile shaped by its environment and use over time. To achieve a comprehensive assessment, the methodology employed advanced sensing technologies and machine-learning algorithms to develop detailed material profiles. This approach provided new ways to view and classify these materials, which is essential for effective salvage and reuse decisions.

3.2.3. Integrated Sensing Framework

To address gaps in material information and enhance the ability to assess salvaged building materials, the research implemented a novel multi-modal sensing approach that integrated complementary technologies into a single, comprehensive tool. This multi-spectral method combined human vision with advanced sensing technologies, each offering unique insights into material properties. The integrated technologies included:

1. Thermal Imaging: The thermal sensing subsystem employed a Micro-Epsilon TIMQVGA029 thermal camera (Micro-Epsilon, Ortenburg, Germany) operating with a diagonal field of view (DFOV) of 2.04 m at a 4 m distance. This module performed three critical functions:
    - Detection of subsurface structural elements through thermal conductivity variations.
    - Assessment of moisture distribution via temperature differential analysis.
    - Evaluation of thermal anomalies indicating potential damage, using pattern recognition algorithms to identify irregularities.
2. Computer Vision Systems: The RGB imaging system used an Intel RealSense camera (Santa Clara, CA, USA) that captured visual and depth information. Key functions performed included:
    - High-resolution surface analysis at 1920 $\times$ 1080 pixels, enabling detection of surface features as small as 0.5 mm.
    - Automated damage detection and classification through TensorFlow-based neural networks.
    - Quantitative assessment of surface degradation using computer vision algorithms that measure crack width and length, surface discoloration area, and paint peeling extent.

3.2.4. Integration and Calibration

The system operates through three synchronized C# programs:

- RGB capture management.
- Depth measurement via RealSense SDK.
- Thermal capture through TIM Connect SDK.

Each SDK is integrated with OpenCV for image processing, establishing a capture frequency of one image every 5 seconds. Each SDK is integrated with OpenCV for image processing, establishing a capture frequency of one image every 5 seconds. The various stream types, their associated hardware/software, and the calibration methods used for each are detailed in Table 1.

For RGB imaging, the calibration involved checkerboard calibration using OpenCV, with color segmentation image preprocessing applied to the checkerboard images. No calibration was necessary for depth measurement, as the depth sensor was used only as a reference. On the other hand, the Thermal Capture stream required more involved calibration. It involved checkerboard calibration using OpenCV, with Gaussian blur preprocessing applied to the checkerboard images. Additionally, the checkerboard was heated so the thermal camera could reliably detect it.

Table 1. Capture system components.

Stream Type	Hardware/Software	Calibration
RGB Imaging	Intel RealSense SDK	Checkerboard calibration using OpenCV; color segmentation image pre-processing applied to checkerboard images.
Depth Measurement	Intel RealSense SDK	No calibration necessary, used as reference only.
Thermal Capture	TIM Connect SDK	Checkerboard calibration using OpenCV; Gaussian blur pre-processing applied to checkerboard images. Checkerboard is heated in order to be detected by thermal camera.

The system employed sequential program execution to optimize data collection, with spatial alignment capabilities enabling multi-modal data fusion. Buffer capture provisions were incorporated into the workflow to support thermal calibration requirements. By combining these sensing methods, the methodology aimed to develop a more comprehensive understanding of salvaged materials, enabling more informed decisions about their potential for reuse.

3.2.5. Machine-Learning Application

To enable comprehensive material assessment and predict the suitability of materials for reuse, advanced machine-learning algorithms were employed for automated feature extraction and classification of sensor data. The system used convolutional neural networks (CNNs) for RGB image analysis, applying feature identification algorithms to assess material properties, conditions, and qualities by highlighting areas of damage.

3.3. Workflow Process

The proposed methodology follows a systematic workflow, as illustrated in Figure 1, to achieve the objectives of non-invasive material assessment and guided deconstruction.

1. **Image Capture:** Data were collected using integrated sensing technologies that captured thermal images, high-resolution RGB images, and electromagnetic readings of drywall assemblies.
2. **Image Processing:** Thermal images were analyzed to identify hidden structures and moisture content, while RGB images underwent processing through object identification algorithms to evaluate surface conditions.
3. **Machine Learning Analysis:** The processed RGB data were input into machine-learning models designed to assess the suitability of materials for reuse. The models analyzed patterns and anomalies to identify damage and potential reusability.
4. **Align Images (for stud location and identification):** The alignment process overlaid RGB images with thermal images to map stud locations to their approximate positions on the wall. This was accomplished through precise edge alignment between image types and systematic minimization of lens distortion effects. The registration process achieved the high spatial accuracy necessary for subsequent deconstruction planning and execution.
5. **Create Digital Twin:** The digital twin was generated by translating pixels from the collected images into geometric representations. This process integrated insights from all sensing technologies and machine-learning analyses into a comprehensive digital model. The resulting twin provided critical information for deconstruction strategies, including wall dimensions, precise stud locations, and parametric definitions for cutting areas through polygon generation.

6. **Project:** A systematic framework was implemented to test the accuracy of the digital twin against real-world conditions. This validation process included a quantitative comparison of predicted versus actual structural element locations, verification of dimensional accuracy, and assessment of the model's utility for guiding deconstruction operation.
7. **Deconstruct:** The deconstruction process was executed using three distinct methodologies: power saw cutting, screw removal, and automated robotic deconstruction. Each approach utilized comprehensive assessment data to implement precise removal methods, with the primary goal of preserving drywall panel integrity throughout the removal process. The execution integrated digital twin guidance to optimize tool paths and removal sequences.

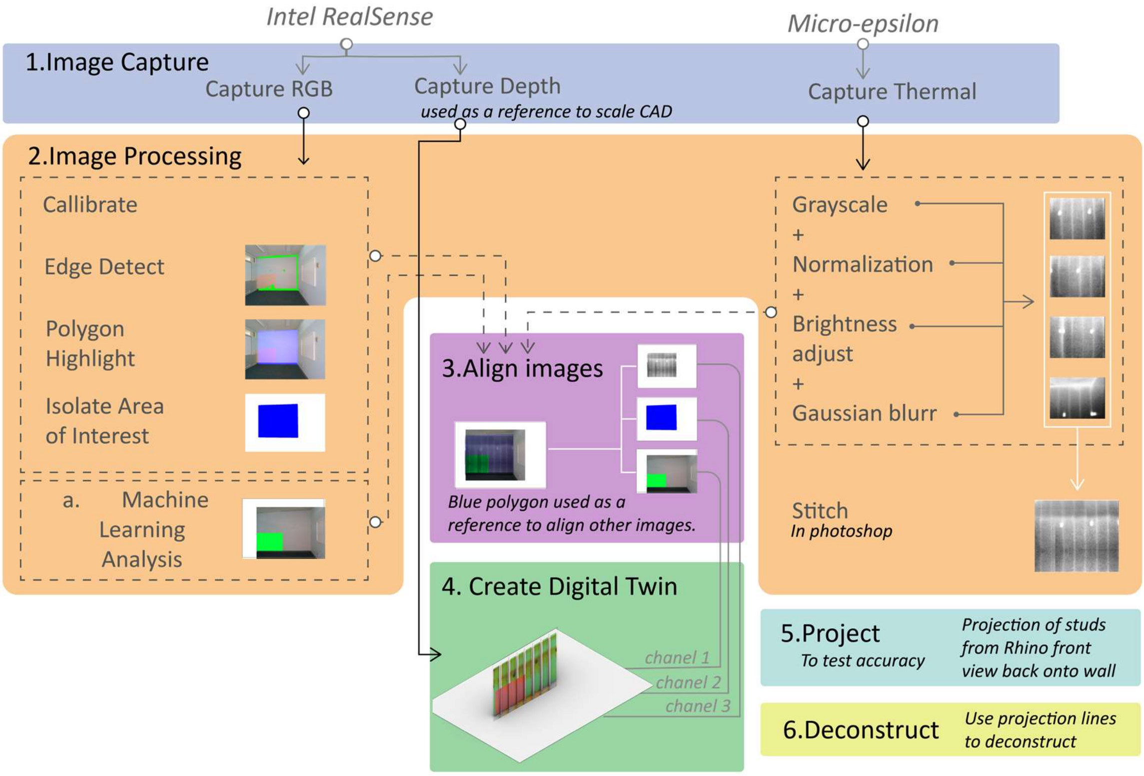

Figure 1. Workflow diagram for assessing salvageable drywall materials using multi-modal sensing and machine learning.

3.4. Validation Through Case Studies

To validate the efficacy of the proposed methodology, multiple case studies were conducted in real-world scenarios, implementing the integrated sensing and analysis approach. These studies provided quantitative assessments of the system's performance in identifying material properties and guiding deconstruction efforts.

4. Results

The analysis evaluates the effectiveness and accuracy of integrating multi-modal sensors and computer vision technologies for non-destructive wall assembly assessment and deconstruction guidance. By examining methodologies for detecting stud positions, assessing material conditions, and guiding the deconstruction process, the study provides insights into the practical applicability and viability of these technologies in real-world construction and demolition scenarios. This section presents quantitative and qualitative findings across four key areas: data capture accuracy, processing efficiency, implementation effectiveness, and real-world validation through case studies.

4.1. Data Capture Performance

Using the integrated sensing framework described in Section 3.2.3, performance analysis of the integrated sensing system revealed significant capabilities in field testing. The system achieved a 92% success rate in perpendicular wall captures and a 78% success rate in angled captures, with spatial resolution maintaining ±2cm accuracy in stud location detection. Processing efficiency averaged 3.5 min per wall section, enabling rapid assessment of multiple wall areas within typical construction timeframes.

Field testing demonstrated successful data collection across various interior wall configurations. The study focused on interior partition walls, including those adjacent to exterior walls. The system provided complete coverage for a standard 2.43 m × 3.65 m (8 ft × 12 ft) wall section, and the modified capture sequences maintained effective performance even in confined spaces. Multiple thermal captures were successfully synthesized into cohesive imagery, while the depth sensing integration provided accurate wall dimension measurements throughout testing.

The combination of RGB, thermal, and depth data streams proved particularly effective for comprehensive wall assessment. As demonstrated in Figure 2, the system successfully produced integrated outputs combining high-resolution RGB imagery, synthesized thermal data, and comprehensive depth information. This multi-modal approach enabled simultaneous evaluation of surface conditions and subsurface features, providing rich data for material assessment decisions. Tables 2 and 3 quantify the detailed performance metrics achieved during field testing, demonstrating consistent performance across varied environmental conditions and wall configurations.

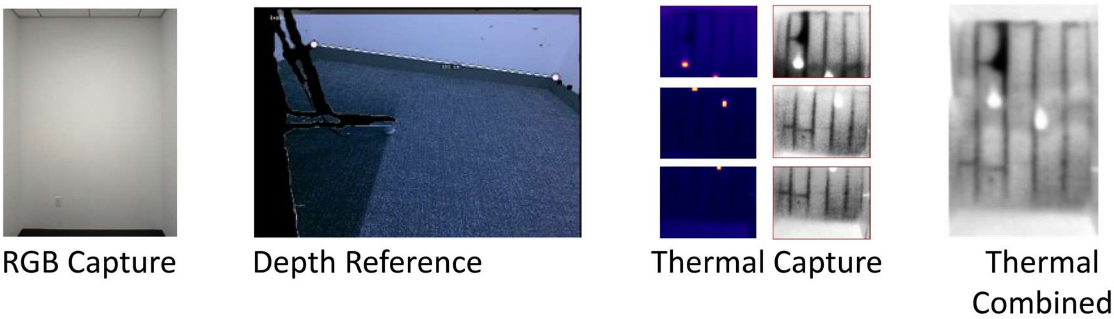

Figure 2. The outputs from image capture programs.

Table 2. System operating parameters.

Parameter	Specification
Optimal Distance	4 m from target wall
Field of View	2.04 m diagonal at 4 m distance (Micro-Epsilon thermal camera)
Capture Rate	One image every 5 s
Coverage Requirements	Minimum 8 thermal captures for 2.43 m × 3.65 m wall

Table 3. Performance metrics.

Metric	Performance
Spatial Resolution	±2 cm accuracy in stud location detection
Processing Time	3.5 min average per wall section
Image Alignment Success Rate (Perpendicular)	92%
Image Alignment Success Rate (Angled)	78%

4.2. Data Processing and Digital Twin Generation

Following image acquisition from the Intel RealSense and thermal cameras, the analysis focused on three critical aspects:

1. Stud visibility and detection clarity
2. Data precision for disassembly instruction generation
3. Environmental conditions affecting image quality

The data processing workflow, shown in Figure 1, demonstrated the systematic approach for RGB and thermal image alignment in digital 3D model creation. Image enhancement techniques were applied, including color vibrance adjustment and visualization clarity improvement. Stud locations were determined using thresholding methods, generating wall edge bounding polylines represented by blue polygons. Before image stitching, the thermal imagery underwent multiple processing steps—grayscaling, normalization, brightness adjustment, and blurring.

A damage detection system was implemented using TensorFlow version 2.9.1 with the Keras API to process and analyze RGB images of walls to identify potential areas of damage. The model architecture utilized ResNet50 as the feature extractor, imported with pre-trained ImageNet weights. This machine-learning model highlighted regions of discoloration by running a feature detection program trained on image data. The damage detection system implementation utilized image datasets with corresponding XML annotations for training. The dataset comprised 30 corresponding images and masks featuring various drywall conditions, including stains, cracks, and paint peeling. The damage detection program was more effective at identifying structural anomalies, such as cracks, than at detecting surface-level discolorations or stains because cracks generally have distinct edges and high-contrast features that feature detection algorithms can easily detect. Figure 3 illustrates the system's enhanced capability in identifying structural anomalies with distinct edges compared to surface discolorations.

Figure 3. Output from the TensorFlow-based damage detection model, highlighting areas of cracks in a previously unseen image. The red highlight outlines some of the training images that were provided as input. The green bounding boxes are drawn around detected crack regions on a test image.

The image preprocessing protocol standardized inputs to 224 $\times$ 224 pixels, incorporating data augmentation for model robustness. The architectural framework consisted of a pre-trained ResNet50 model with fine-tuning capabilities, enhanced by Global Average Pooling, dropout regularization, and dense layers for bounding box prediction.

Model training was conducted using the mean-squared error (MSE) as the loss metric, with parameters optimized via the Adam optimizer (learning rate: 1×10^{-4}), utilizing learning rate reduction and TensorBoard monitoring (TensorFlow, Mountain View, CA, USA) during the 15-epoch training cycle. The crack detection function was designed to take an input image and process it using a trained model. It then visualized the results by highlighting the detected damaged areas with green rectangles. The bounding box coordinates were normalized and constrained within the image dimensions to ensure accurate visualization.

The validation of the damage detection model was based on visually examining detected damage regions in test images, assessing the model's capability to identify surface anomalies in previously unseen drywall samples. Using a ResNet50-based architecture, the system achieved 88% accuracy in detecting cracks and 72% in identifying surface discoloration. Although the data used in training were drywall-specific, the underlying architecture and fundamental feature detection principles are inherently generic, suggesting adaptability to other construction materials through transfer learning. Future implementations would benefit from including quantitative validation metrics, such as MSE, for a more precise evaluation of predicted damage regions.

After the digital alignment of the three output images ensured consistent size and position, each layer underwent individual export for specialized processing. A custom pixel color selection program analyzed these layers through distinct filtering criteria for each input type. The visible light image processing isolated the blue color channel for polygon shape extraction. In contrast, thermal imagery processing employed an adjustable threshold filter to identify high-intensity areas correlating to stud locations. The dimensional analysis utilized pixel-based calculations to determine total wall area measurements.

The processed data facilitated three primary outcomes:

1. Precise stud location mapping from thermal signatures.
2. Total wall surface area calculation.
3. Salvageable drywall area estimation, accounting for stud positions and safety margins.

This computational methodology enabled systematic planning for selective drywall removal while maintaining maximum material preservation between stud locations. Tables 4–6 summarize the quantitative performance metrics achieved during the image processing and analysis phase, demonstrating the system's capability for accurate structural element detection and dimensional analysis.

Table 4. Stud detection performance metrics.

Parameter	Performance
Metal Stud Detection Rate	95%
Wood Stud Detection Rate	67%
Average Position Deviation	±5 cm

Table 5. Damage detection system performance.

Parameter	Accuracy
Crack Detection	88%
Surface Discoloration Detection	72%

Table 6. TensorFlow model performance.

Metric	Value
Training Accuracy (30-image dataset)	91%
Validation Accuracy (unseen images)	86%
Processing Speed	1.2 s/image

The data acquisition and processing methodology extends beyond traditional scan-to-BIM workflows. While conventional approaches typically capture only geometric information, this multi-modal sensing system enables the creation of enriched digital twins by extracting detailed material condition data, subsurface structural information, and potential reuse characteristics. This comprehensive digital documentation can be integrated into existing BIM systems to enhance deconstruction planning and material tracking. For example, thermal imaging data revealing stud locations and RGB analysis identifying surface conditions can be incorporated as parametric data within BIM elements, providing valuable information for deconstruction sequencing and material recovery assessment.

Image Preprocessing and Noise Reduction

The optimization of thermal imagery for stud detection required specific preprocessing techniques based on environmental conditions. Multiple factors influenced image quality, including ambient temperature, stud material composition, and environmental context. The processing pipeline implemented multiple correction stages to address these variables.

The preprocessing methodology used a sequence of image adjustments calibrated to specific site conditions. These included brightness correction, normalization techniques, and targeted blurring algorithms. The case studies demonstrated distinct preprocessing requirements. Due to varying environmental conditions, thermal image corrections for the office environment differed significantly from those required in the high school case study.

Similar preprocessing approaches could be applied to damage detection and the processing of RGB images. Implementing denoising filters, adaptive histogram equalization, and multi-scale normalization techniques established consistent baseline image quality for analysis. This systematic approach to environmental noise management can enhance the reliability of material assessment across diverse building conditions.

4.3. Projection and Deconstruction Methods

This section outlines the projection and deconstruction steps shown in Figure 1 and elaborates on the methodology for translating processed imagery into physical deconstruction guidance. Three distinct deconstruction techniques were assessed for optimal material recovery.

4.3.1. Projection System

The projection phase validated the accuracy of thermal and RGB image mapping for physical deconstruction guidance. The digital twin data, derived from thermal and RGB analysis, enabled the projection of identified structural elements onto the wall surface. Figure 4 demonstrates how this projection system created visual guidance for workers, revealing subsurface structural elements. The critical projection system components included:

- Calibrated projector implementation for alignment accuracy between the digital model and the physical wall.
- Color-coded visualization system:
  - Green zones indicate safe-cutting areas.
  - Red zones mark stud locations and restricted cutting areas.

4.3.2. Deconstruction Methods

This research explored three distinct deconstruction methods, each offering different advantages in terms of material salvage and efficiency.

Manual Deconstruction Approaches

Method 1: Projection-Guided Saw Cutting

In this method, power saw cutting followed projected polygon boundaries between identified stud locations. This method achieved rapid drywall section removal but resulted in smaller salvaged pieces due to necessary cuts near stud locations. Material recovery rates varied based on stud spacing and wall dimensions (Figure 4).

Figure 4. Testing site of polygon cutting from guided projection.

Method 2: Projection-Guided Screw Removal

This method employed projected stud locations combined with magnetic screw detection for fastener removal. Implementation required magnetic detection tools for precise fastener location, followed by systematic screw removal along identified stud lines and controlled drywall extraction from attachment points. This method demonstrated superior material preservation through full-sheet recovery capabilities.

The experimental data showed viability in both manual deconstruction methods, with the screw removal technique achieving better drywall recovery rates. However, selecting the optimal deconstruction method depends on project-specific parameters, including time constraints, wall assembly conditions, and material preservation requirements.

Robotic Deconstruction System

Building upon the manual deconstruction methods, the experimental scope expanded to incorporate robotic deconstruction techniques. This automated approach evaluated the feasibility of reduced human intervention through advanced robotics implementation, enhancing both efficiency and precision in the deconstruction process. The experimental results demonstrated the potential of current technological capabilities while establishing foundational parameters for a fully integrated, turn-key robotics software, and hardware platform. The developed system architecture incorporated sensor integration and automated control systems, providing a comprehensive framework for industrial-scale deconstruction applications. Figure 5 illustrates the key components and operational sequence of robotic integration.

Figure 5. Robotic deconstruction system. Left, digital twin simulation from internal research robotics platform. Middle, robotic milling operation cutting drywall. Right, robotic extraction with vacuum gripper.

Workcell Setup

The experimental setup utilized an ABB IRB 4600 industrial robot (ABB Engineering, Shanghai, China) with a 40 kg payload capacity and a 2.55 m reach, controlled through an IRC5 system running external guided motion. The robot was securely mounted on an acorn welding table, providing stability and mobility via pallet jack repositioning. Primary cutting operations employed a high-speed electric spindle manufactured by Elettromeccanica Giordano Colombo (Carate Brianza, Italy), operating at a maximum frequency of 400 Hz and delivering up to 24,000 RPM. The cutting tool consisted of a 12.7 mm (half-inch) high-speed steel square end mill featuring two flutes. The milling operation was programmed to cut the identified section of drywall, ensuring minimal damage to the material and maximizing the area that could be salvaged while maintaining structural integrity. Following the milling process, a Schmalz vacuum area gripping system with an integrated pneumatic vacuum generator was deployed to securely attach to the cut piece of drywall, facilitating precise and controlled extraction from the wall, as demonstrated in Figure 5 (middle and right images).

The robotic setup, including all necessary components and software, is priced at USD 67,000. The robot has positional repeatability of 0.06 mm and path repeatability of up to 0.28 mm. With maximum axis speeds ranging from 175°/s to 360°/s, the ABB IRB 4600 is engineered for high precision and rapid execution, which is essential for reducing cycle times and maximizing production efficiency. ABB Industrial robots' high repeatability ensures operations can be conducted with consistent accuracy, which is crucial for tasks like milling, where exact dimensions are critical.

During the milling experiments, operations were conducted at a conservative speed of 100 mm/s for testing purposes, but there is potential to increase this speed significantly through further process optimization. At the conservative rate of 100 mm per second, the robot can cut out approximately 439 square meters of drywall in 1 h. For the tasks at hand, the robot was configured to mill areas up to 5 m^2 from a single stationary position. To accommodate larger panels or extend the operational range without compromising precision, the system can be adapted with additional mobility solutions. Integration of a track, gantry, or mobile platform enables the robot to traverse larger distances smoothly, expanding its capability to handle bigger or irregularly shaped materials without the need for manual repositioning. This modular approach to workspace configuration allows for scalable automation tailored to project-specific requirements.

The work cell safety implementation adhered to industry standards through multiple integrated systems to ensure operator safety and compliance. Perimeter protection consisted of polycarbonate hard guarding installed around the work cell's perimeter, complemented by a door-integrated safety interlock system. This interlock mechanism automatically powered down both the robot and the spindle systems upon door activation during operation, preventing unauthorized access and accidental exposure to operational components or moving parts. Additional safety protocols incorporated ABB's SafeMove technology, an advanced safety solution providing safety-certified monitoring of robotic motion, including tool positioning, standstill supervision, and integrated speed limitation features. The SafeMove system established defined operational zones, implementing collision prevention parameters for the floor, ceiling, and surrounding structural elements, ensuring operational safety while maintaining workflow efficiency.

Due to the advanced safety measures in place, the safety risk within this robotic work cell is minimized. However, it is crucial to conduct regular safety audits and continuous training for all operators. These practices ensure that safety protocols adapt to any changes in operational procedures or configurations and that all personnel are aware of how to act safely around the robotic system. Moreover, maintaining a routine check on all safety features for their operational integrity is essential for sustaining a safe working environment.

For labor requirements, skilled integrators are needed to install and configure the industrial robot and associated equipment. This includes mechanical installation, electrical integration, and initial software setup. Additional personnel must be trained in operating the robotic equipment and safety protocols specific to the robotic environment. Due to the complexity of the system, the initial setup may take several days. However, once the system is running, the labor required to operate the robotic work cell is significantly reduced compared to manual operations. A couple of skilled operators can manage the system, overseeing the robot's performance and intervening only when calibration, adjustments, or troubleshooting is necessary.

Effective robotic operations require careful consideration of physical space, integration with other systems, and environmental controls. These factors must be planned during the workspace design phase to accommodate all necessary equipment and safety features without restricting the robot's operational capabilities. Depending on the end effector and other auxiliary stems, the workspace must have provisions for power supplies and pneumatics lines. The installation of safety barriers and the integration of safety interlocks also dictate spatial requirements, ensuring ample room for these systems without compromising their functionality or accessibility.

Automated Robotic Deconstruction Workflow Using CAD-Informed Path Planning

A CAD-based approach was employed to optimize the robotic deconstruction process using a robotics software research platform integrated with Autodesk Fusion through Autodesk Platform Services [30], as illustrated in Figure 5 (left image). This methodology enhanced operational accuracy and streamlined the transition from planning to execution.

The platform enabled comprehensive digital twin modeling of all work cell elements, including the industrial robot, end effector, target wall, and peripheral structural components. Data from thermal and RGB image analyses were integrated into the CAD model of the wall, facilitating precise localization of the robot's base coordinate system relative to environmental elements. This spatial registration ensured that all subsequent robot actions were accurately oriented and aligned in both the simulation and the physical environment.

Using the detailed CAD data, critical structural elements such as studs and regions of drywall damage were identified and localized within the wall's coordinate system. Toolpaths were generated that avoided these elements, optimizing the salvageable drywall area. This strategic planning phase eliminated the need for manual projection, depicted in the Projection step in Figure 1, by automating the path generation process.

The CAD-informed path planning system translated digital twin data into executable robotic commands. Comprehensive simulation capabilities enabled preemptive verification, troubleshooting, and optimization of robotic trajectories before physical deployment. The control architecture incorporated dynamic adjustment capabilities through real-time environmental feedback, ensuring high precision and adaptability during deconstruction. This responsive system enhanced the robot's ability to execute tasks with greater accuracy and adapt to on-site variables, which is critical in dynamic environments with potential variability and change.

Future system development includes integrating advanced vision systems to provide enhanced real-time sensing capabilities, facilitating process optimization, and improving collision avoidance protocols. These implementations will augment safety redundancy while maintaining responsiveness to deviations from the predefined digital model. The enhanced error-handling framework will enable the robot to autonomously adjust its operations and recover from unexpected changes or obstacles, thereby maintaining operational efficiency and safety without human intervention.

The advanced workflow improved deconstruction efficiency by eliminating the manual projection step and enhanced operational safety and precision. By utilizing CAD data to inform robotic path planning directly, each movement was optimized for speed and accuracy, significantly improving material recovery rates and operational safety metrics.

Table 7 presents a comprehensive comparison of deconstruction method performance metrics.

Table 7. Comprehensive performance analysis of manual and robotic deconstruction methods.

Performance Metric	Method 1: Saw Cutting	Method 2: Screw Removal	Method 3: Robotic System
Processing Speed	10 min/section	15–18 min/section	100 mm/s (439 m^2/h)
Material Recovery Rate	75–80%	100%	95% with precision cutting
Precision Accuracy	80%	100% at fastener points	100%
Equipment Cost	Low (<USD 500)	Low (<USD 200)	High (USD 67,000)
Skill Level Required	Minimal	Minimal	Technical expertise required
Workspace Constraints	Minimal	Minimal	5 m^2 from fixed position
Safety Risk Level	Moderate (saw operation)	Low (hand tools)	Minimal (automated safety systems)
Maximum Panel Size	Limited by stud spacing	Full sheet recovery	5 m^2 per position
Labor Requirements	1–2 workers	1–2 workers	2 skilled operators
Environmental Control	Minimal	Minimal	Climate-controlled space required
Setup Time	Immediate	Immediate	Several days of initial setup
Operational Flexibility	High	High	Limited by workspace bounds
Material Preservation	Produces smaller sections due to saw kerf and stud proximity.	Maximum preservation potential; enables recovery of full-sized sheets.	Optimized preservation through precise cutting paths and controlled extraction.
Applicability	Suitable for rapid demolition projects with flexible material recovery targets.	Optimal for high-value material recovery in accessible conditions.	Ideal for large-scale industrial applications with consistent wall configurations.

4.4. Case Studies

Two on-site field tests were conducted to validate the methods for stud type and location identification, as illustrated in Figures 6 and 7. These case studies evaluated system performance and aimed to understand the practical challenges associated with scanning and processing images under real-world conditions.

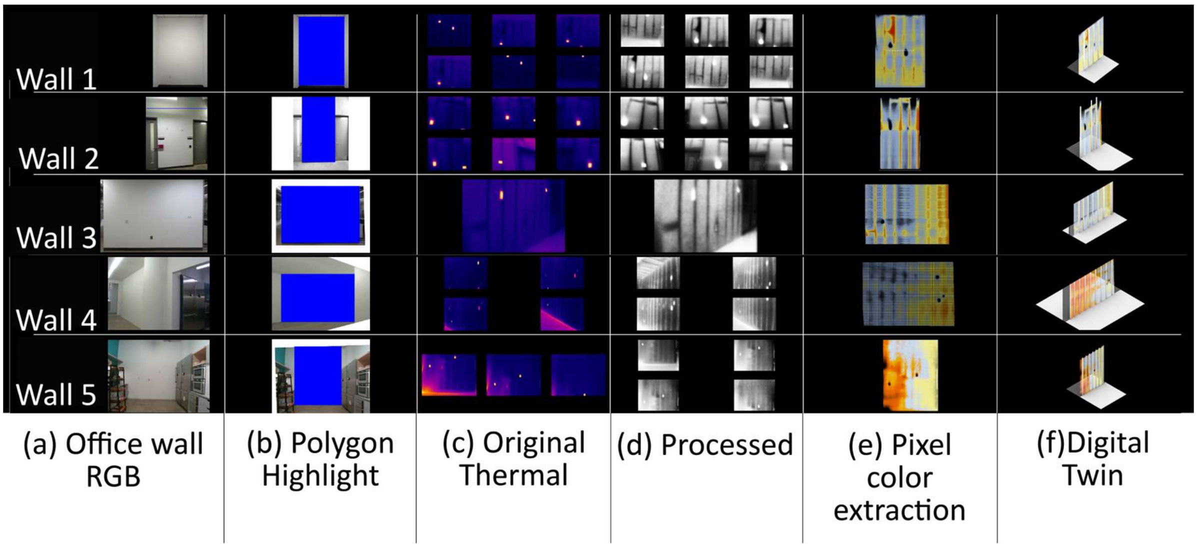

Figure 6. Multi-modal wall analysis sequence from commercial office implementation: (**a**) RGB captures, (**b**) polygon highlighting from edge detection output, (**c**) thermal imaging data (original), (**d**) processed thermal image data, (**e**) thermal image pixel extraction, (**f**) resultant digital model placing studs on the detected stud areas based on the pixel color.

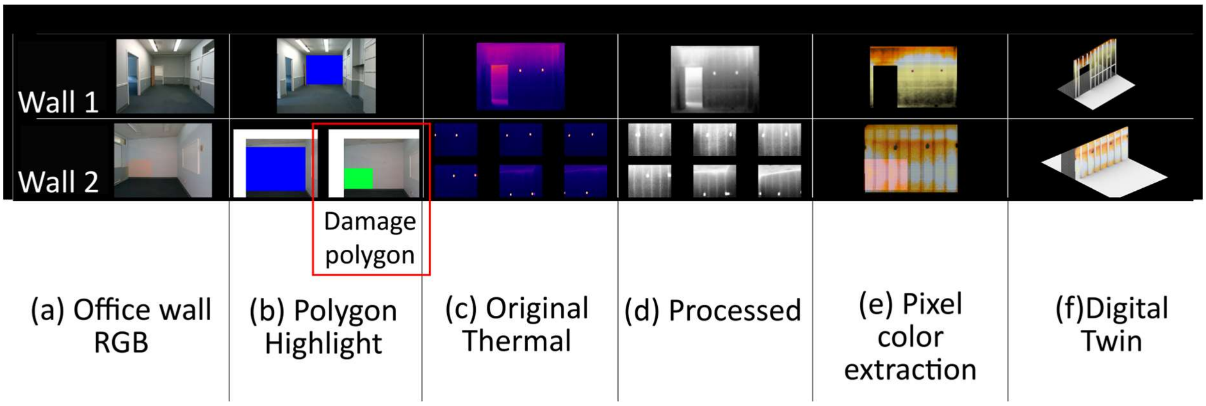

Figure 7. Multi-modal wall analysis sequence from an educational facility: (**a**) RGB captures, (**b**) polygon highlighting from edge detection output, (**c**) thermal imaging data (original), (**d**) processed thermal image data, (**e**) thermal image pixel extraction, (**f**) resultant digital model placing studs on the detected stud areas based on the pixel color.

4.4.1. Case Study 1: Office Wall Scanning

The first field validation occurred in a 2010s-era commercial office building in Boston, examining five distinct wall sections from June 2024 to July 2024. The study evaluated scanning methodologies through varied hand motion patterns while maintaining consistent processing protocols. Scanning efficiency analysis revealed distinct performance variations between motion protocols. Horizontal scanning patterns demonstrated increased capture duration and presented significant challenges in image alignment, particularly due to the homogeneous nature of wall surfaces lacking distinctive features for algorithmic stitching reference points. In contrast, vertical scanning motions exhibited superior performance on tall, narrow wall sections, facilitating more efficient image alignment and stitching processes.

The image processing workflow achieved successful stitching across all captured samples through the implementation of reference markers, which significantly enhanced alignment accuracy. Subsequent analysis in Grasshopper enabled comprehensive digital twin generation for each wall section. Pixel extraction identified areas with consistent thermal signatures by segmenting pixels based on brightness or color values. The process isolated regions with similar thermal properties, enabling the detection of structural elements like studs through distinct thermal patterns. Validation of the digital models against subsurface scan data confirmed accurate scaling of stud spacing measurements, demonstrating the methodology's precision in structural element mapping. Figure 6 illustrates the complete data acquisition and processing sequence, including RGB capture, thermal imaging, and digital model generation for all five wall sections. Tables 8 and 9 present the implementation parameters and quantify scanning efficiency and processing accuracy metrics achieved during this validation phase.

Table 8. Office wall scanning implementation parameters.

Parameter	Specification
Facility Type	Commercial office, Boston (constructed 2010s)
Duration	June–July 2024
Sample Size	5 walls
Construction Type	Metal stud framing
Scanning Protocol	Variable hand motion patterns
Processing Method	Standardized across all samples

Table 9. Key performance findings from office scanning.

Assessment Category	Key Findings
Horizontal Scanning	Extended capture duration Alignment challenges during stitching Limited effectiveness with homogeneous surfaces
Vertical Scanning	Enhanced stitching accuracy Improved efficiency for narrow wall sections Superior alignment outcomes
Image Processing	Successful image stitching with marker assistance Digital twin generation achieved Verified stud spacing accuracy through subsurface validation

4.4.2. Case Study 2: High School Wall Scanning

The second field validation examined eight wall sections at a high school facility scheduled for demolition, with data collection completed within 75 min. Table 10 summarizes the implementation parameters, including facility characteristics, sample size, and the scanning protocol employed. The developed scanning rig demonstrated enhanced maneuverability and operational efficiency in the demolition environment, enabling rapid multi-wall assessment. However, the wood stud construction presented significant challenges for thermal imaging effectiveness, resulting in reduced thermal contrast compared to metal stud implementations in the first case study.

Table 10. High school wall scanning implementation parameters.

Parameter	Specification
Location	Secondary school scheduled for demolition
Duration	75 min total scanning time
Sample Size	8 wall sections
Construction Type	Wood stud framing
Processing Method	Thermal-RGB protocol

The low thermal contrast characteristics of wood frame construction significantly impacted data extraction capabilities and digital twin generation accuracy. The established processing methodology, which had performed effectively with metal stud construction, exhibited reduced effectiveness in isolating structural elements from the thermal signatures of wood framing members. Table 11 quantifies these performance limitations across scanning system efficiency, thermal imaging constraints, material impact factors, and processing outcomes.

Table 11. Key performance findings from high school scanning.

Assessment Category	Key Findings
Scanning System Performance	Enhanced rig maneuverability in the demolition environment Efficient multi-wall scanning capability Effective equipment mobility between scan locations
Thermal Imaging Limitations	Minimal thermal contrast in wood stud construction Reduced feature extraction capability Limited digital twin accuracy due to low thermal signatures
Material Impact Analysis	Significantly reduced detection rates compared to metal studs Processing algorithm limitations with wood construction Thermal signature variations between construction types
Processing Outcomes	Reduced accuracy in structural element mapping Limited effectiveness of standard processing protocols Decreased reliability in digital twin generation

Figure 7 presents representative data acquisition and processing sequences for two of the eight analyzed wall sections, illustrating the challenges encountered with thermal contrast and feature extraction.

4.4.3. Cost–Benefit Analysis

A detailed cost–benefit analysis comparing demolition to deconstruction methods was conducted on a 90-square-foot wall section at Stoneham High School. Cost data were sourced from RSMeans Online [49] using commercial new construction unit costs, standard union labor rates, and Boston location factors. Material handling costs include collection, transportation, storage, processing, and disposal expenses. Tables 12–16 present a comprehensive analysis of demolition costs, deconstruction costs, total costs and benefits, and overall cost–benefit comparisons.

The baseline demolition approach cost USD 102.11 with no material recovery benefit. Analysis revealed that while manual deconstruction methods required higher initial investment, both approaches demonstrated positive net benefits. The saw-cutting method (78% material retrieval) yielded a net benefit of USD 71.92 despite higher total costs (USD 199.37). In comparison, the screw removal method (100% material retrieval) achieved a net benefit of USD 121.01 with total costs of USD 226.80.

These net benefits were realized through multiple factors:

- Material savings from avoided new drywall purchases.
- Waste handling savings from reduced transportation and processing.
- Disposal savings from avoided landfill fees.
- Carbon emission reductions through material reuse.

Table 12. Demolition phase costs and environmental impact.

Demolition Parameters	Baseline Demolition	Deconstruction Method 1: Saw Cutting	Deconstruction Method 2: Screw Removal
Disposal Quantity (SF)	90	19.80	-
Disposal Quantity (Tons)	0.10	0.02	-
Demolition Duration (Hours)	0.72	0.16	-
Demolition Duration (Minutes)	43.200	9.504	-
CO_2 Emissions from Disposal ($kgCO_2$)	1.80	0.40	-
Labor Costs (USD)	49.50	10.89	-
Overhead and Profit (USD)	24.30	5.35	-
Waste Material Handling Costs (USD)	20.29	4.46	-
Waste Dump Charges (USD)	8.02	1.76	-

Table 13. Deconstruction phase costs.

Deconstruction Parameters	Baseline Demolition	Deconstruction Method 1: Saw Cutting	Deconstruction Method 2: Screw Removal
Reusable Quantity (SF)	-	70.20	90
Reusable Quantity (Tons)	-	0.08	0.10
Deconstruction Duration (Hours)	-	2.55	6.55
Deconstruction Duration (Minutes)	-	153.16	392.73
Labor Costs (USD)	-	41.42	53.10
Overhead and Profit (USD)	-	18.95	24.30
Salvaged Material Post-Processing Costs (USD)	-	116.53	149.40

Table 14. Total cost summary.

Costs	Baseline Demolition	Deconstruction Method 1: Saw Cutting	Deconstruction Method 2: Screw Removal
Total Costs (USD)	102.11	199.37	226.80
Total Labor (Hours)	0.72	2.71	6.55
Total Carbon ($kgCO_2$)	1.80	0.40	0.00

Table 15. Total benefit summary.

Benefits	Baseline Demolition	Deconstruction Method 1: Saw Cutting	Deconstruction Method 2: Screw Removal
Material Savings (USD)	-	217.62	279.00
Waste Handling Savings (USD)	-	15.83	20.29
Disposal Savings (USD)	-	6.25	8.02
Carbon Offsets (kg CO_2)	-	31.59	40.50
Total Estimated Benefits (USD)	-	271.29	347.81

Table 16. Total cost–benefit analysis summary.

	Baseline Demolition	Deconstruction Method 1: Saw Cutting	Deconstruction Method 2: Screw Removal
Total Costs (USD)	102.11	199.37	226.80
Total Benefits (USD)	-	271.29	347.81
Net Benefits (USD)	(102.11)	71.92	121.01

Carbon offset calculations indicate that drywall reuse can achieve approximately 0.45 kg CO_2 savings per square foot. This figure combines emissions avoided from new drywall production (0.43 kg CO_2/SF for lifecycle stages A1–A3) [50] and disposal (0.02 kg CO_2/SF for stages C1–C4) [51], based on environmental product declaration data and disposal impact studies.

The analysis demonstrates that while deconstruction methods require 2.71–6.55 labor hours compared to 0.72 h for demolition, significant material recovery benefits offset the additional time investment. Notably, these labor calculations were based on observations of novice researchers and do not account for potential efficiency gains through learning and experience curves.

While the robotic deconstruction system requires higher initial equipment investment (USD 67,000) and climate-controlled space, it offers potential long-term economic advantages through increased processing speeds (439 m^2/h) and consistent 95% material recovery rates. Future studies should conduct a detailed return-on-investment analysis comparing robotic implementation costs against labor savings and material recovery benefits on the commercial scale. This analysis would provide valuable insights into automation viability across different project scales and material recovery scenarios.

A comprehensive breakdown of the cost–benefit analysis methodology and calculations can be found in File S1.

4.5. Digital Model Accuracy Analysis

A detailed accuracy assessment of the digital models was conducted to evaluate system reliability across various capture scenarios. Figure 8 presents the correlation between capture methodologies, processing approaches, and resultant accuracy metrics. The analysis quantified accuracy variations based on capture methods and image distortion levels. The validation methodology evaluated digital twin accuracy through a systematic four-phase analysis. Initial computations established predicted stud spacing patterns, followed by an assessment of various capture techniques, including single-shot, double-shot, perpendicular, and angled image acquisition. Image processing protocols, detailed in Section 4.2, implemented calibration and perspective correction where required.

Physical validation using stud detection equipment provided ground-truth measurements for accuracy calculation. Mean deviation percentages were derived by measuring displacement between predicted and actual stud positions, with results normalized against total stud count to establish overall system accuracy metrics. Table 17 quantifies the influence of capture methods, image distortion, material properties, and environmental conditions on these accuracy measurements, demonstrating superior performance with vertical scanning motions and perpendicular wall captures.

The experimental demonstrations detailed in Sections 4.3 and 4.4 revealed both the capabilities and limitations of the methodology. The accuracy analysis presented in Table 17 demonstrated the critical importance of optimized scanning techniques while identifying areas requiring algorithmic refinement, particularly for wood stud detection and distorted image processing scenarios. While the system achieved high accuracy under optimal conditions, establishing a foundation for practical deconstruction applications, the analysis highlighted opportunities for enhanced reliability across diverse building types and environmental conditions. These findings support the continued refinement of the scanning and analysis protocols to develop a robust implementation framework suitable for varied deconstruction scenarios.

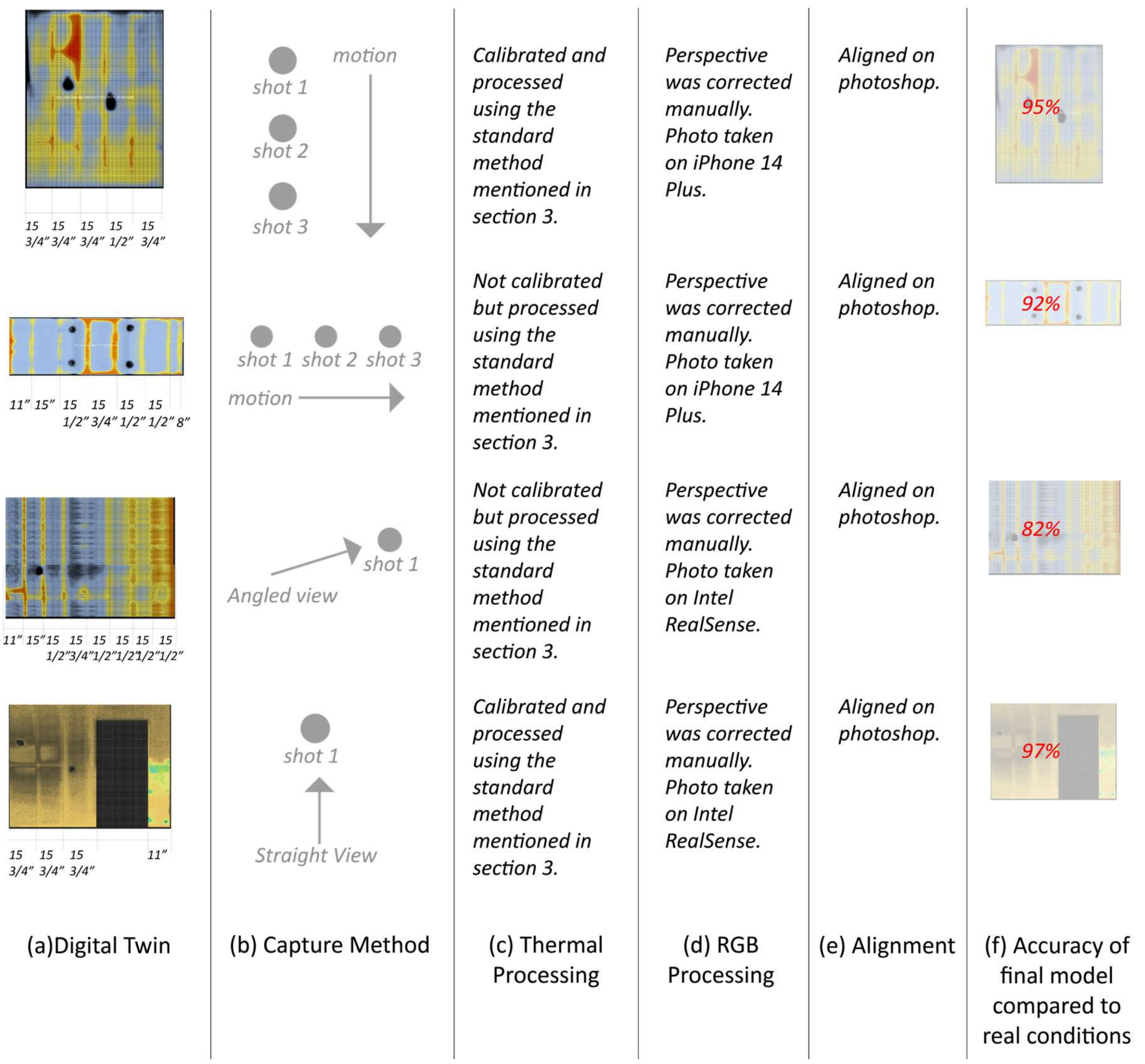

Figure 8. Digital twin validation sequence showing: (**a**) predicted stud spacing, (**b**) capture methodologies, (**c**) and (**d**) processing protocols, (**e**) thermal image pixel extraction, and (**f**) physical verification results with calculated accuracy percentages (accuracy is calculated based on the average correctness of locations across all predicted stud positions for the wall being tested).

Table 17. Digital model accuracy influencing factors.

Process Parameter	Performance Observations
Capture Method	Vertical scanning: Enhanced accuracy Horizontal scanning: Reduced precision
Image Distortion	Perpendicular captures: Maximum accuracy Angled captures: Increased deviation
Material Type	Metal studs: High thermal contrast, superior detection Wood studs: Limited thermal differentiation
Environmental Conditions	Enhanced clarity with larger thermal gradients Optimal interior-exterior temperature differential: >5 °C
Digital Twin Fidelity	Metal stud spacing accuracy: ±50.8 mm (±2″) Calibrated capture success rate: 95%

5. Discussion

The discussion synthesizes findings from industry interviews, technical implementation challenges, and future development prospects to evaluate technological solutions for sustainable construction and demolition practices.

5.1. Industry Insights

Semi-structured interviews with industry professionals from the construction and demolition sectors revealed significant limitations in current assessment practices. Industry professionals reported that traditional visual inspection and manual probing methods are time-consuming, often requiring multiple passes to identify stud locations, assess material conditions, and document findings. The professionals also emphasized three critical factors affecting material reuse potential: accurate stud type identification, asbestos detection, and mold assessment.

The integrated sensing system developed in this research demonstrated capabilities that address some of these industry challenges. The multi-modal approach achieved 92% accuracy in perpendicular captures while processing wall sections in an average of 3.5 min. While accuracy decreased to 78% for angled captures, the system maintained simultaneous assessment capability for both surface and subsurface conditions in a single pass. This advancement in assessment efficiency and accuracy directly addresses the time and labor constraints identified by industry professionals.

While effective for distinguishing between wood and metal studs, current thermal imaging technology demonstrates significant limitations in detecting hazardous materials and assessing material conditions. Emerging advanced sensing technologies show promise in addressing these detection limitations. Recent developments in short-wave infrared (SWIR) spectral ranges demonstrate particular potential for hazardous material detection. Research has shown that various construction materials exhibit distinctive spectral characteristics in specific wavebands, enabling their identification and characterization. While current commercially available sensors operate in limited spectral ranges, next-generation technologies could expand detection capabilities across broader wavelength bands.

The integration of advanced sensing technologies into existing multi-modal workflows addresses key challenges identified through industry interviews while supporting the development of more comprehensive material assessment systems. These enhanced capabilities promote efficient and sustainable industry practices by enabling better identification of salvageable materials and ensuring safety through improved detection of hazardous substances.

5.2. Implementation Challenges and Technical Feasibility

The practical implementation of these innovative approaches has revealed several critical challenges that require careful consideration. A primary concern involves physical constraints in data capture, where the effectiveness of the imaging system significantly depends on proper rig positioning. While the increased distance between the rig and the wall generally yields superior results, real-world settings often present space limitations and cluttered environments that compromise ideal positioning.

The case studies demonstrated considerable variability in data quality across different environments. For instance, scans conducted at the high school demolition site yielded minimal usable data due to suboptimal conditions despite substantial effort invested in the scanning process. In contrast, scans performed at the Autodesk office featuring metal framing produced accurately processable data for all but one wall, which was excluded due to excessive thermal patches in the kitchen area. This disparity highlights the significant impact of building materials and construction methods on current imaging and processing techniques.

The data processing pipeline presents additional technical challenges requiring attention. While programmatic solutions for image processing and polygon highlighting have been successfully implemented, several critical steps remain manual, including matching RGB images to thermal images and damaging polygons. These current thermal image stitching limitations require manual interventions, which not only reduce efficiency but also introduce potential inconsistencies in the workflow.

5.3. Recommendations for Future Research

Based on the findings and challenges identified in this study, several key areas warrant further investigation to advance the field of automated construction and demolition material assessment. Future research should focus on developing and validating advanced imaging algorithms to eliminate manual processing steps and enhance system reliability. Specifically, research efforts should prioritize automated thermal image stitching algorithms and RGB-to-thermal image matching techniques to create a more streamlined and efficient workflow.

Future studies should expand environmental condition testing beyond interior partitions. While this research demonstrated effective sensing capabilities for interior walls, including those with exterior exposure, comprehensive testing across different environmental conditions would provide valuable insights into system reliability and potential applications. Investigating temperature differential impacts on thermal contrast could inform optimization strategies for varied interior wall configurations.

Additional research is needed to improve the accuracy and robustness of damage detection models. This includes expanding training datasets to encompass a broader range of material conditions, damage types, and environmental variables. It is also important to note that the training set used for damage detection consisted of images of white walls only. The training set would need to include a broader diversity of finishes and colors to accurately detect damage in scenarios where drywall is colored with darker tones, glossy finishes, and other more nuanced qualities. Future studies should also explore adaptive imaging techniques that maintain consistent performance across varying environmental conditions and building configurations. Developing integrated data capture and processing tools represents another crucial research direction, potentially leading to more efficient and user-friendly systems for industry implementation.

Material detection capabilities require further refinement through dedicated research efforts, particularly for wood stud identification. Future studies should investigate novel sensing approaches and detection algorithms optimized for different building materials and construction methods. This research direction would contribute to more reliable and comprehensive material assessment capabilities across diverse construction scenarios.

The development of integrated robotic automation systems presents a promising avenue for future research. Studies should examine the integration of advanced vision systems, real-time sensing capabilities, and autonomous error-handling frameworks. Research efforts should focus on optimizing robotic path planning algorithms, enhancing collision avoidance protocols, and developing robust error recovery mechanisms. Investigations into human–robot interaction and safety protocols within construction environments would also contribute valuable insights for system implementation.

Future research initiatives should additionally consider the economic and practical implications of these technological developments, including cost–benefit analyses, implementation strategies, and industry adoption barriers. Longitudinal studies examining the long-term performance and reliability of automated systems in real-world construction and demolition settings would provide valuable data for continued system refinement and optimization.

6. Conclusions

This research demonstrated the technical viability of contactless material assessment for building deconstruction by integrating multi-modal sensing technologies and machine learning. The experimental results established quantifiable benchmarks for automated assessment systems, with the sensing system achieving significant detection accuracy across multiple modalities. Performance metrics showed 95% accuracy in metal stud detection and 67% in wood stud detection, with success rates of 92% for perpendicular wall capture and 78% for angled capture. The system maintained a spatial resolution of ± 2 cm accuracy in stud location detection while processing wall sections in an average of 3.5 min.

The damage detection system demonstrated robust performance through multiple validation metrics. Testing revealed 88% accuracy in crack detection and 72% in surface discoloration detection. The machine-learning model achieved 91% training accuracy on the 30-image dataset and maintained 86% validation accuracy on previously unseen images. These results validated the system's ability to reliably identify and classify material conditions across diverse scenarios.

The robotic implementation demonstrated the feasibility of automated material recovery. It operated at speeds of 100 mm/s and covered 439 square meters per hour. The system achieved positional repeatability of 0.06 mm and path repeatability up to 0.28 mm, enabling precise material extraction with maximum panel sizes of 5 m^2 per position. These specifications showed the potential for scaled implementation in industrial applications.

Case studies validated the system performance in real-world conditions, though significant variations exist between different building types. Metal stud construction showed superior detection rates compared to wood frame buildings, indicating the need for further development in wood stud detection algorithms. Environmental factors, including surface colors and temperature differentials, impacted system performance and required consideration during implementation.

While this research demonstrates promising results through non-invasive multi-modal sensing methods, future work should include systematic comparisons with invasive inspection methods. Direct correlation studies between sensor readings and physical verification through conventional destructive testing would further validate the accuracy of the proposed methodology. Such validation studies would strengthen the reliability assessment of contactless methods as alternatives to traditional invasive inspection techniques.

The demonstrated integration of thermal imaging, RGB analysis, and depth sensing establishes a new benchmark for automated material assessment in construction. While certain limitations remain, particularly in wood stud detection and varied surface conditions, the system's performance validates the potential for automated approaches to transform material recovery and reuse in construction. Future research priorities include expanding the machine-learning dataset to include diverse building conditions, developing enhanced detection capabilities for wood frame construction, and establishing standardized protocols for system implementation across varying environmental conditions.

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