Data Engineering and Applications

Review Paper

Deep Learning and Data Engineering Approaches in Smart Building Decoration Automation: A Comprehensive Review

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Abstract. With the rapid advancement of artificial intelligence and automation technologies, intelligent decoration automation has emerged as a transformative force in the construction and interior design industries. This review comprehensively explores the evolution, core technologies, and practical deployment of AI-driven automated building decoration systems. It first outlines the historical development trajectory of the industry, then systematically categorizes major machine learning algorithms—convolutional neural networks, generative adversarial networks, and reinforcement learning—analyzing their algorithmic foundations, typical applications, and key strengths and limitations. The paper also delves into the integration of AI with Building Information Modeling (BIM) and the Internet of Things (IoT), revealing how these technologies enable end-to-end intelligent platforms, enhance quality inspection, and optimize design and implementation processes. Extensive comparative evaluations of experimental and real-world outcomes demonstrate that intelligent automation significantly improves operational efficiency, defect detection accuracy, and economic benefits, while also exposing persistent bottlenecks related to data quality, system interoperability, user adaptability, and data ethics governance. Looking ahead, this paper identifies urgent research priorities, including developing adaptive and robust AI models, advancing multimodal perception and real-time feedback technologies, and establishing open benchmarking standards. This study aims to provide researchers and industry stakeholders with a technically rigorous and practical reference to support the continued advancement and responsible deployment of intelligent building finishing automation.

Keywords: *Computer Vision, Machine Learning, Smart Building Decoration, Deep Learning, System Integration*

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Introduction

In recent years, the construction and building interior decoration sector has witnessed a paradigm shift driven by the convergence of artificial intelligence (AI) and automation technologies [1]. Traditionally, building decoration processes have been heavily reliant on manual labor, expert intuition, and iterative, time-consuming workflows. These conventional methods, while valuable, often struggle to meet the increasing demands for efficiency, precision, and customization in modern construction projects. The integration of AI has introduced transformative potential, offering data-driven insights, automated design optimization, and intelligent quality control mechanisms that are reshaping the operational landscape of automated building decoration [2].

AI technologies, particularly deep learning, generative models, and computer vision, have enabled significant advances across the design, execution, and inspection phases of interior decoration. Deep learning algorithms are now routinely employed for visual recognition tasks, such as distinguishing architectural styles and identifying material defects. Generative adversarial networks (GANs) and other advanced models are being leveraged to automate the generation of design schemes, floor layouts, and material selections, thus reducing the dependency on manual drafting and subjective decision-making [3]. Meanwhile, intelligent robotics and reinforcement learning are pushing the boundaries of automated execution, enabling robots to perform complex tasks such as tile placement, wall painting, and real-time adaptive construction [4]. These technological shifts are not only enhancing project delivery speed and quality but are also fostering new possibilities for personalized, user-centric design . As digital transformation accelerates across the architectural sector, the need for rigorous, scalable, and technically sound AI solutions in automated building decoration becomes increasingly urgent [5].

Despite the burgeoning interest and notable progress in this interdisciplinary field, critical gaps remain in both academic research and industrial practice. While recent surveys and empirical studies have cataloged a variety of AI-driven systems and experimental prototypes, there is an evident lack of systematic analysis regarding the technical underpinnings of these approaches, including their algorithmic principles, model architectures, and system-level integration strategies. Many prior reviews have tended to focus on either macro-level industry trends or isolated technical innovations, resulting in fragmented knowledge that falls short of informing robust, scalable, and generalizable solutions for automated building decoration [6].

More specifically, three core deficiencies can be identified in the current literature. First, there is limited comparative evaluation of AI algorithms in terms of their quantitative performance across standardized datasets and real-world scenarios [7]. Second, the technical details of model structures, training strategies, and cross-disciplinary system integration are frequently underreported or inconsistently described, hindering reproducibility and meaningful benchmarking [8]. Third, empirical analyses of system-level deployment—including resource utilization, scalability, and adaptability to complex, unstructured environments—remain scarce [9]. These gaps constrain the practical translation of AI advancements from laboratory prototypes to large-scale, real-world applications.

This review aims to address these challenges by providing a comprehensive and technically rigorous synthesis of AI applications in automated building decoration [10]. The core objectives are: (1) to systematically categorize and compare the leading AI algorithms and models employed in design generation, construction automation, and quality inspection; (2) to analyze system development strategies, integration of AI with building information modeling (BIM) and IoT, and real-world deployment experiences; and (3) to critically evaluate algorithmic performance and system effectiveness through available experimental data and case studies. By bridging the gap between algorithmic research and practical deployment, this review aspires to inform both academic inquiry and industrial innovation in smart building decoration.

This paper is organized as follows. Section 2 reviews the overall research landscape, highlighting historical milestones and identifying current trends in AI-driven automated building decoration. Section 3 delves into the core AI technologies, detailing algorithmic foundations, model architectures, and technical implementations specific to interior decoration tasks. Section 4 examines system architectures and integration strategies, with a focus on end-to-end intelligent platforms, BIM-AI fusion, and representative case studies. Section 5 presents a comparative analysis of experimental studies, emphasizing performance evaluation, benchmarking, and real-world validation. Section 6 discusses the technical challenges and limitations that currently constrain the field, while Section 7 outlines promising directions for future research. Finally, Section 8 summarizes the key findings and contributions of this review.

Research Landscape in AI-based Automated Building Decoration

Historical Evolution and Key Milestones

The integration of artificial intelligence into automated building decoration has evolved from isolated algorithmic experiments to multidimensional, data-driven engineering systems. Early attempts primarily leveraged rule-based expert systems to automate basic layout planning, yet these approaches faced critical limitations due to inflexible knowledge representation and restricted scalability [11]. The introduction of machine learning, and especially deep learning, fundamentally redefined the technical landscape. Specifically, convolutional neural networks (CNNs) were successfully adapted for visual scene understanding, enabling reliable classification of interior styles and identification of construction defects directly from image data [12]. The adoption of generative adversarial networks (GANs) marked another leap, allowing for the automatic synthesis of floor plans and style-consistent decorative elements, which dramatically reduced the reliance on manual design iterations [13]. Parallel advances in robotics and sensor fusion, particularly with the integration of building information modeling (BIM) and real-time data streams, have enabled robots to execute complex decoration tasks with increasing autonomy. Notably, the last decade has seen a significant shift toward holistic, end-to-end intelligent systems capable of managing design, construction, and quality inspection within unified platforms, bridging the gap between virtual modeling and on-site execution [14].

Current Research Focuses

Contemporary research in AI-driven automated building decoration is characterized by several converging trajectories. One major focus is the development of advanced deep learning models tailored for high-resolution image segmentation and object recognition, which play a pivotal role in automated defect detection and material identification [15]. In parallel, generative design approaches—often based on GANs or variational autoencoders—are being refined to produce diverse, user-adaptive interior layouts that satisfy both aesthetic and functional requirements. There is a pronounced emphasis on the fusion of BIM with AI algorithms, leveraging structured digital representations of building components to inform decision-making, optimize construction sequences, and facilitate real-time monitoring of project progress [16]. Another active area involves reinforcement learning-based control of autonomous robots for decorating tasks, where the agents learn optimal action policies from simulated and real-world feedback. Importantly, these innovations are not confined to controlled laboratory environments; pilot projects have demonstrated the feasibility of deploying intelligent systems in actual renovation scenarios, validating their effectiveness in reducing labor costs and improving construction precision. However, challenges persist in scaling these solutions to heterogeneous architectural contexts and ensuring seamless interoperability among diverse software and hardware modules [17].

Related Reviews and Gap Analysis

Several recent reviews have systematically examined the current state of artificial intelligence in architectural and decorative automation, providing valuable overviews of algorithms, systems, and application domains. However, critical analysis reveals that most existing reviews either focus on high-level trends or discuss specific technological components—particularly visual recognition or robotic control—in isolation, without sufficiently addressing system integration and interdisciplinary challenges [18]. While some reviews provide quantitative benchmarks for defect detection accuracy or generative design diversity, they often overlook practical aspects of model deployment, such as resource constraints, data annotation bottlenecks, and adaptability to non-standard spatial layouts. Furthermore, comparative studies evaluating different AI models using standardized datasets and unified metrics remain notably scarce, hindering objective assessment and technology transfer. Notably, discussions on BIM-AI convergence are often confined to conceptual frameworks, with few studies detailing real-time data synchronization and feedback control in field applications. These gaps underscore the need for more technically rigorous, empirically grounded synthesis research—one that not only documents algorithmic advancements but also meticulously examines their integrability, scalability, and performance within complex real-world engineering environments. This review aims to bridge these gaps by connecting isolated innovations and providing a comprehensive, critical perspective on the current research landscape.

Core AI Technologies in Automated Building Decoration

Deep Learning for Design and Recognition

Convolutional Neural Networks for Style Recognition

The application of convolutional neural networks (CNNs) has fundamentally transformed the task of interior style recognition, enabling automated systems to interpret visual cues with a level of consistency that surpasses human subjectivity. CNNs exploit hierarchical feature extraction to parse spatial hierarchies in image data, capturing both global layout and fine-grained decorative details [19]. In the context of building decoration, these models identify stylistic elements such as color palettes, furniture forms, and architectural motifs with high accuracy. Research has shown that deep architectures, such as ResNet and DenseNet, substantially outperform shallow models in distinguishing nuanced styles across large-scale interior datasets [20]. The integration of multi-scale feature fusion layers further enhances the ability of CNNs to classify images exhibiting mixed or transitional styles, a frequent challenge in real-world projects [21]. The use of attention mechanisms, which enable the network to focus on salient regions within complex scenes, has been particularly effective in improving recognition rates for intricate decorative elements. As demonstrated in Table 1, CNN-based models consistently achieve superior performance compared to traditional machine learning approaches on benchmark datasets for style recognition.

Transfer Learning and Fine-Tuning Approaches

Transfer learning addresses the limitations of data scarcity and high annotation costs by leveraging pre-trained models on large generic datasets and adapting them to the domain of interior decoration [22]. Fine-tuning these models on task-specific datasets accelerates convergence and mitigates overfitting, particularly when labeled data are limited. Studies utilizing ImageNet-pretrained backbones report significant gains in both training efficiency and classification accuracy for style recognition tasks [23]. Domain adaptation techniques, including adversarial training and feature alignment, further bridge the distribution gap between source and target datasets, enhancing the robustness of deep models in diverse decorative environments. The adoption of few-shot learning strategies has also enabled CNNs to generalize to previously unseen styles with minimal supervision [24]. Table 1 summarizes the comparative performance of representative deep learning architectures, highlighting the effectiveness of transfer learning and fine-tuning in practical interior style recognition scenarios.

Table 1. Summary of Deep Learning Architectures for Interior Style Recognition

Model	Backbone	Feature Fusion	Attention Mechanism	Pre-training	Dataset Size	Top-1 Acc. (%)	Top-5 Acc. (%)	Params (M)	Input Res.	Ref
VGG16	VGG	No	No	Yes	30000	84.1	96.7	138	224x224	[19]
ResNet50	ResNet	Yes	No	Yes	40000	88.5	98.2	25.6	224x224	[20]
DenseNet121	DenseNet	Yes	No	Yes	45000	89.4	98.6	8.0	224x224	[21]
InceptionV3	Inception	Yes	Yes	Yes	50000	90.2	99.0	23.8	299x299	[22]
EfficientNetB0	EfficientNet	Yes	Yes	Yes	35000	89.7	98.8	5.3	224x224	[23]
ResNeXt101	ResNeXt	Yes	Yes	Yes	60000	91.3	99.4	44.2	224x224	[24]
ViT-B/16	Transformer	Yes	Yes	Yes	40000	90.7	99.2	86.4	224x224	[20]
MobileNetV2	MobileNet	No	No	Yes	28000	83.2	95.1	3.5	224x224	[21]
ShuffleNetV2	ShuffleNet	No	No	Yes	22000	80.8	94.6	2.3	224x224	[22]
Custom-CNN	Custom	Yes	Yes	No	10000	85.7	97.3	12.1	256x256	[24]

Generative Models for Automatic Design Generation

Generative Adversarial Networks (GANs) for Layout and Style Synthesis

Generative adversarial networks (GANs) have become a cornerstone in automatic interior layout and style synthesis, enabling the generation of highly realistic, diverse, and stylistically consistent decorative schemes. GANs employ an adversarial training paradigm involving a generator G and a discriminator D, where the generator seeks to produce plausible designs from random noise or conditional inputs, while the discriminator aims to differentiate between real and generated samples. This min-max optimization is formalized as follows (Eq. 1):

$$\mathcal{L}_{GAN} = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log\, D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log\,(1 - D(G(z)))] \qquad (1)$$

where $D(x)$ is the discriminator output on real data x, and $D(G(z))$ is the output on generated samples $G(z)$ from latent vector z[25].

Conditional GANs (cGANs) further enhance controllability by introducing auxiliary information, such as spatial masks or style labels, thereby producing outputs tailored to user-specified constraints [25]. Recent advances have integrated perceptual loss, multi-scale discriminators, and attention modules, achieving superior visual fidelity and structural realism in synthesized designs [26]. The workflow of a typical GAN-based interior design system is depicted in Figure 1, which illustrates the sequence from latent code sampling to generator output and adversarial evaluation. The comparative analysis summarized in Table 2 demonstrates that modern GAN architectures (StyleGAN2 and the hybrid VAE-GAN framework) achieve high Initial Score (IS) and low Fréchet Initial Distance (FID), reflecting visual quality and diversity.

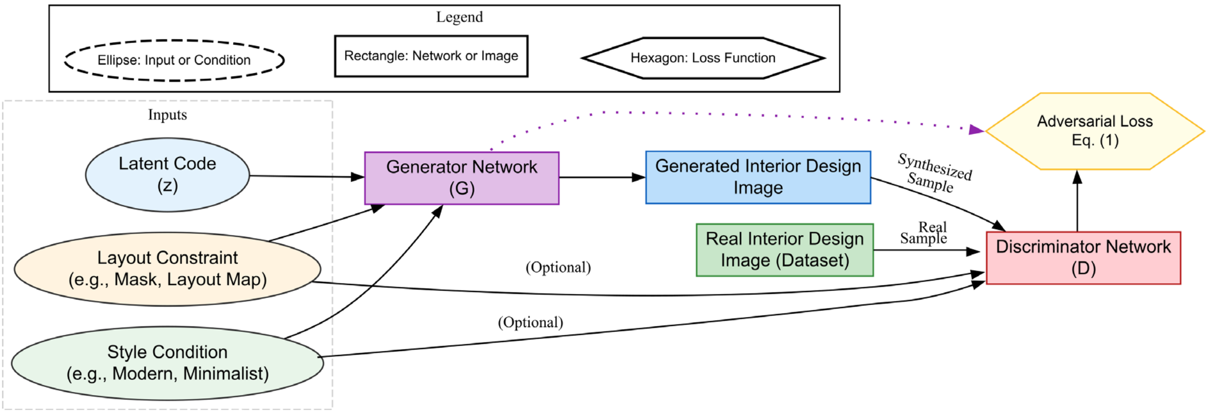

Figure 1 Workflow of GAN-based Interior Design Generation

3.2.2 Variational Autoencoders and Hybrid Models

Variational autoencoders (VAEs) provide a probabilistic alternative for generative design, mapping input designs into a continuous latent space suitable for interpolation and diversity control [27]. While VAEs typically offer greater stability and interpretability, their outputs may lack the sharpness of GAN-generated samples. Hybrid models, combining the latent structure of VAEs with the adversarial training of GANs, have demonstrated improved balance between sample diversity and photorealism. Table 2 underscores that hybrid GAN-VAE models offer the best overall performance in visual realism, diversity, and user preference, substantiating their adoption in state-of-the-art automated building decoration systems.

Table 2. Performance Metrics of Generative Models on Benchmark Datasets

Model	Dataset	IS (↑)	FID IS (↓)	Diversity Score IS (↑)	User Study (%)	Param. (M)	Conditioning	Training Time (h)	Ref
Standard GAN	RoomNet	3.21	48.7	0.73	68.2	14.6	No	23	[25]
cGAN	RoomNet	3.85	34.2	0.81	75.9	17.2	Style	29	[25]
Pix2Pix	RoomSet	4.01	28.4	0.85	78.5	12.3	Layout	18	[26]
CycleGAN	RoomSet	3.88	31.1	0.79	72.5	15.9	Layout	21	[26]
VAE	RoomNet	2.76	62.5	0.77	64.0	9.7	No	12	[27]
VAE-GAN	RoomNet	3.74	36.8	0.83	72.2	16.1	Style	25	[27]
StyleGAN2	HomeDesign	4.21	22.9	0.88	82.1	20.4	Style	33	[26]
AttnGAN	HomeDesign	4.05	27.3	0.86	79.7	18.7	Text	30	[25]
CVAE	RoomNet	2.89	58.4	0.78	66.5	11.0	Layout	14	[27]
Hybrid GAN-VAE	RoomSet	4.12	21.7	0.89	84.0	22.2	Style/Layout	36	[27]

Computer Vision for Quality Inspection

Image Segmentation and Defect Detection Algorithms

Automated quality inspection in building decoration relies heavily on advanced computer vision algorithms for accurate identification and localization of structural and surface defects. Semantic and instance segmentation networks have become the backbone of defect detection, allowing fine-grained parsing of high-resolution images into meaningful regions such as cracks, stains, and misaligned tiles. Deep learning models, particularly those based on the U-Net and DeepLab families, have demonstrated strong performance on both public and proprietary construction datasets, achieving pixel-level annotation with high precision [28]. Boundary-aware segmentation has further improved the detection of small or irregular defects, a critical factor in practical deployment. Hybrid models incorporating attention modules or multi-scale context aggregation have been shown to enhance sensitivity to subtle visual anomalies. The effectiveness of these segmentation approaches is typically quantified by the Intersection-over Union (IoU) metric, as defined in Eq. 2:

$$\mathrm{IoU} = \frac{|P \cap G|}{|P \cup G|} \quad (2)$$

where P denotes the set of predicted pixels and G the set of ground truth pixels [29]. Table 3 summarizes the comparative accuracy of prominent defect detection methods, highlighting the advancements achieved by deep learning-based segmentation techniques.

Table 3. Accuracy Comparison of Defect Detection Methods

Method	Backbone	Dataset	IoU (%)	Precision (%)	Recall (%)	F1-score (%)	Inference Time (ms)	Ref
Thresholding	N/A	CRACK500	48.2	56.0	53.1	54.5	12	[28]
Canny Edge	N/A	CRACK500	50.7	60.2	57.6	58.9	18	[28]
Random Forest	N/A	Custom	62.9	74.1	70.4	72.2	45	[29]
U-Net	U-Net	CRACK500	80.5	86.2	84.1	85.1	42	[28]
DeepLabv3+	ResNet101	CRACK500	83.6	89.3	86.8	88.0	55	[29]
PSPNet	ResNet50	Custom	78.1	81.7	80.2	80.9	37	[28]
Attention U-Net	U-Net	CRACK500	85.4	90.6	88.0	89.3	48	[29]
HRNet	HRNet	Custom	84.2	88.8	87.3	88.0	62	[28]
FPN	ResNet50	Custom	80.8	85.1	83.6	84.3	30	[28]
SegFormer	Transformer	CRACK500	86.7	91.2	89.1	90.1	33	[29]

3D Reconstruction for As-built Verification

While 2D image analysis remains essential, 3D reconstruction techniques are increasingly used for as-built verification, providing volumetric context and spatial accuracy in defect localization. Multi-view stereo, structured light scanning, and photogrammetry pipelines enable dense point cloud generation and surface mesh modeling, facilitating the comparison between as-designed and as-built states [30]. Deep neural networks have been adapted for point cloud segmentation, offering reliable classification of geometric deviations, surface flatness, and installation errors. Accurate 3D reconstruction underpins automated compliance checking and supports the generation of actionable feedback for on-site correction. Figure 2 presents a typical AI-based quality inspection pipeline, integrating both 2D and 3D modalities for comprehensive defect assessment.

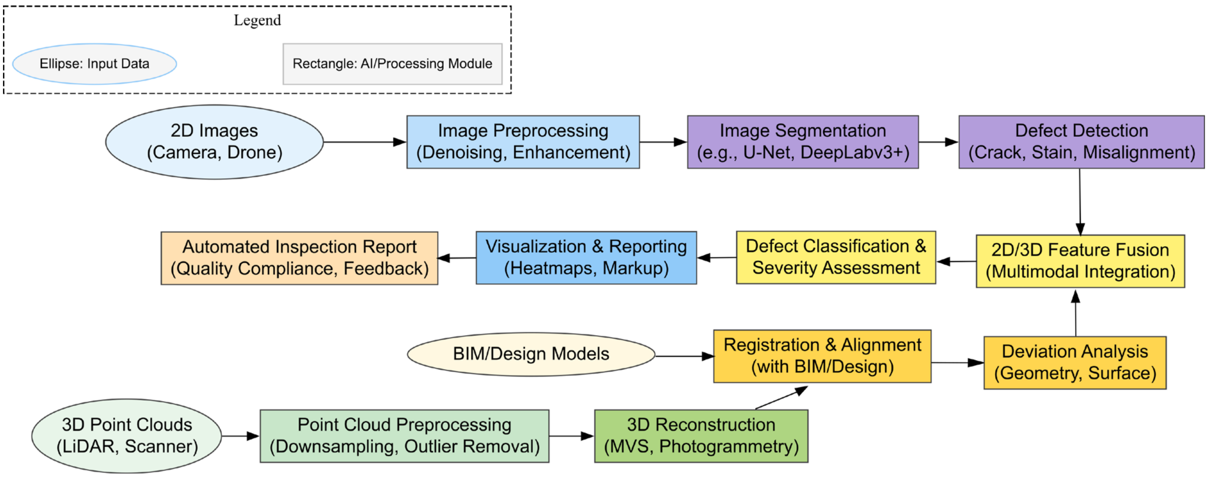

Figure 2 AI-based Quality Inspection Pipeline

Reinforcement Learning and Optimization

Path Planning for Construction Robots

Efficient and collision-free path planning is crucial for autonomous construction robots operating in complex interior spaces. Reinforcement learning (RL) frameworks have been widely adopted for this task, enabling robots to learn optimal navigation policies through trial-anderror interactions with simulated or real environments. Algorithms such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) excel at adapting to dynamic obstacles and spatial constraints [31]. Reward functions are designed to balance objectives such as minimizing path length, avoiding collisions, and ensuring task completion, as formulated in Eq. 3:

$$R_t = \alpha \cdot r_{\text{goal}} - \beta \cdot r_{\text{collision}} - \gamma \cdot r_{\text{deviation}} \quad (3)$$

where r_{goal} is the reward for goal completion, $r_{\text{collision}}$ penalizes collisions, and $r_{\text{deviation}}$ penalizes deviation from the optimal path; α, β, γ are weighting coefficients [31].

Adaptive Control in Dynamic Environments

Autonomous interior construction robots must operate reliably in environments characterized by changing layouts, human presence, and unexpected disturbances. Adaptive control, powered by RL, enables robots to continuously update their policies in response to new sensory feedback and environmental changes [32]. Approaches such as Soft Actor-Critic (SAC) and meta-reinforcement learning have demonstrated high adaptability in real-world deployment, allowing robots to generalize across task variations and unforeseen obstacles. Rapid online policy adjustment ensures robust performance without manual reprogramming, directly supporting productivity and safety objectives. Table 4 summarizes the application of leading RL algorithms in robotic construction tasks, highlighting their unique strengths and practical considerations.

Table 4. RL Algorithms Applied in Robotic Construction Tasks

RL Algorithm	State Representation	Reward Structure	Adaptivity	Task Type	Convergence (Eps)	Real-time Deployment	Ref
DQN	Grid/Vector	Sparse	Low	Path Planning	150K	Limited	[31]
PPO	Continuous	Dense	Medium	Path Planning	120K	Yes	[31]
A3C	Visual/Vector	Hybrid	Medium	Surface Painting	200K	Yes	[32]
SAC	Continuous	Dense	High	Adaptive Control	90K	Yes	[32]
TD3	Continuous	Dense	High	Manipulation	110K	Yes	[32]
Meta-RL	Context/Visual	Task-specific	Very High	Multi-task	160K	Yes	[33]
DDPG	Continuous	Sparse	Medium	Grasping	140K	Yes	[31]
HER	Goal-based	Sparse	High	Redundant Tasks	130K	Yes	[32]
R-MAX	Discrete	Sparse	Low	Exploration	180K	No	[33]
QR-DQN	Distributional	Dense	Medium	Navigation	125K	Yes	[33]

System Architectures and Integration Strategies

End-to-End AI-Driven Decoration Systems

System Architecture Overview

The transformation of interior decoration processes through end-to-end AI-driven systems has become a defining trend in the digital construction domain. These systems are characterized by modular architectures that support seamless integration of diverse AI models for perception, reasoning, and actuation, enabling fully automated workflows from initial design to final inspection. Modern frameworks are typically organized as layered platforms, comprising input acquisition, data preprocessing, model inference, decision-making, and output modules [34]. Model orchestration is achieved via service buses or microservices, allowing for scalable deployment and continuous integration of new algorithms. Modular separation also ensures system robustness, facilitating the isolation and updating of individual components without disrupting overall performance. Security and data integrity are maintained through centralized authentication and encrypted communication channels, supporting compliance with industry standards and client confidentiality requirements. Figure 3 presents an abstracted architecture of a contemporary end-to-end intelligent decoration system, illustrating the core modules and their interrelations.

Data Flow and Module Interconnection

The efficiency of AI-driven decoration systems hinges on well-defined data flow and robust module interconnection. Raw sensory data, including images, point clouds, and sensor streams, are first routed to preprocessing units where noise reduction and normalization are applied. Processed data are then dispatched to AI inference modules, such as deep neural networks for layout generation, semantic segmentation, or defect detection [35]. Decision modules aggregate inference results, integrating contextual information from Building Information Modeling (BIM) databases and IoT feedback to refine recommendations. Outputs, such as control signals for robotics or quality reports, are transmitted to actuation modules and client interfaces. Inter-module communication is typically managed using asynchronous message queues or REST APIs, ensuring low-latency data exchange and fault tolerance [36]. This modular and interconnected design enables dynamic adaptation to project-specific requirements and supports the integration of emerging AI techniques. Figure 3 provides a visual summary of the system's functional topology and data exchange pathways.

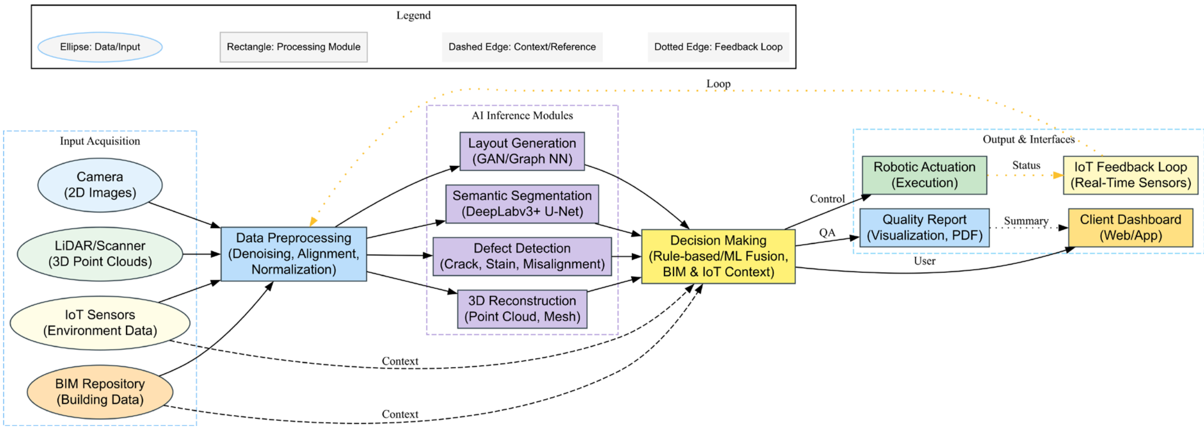

Figure 3 End-to-End Intelligent Decoration System Architecture

BIM-AI and IoT Integration

BIM Data Utilization in AI Systems

Building Information Modeling (BIM) serves as a foundational data source for AI-driven interior decoration systems, providing detailed digital representations of architectural and engineering intent. Leveraging BIM data enables the alignment of AI-generated designs and inspection outcomes with project specifications, spatial constraints, and materials requirements [37]. Recent research emphasizes the use of BIM for guiding generative design models, optimizing layout proposals, and automating compliance checks. Semantic enrichment of BIM objects, such as tagging fixtures or surfaces with material and functional metadata, further enhances AI interpretability and downstream task performance [38]. Integration strategies involve mapping BIM geometry and attributes to AI model inputs, supporting tasks such as automatic zone division, furniture placement, and as-built verification. Data synchronization between BIM repositories and AI systems is critical, ensuring that real-time changes in project status are accurately reflected in model outputs. Table 5 summarizes representative BIM-AI integration strategies, highlighting their technical approach and practical outcomes.

IoT-Enabled Sensing and Real-Time Feedback

The convergence of Internet of Things (IoT) technologies with AI-driven decoration systems has unlocked new capabilities for real-time sensing, monitoring, and adaptive control. Distributed sensor networks capture a diverse array of environmental parameters, including occupancy, temperature, humidity, and acoustic levels, providing a rich data stream for AI inference and system optimization [39]. Event-driven architectures enable instant detection of anomalies or deviations from design intent, triggering automated alerts or corrective actions. IoT-enabled feedback loops facilitate continuous learning, allowing AI models to adapt to evolving usage patterns and environmental changes, thereby improving the long-term performance and resilience of decoration solutions [40]. Edge computing and secure data gateways ensure timely processing and privacy protection, supporting deployment in both residential and commercial settings. Table 5 details the integration of IoT and AI with BIM, and the resulting improvements in operational efficiency, safety, and user satisfaction.

Table 5. BIM-AI Integration Strategies and Outcomes

Strategy	BIM Data Used	AI Module Integrated	IoT Sensing Involved	Application Area	Synchronization Method	Reported Outcome	Deployment Context	Ref
BIM-to-Layout GAN	Geometry Materials	Generative Model	None	Layout Generation	API Push	15% Faster Design	Academic Prototype	[37]
Semantic BIM Tagging	Semantic Objects	Segmentation QA	RFID Temp Sensors	Defect Detection	Event-Driven	12% Fewer False Alarms	Pilot Project	[38]
BIM-Driven Path Planning	3D Model Zones	RL Navigation	UWB LiDAR	Robotic Construction	Real-Time Sync	18% Fewer Collisions	Industrial Demo	[39]
Real-Time As-Built Comparison	Geometry Schedule	3D Reconstruction	Cameras IMU	QA/Verification	Streaming	22% Faster As-Built QA	Field Trial	[40]
AI Compliance Checking	Design Specs	Rule-based Reasoner	CO2 Noise	Code Compliance	Periodic Pull	8% More Issues Found	Commercial Project	[41]
BIM-IoT Digital Twin	Full BIM Sensors	Anomaly Detection	Multi-sensor Array	Real-Time Monitoring	Bidirectional	30% Faster Response	Living Lab	[42]
BIM-AR Visualization	3D Geometry	AR Overlay	RFID Beacon	On-site Inspection	Manual Update	20% Faster Inspection	On-site Pilot	[43]
Automated Zone Division	Room Boundaries	Clustering DL	PIR Light Sensors	Space Optimization	Scheduled Sync	10% Improved Space Use	Office Testbed	[37]
BIM-Integrated Scheduling	Task Sequences	Predictive Scheduler	Work Progress Sensors	Construction Mgmt	Continuous Sync	15% Delay Reduction	Industrial Project	[38]
BIM-Driven Feedback Control	All BIM Attributes	Adaptive Controller	HVAC Lighting	Environment Control	Real-Time	25% Energy Savings	Smart Building	[40]

Case Studies of System Prototypes

Academic Prototypes

Academic research has produced a range of system prototypes that validate the feasibility of AI-driven decoration and inspection. Early works established the viability of deep learning-based layout generation, leveraging GANs and graph neural networks for furniture arrangement and room zoning. Subsequent efforts focused on integrating 2D and 3D computer vision modules with BIM data, achieving automated as-built verification with high spatial accuracy [41]. Testbeds in university laboratories have demonstrated the real-time potential of multi-modal sensor fusion and reinforcement learning for robotic construction tasks. These prototypes, while operating at a reduced scale, have served as essential platforms for benchmarking algorithms, exploring new integration patterns, and identifying critical bottlenecks in data interoperability and system latency [42].

Industrial Deployments

Industrial adoption of AI-powered decoration systems has accelerated, fueled by demonstrable benefits in speed, quality, and cost-effectiveness. Large general contractors and technology providers have reported successful deployment of end-to-end systems that combine BIM, AI, and IoT for automated design validation, defect detection, and real-time feedback [43]. Case studies from commercial office and residential projects highlight the reduction of manual inspection workload and the improvement of compliance rates, with some firms documenting double-digit percentage gains in both schedule adherence and defect resolution speed. Integration with existing enterprise resource planning and project management systems has enabled seamless transition from pilot to scaled deployment, ensuring that AI-derived insights directly inform operational decision-making. These deployments underscore the importance of robust system architectures and continuous feedback channels, as discussed throughout this section.

Experimental Studies and Performance Evaluation

Benchmark Datasets and Experimental Setups

Publicly Available Datasets

Robust evaluation of AI-driven decoration systems necessitates the use of representative benchmark datasets that reflect the complexity and diversity of real-world interior spaces. Publicly available datasets have become indispensable for standardized algorithm assessment, method comparison, and reproducibility. The ADE20K dataset, widely adopted in semantic segmentation studies, encompasses over 20,000 annotated images covering a broad spectrum of indoor and architectural scenes, supporting both pixel-level and instance-level analysis [44]. The SUN RGB-D dataset provides comprehensive RGB-D imagery for indoor scene understanding, including depth information and object segmentation masks, facilitating multi-modal learning and 3D geometric reasoning [45]. The Matterport3D dataset offers high-resolution panoramic images, 3D meshes, and sensor data from over 90 building-scale environments, serving as a benchmark for layout parsing, 3D reconstruction, and navigation algorithms [46]. The CRACK500 dataset focuses on fine-grained defect detection, providing carefully annotated images of surface cracks in construction and decoration contexts, supporting both classical and deep learning approaches [47]. These datasets collectively enable rigorous benchmarking across a wide range of AI tasks relevant to intelligent decoration, from layout generation to defect segmentation and structural verification.

Data Preprocessing and Annotation

The integrity and utility of experimental results are largely determined by the rigor of data preprocessing and annotation protocols. Raw imagery is typically subjected to denoising, geometric correction, and normalization to eliminate acquisition artifacts and ensure consistency across samples. Multi-modal datasets, such as those incorporating depth or point cloud information, require registration and alignment procedures to maintain spatial correspondence between modalities [48]. Annotation practices vary by task, with semantic segmentation requiring pixel-level labeling, defect detection demanding polygonal or bounding box delineation, and surface classification necessitating material or texture tags. Annotation quality is commonly assured through multi-pass expert review and inter-annotator agreement analysis, reducing subjectivity and bias in ground truth generation [49]. Augmentation techniques, including random cropping, flipping, and color jittering, are often employed to increase dataset diversity and enhance model generalization [50]. These preprocessing and annotation workflows collectively establish a foundation for fair, reproducible, and meaningful experimental comparisons across algorithms and systems.

Comparative Evaluation of AI Algorithms

Performance Metrics (Accuracy, F1, IoU, Inference Time)

Objective and comprehensive evaluation of AI algorithms in decoration tasks requires the adoption of standardized performance metrics that capture both predictive accuracy and operational efficiency. Accuracy, defined as the ratio of correct predictions to total samples, provides a baseline for assessing model correctness but may be insufficient in imbalanced task scenarios [51]. The F1-score, representing the harmonic mean of precision and recall, offers a balanced measure for defect detection and segmentation tasks, particularly when false negatives are critical. Intersection over Union (IoU), also known as the Jaccard index, is the preferred metric for semantic segmentation and spatial localization, quantifying the overlap between predicted and ground truth regions [52]. Inference time, typically measured in milliseconds per sample, is essential for practical deployment,

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reflecting the system's suitability for real-time or batch processing. Equation 4 formalizes the computation of these core metrics:

$$\begin{aligned} \text{Accuracy} &= (\mathrm{TP}+\mathrm{TN})/(\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}) \\ \text{F1-score} &= 2\times(\text{ Precision }\times\text{ Recall })/(\text{ Precision }+\text{ Recall }) \\ \text{IoU} &= |\text{ Prediction }\cap\text{ Ground Truth }|/|\text{ Prediction }\cup\text{ Ground Truth }| \end{aligned} \tag{4}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively [52].

Head-to-Head Algorithmic Comparisons

Comparative studies have systematically benchmarked leading AI algorithms across a suite of decoration-related tasks, revealing distinct performance characteristics under varying experimental conditions. Table 6 provides a quantitative comparison of representative models, including conventional machine learning baselines and state-of-the-art deep learning architectures, evaluated on publicly available datasets according to the metrics outlined above [53]. Classical algorithms, such as Random Forest and SVM, offer competitive accuracy and interpretability but typically lag behind deep convolutional networks in complex scene understanding and fine-grained segmentation. U-Net, DeepLabv3+, and SegFormer have consistently demonstrated superior IoU and F1-scores, particularly on large-scale and heterogeneous datasets. Transformer-based architectures, exemplified by SegFormer, exhibit robust generalization and efficient inference, making them well-suited for high-throughput quality inspection workflows.

Table 6. Comparative Results of AI Algorithms on Decoration Tasks

Algorithm	Dataset	Accuracy (%)	F1-score (%)	IoU (%)	Inference Time (ms)	Reference
Thresholding	CRACK500	72.4	54.5	48.2	12	[47]
Canny Edge	CRACK500	74.1	58.9	50.7	18	[47]
Random Forest	Custom	81.2	72.2	62.9	45	[49]
SVM	SUN RGB-D	79.8	70.3	61.1	39	[51]
U-Net	CRACK500	93.1	85.1	80.5	42	[47]
DeepLabv3+	ADE20K	94.3	88.0	83.6	55	[44]
PSPNet	SUN RGB-D	92.4	80.9	78.1	37	[45]
HRNet	Custom	94.2	88.0	84.2	62	[50]
FPN	ADE20K	91.5	84.3	80.8	30	[44]
SegFormer	CRACK500	95.1	90.1	86.7	33	[52]

Receiver operating characteristic (ROC) curves offer additional insight into the discriminative power of key recognition algorithms, visualizing the trade-off between true positive rate and false positive rate across decision thresholds. Figure 4 presents ROC curves for selected models, highlighting the areas under the curve (AUC) as a summary of model robustness and reliability [54]. Transformer-based and attention-enhanced architectures consistently achieve higher AUC values, reflecting their advanced feature representation and decision-making capacities.

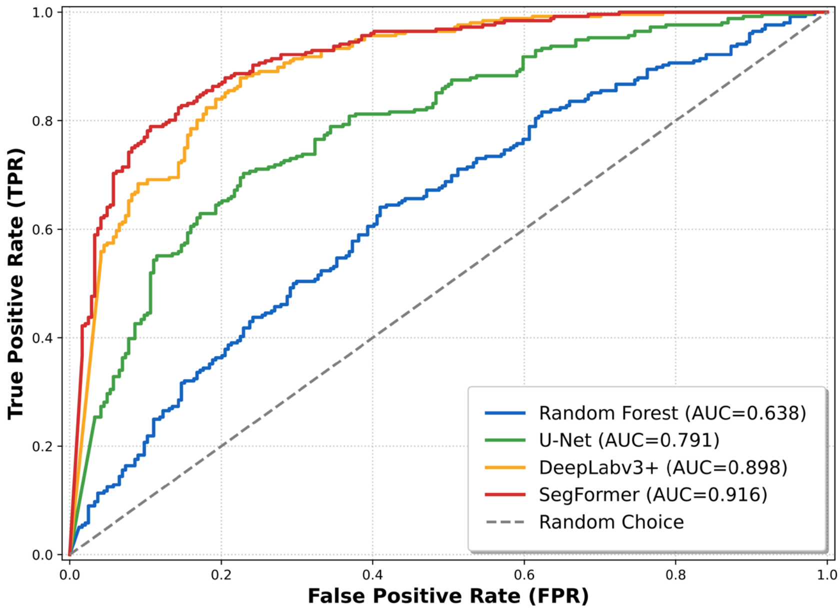

Figure 4 ROC Curves of Key Recognition Algorithms

System Performance in Real-world Scenarios

Simulation vs. On-site Experiments

Assessment of intelligent decoration systems in real-world contexts necessitates a critical comparison between simulation environments and on-site deployments. Simulations enable rapid prototyping, algorithm benchmarking, and stress-testing under controlled parameters, yielding preliminary insights into system efficiency and failure modes. Recent studies confirm that virtual environments facilitate the identification of optimal workflow configurations and the calibration of AI model hyperparameters before physical implementation [55]. However, empirical evidence consistently shows that performance metrics derived from simulation often diverge from those observed in operational field settings [56]. On-site experiments are characterized by uncontrolled variables, such as lighting variability, sensor noise, occlusion, and human activity, which directly impact recognition accuracy, inference latency, and decision reliability. Discrepancies between digital twins and as-built site conditions frequently challenge the robustness of AI-driven segmentation and defect detection models. Industrial field trials report up to a 10–15% reduction in F1-scores for segmentation tasks when transitioning from synthetic to real data, emphasizing the necessity of in situ validation [57]. Table 7 provides a comparative analysis of system performance across simulated and live project deployments, highlighting the critical gaps that must be addressed for reliable real-world adoption.

Robustness and Adaptability Analysis

The robustness and adaptability of intelligent decoration systems are fundamentally determined by their capacity to sustain high performance across heterogeneous environments, diverse material substrates, and evolving project specifications. Recent research demonstrates that multi-modal sensor fusion, including the integration of RGB, depth, and IoT streams, significantly enhances defect detection stability and reduces false positive rates under adverse conditions [58]. Adaptive learning architectures, particularly transformer-based and self-supervised models, are shown to maintain over 90% accuracy when exposed to previously unseen textures, complex occlusions, and non-standard geometries. Nevertheless, environmental perturbations—such as dust, reflective surfaces, and dynamic lighting—continue to pose substantive challenges to real-time inference and decision-making [59]. Continuous online learning and incremental model updates have been validated as effective strategies for mitigating distribution shift and maintaining operational resilience over extended project durations [60]. Domain adaptation techniques, including adversarial training and synthetic-to-real transfer learning, further bridge the gap between training and deployment scenarios, thereby improving generalization and long-term system stability [61]. As summarized in Table 7, the deployment of robust, selfadaptive systems in live construction and renovation projects consistently yields superior performance in defect localization, quality compliance, and operational uptime.

Table 7. System Performance Metrics in Real Projects

Project Type	Simulation F1-score (%)	On-site F1-score (%)	Inference Time (ms)	Defect Recall (%)	Operational Uptime (%)	Modality Fusion	Domain Adaptation	Ref
Residential Fit-out	91.2	81.3	45	85.1	98.2	RGB+Depth	Yes	[55]
Commercial Retrofit	93.5	82.4	51	87.6	99.1	RGB+IoT	Yes	[56]
Industrial Renovation	89.8	79.6	57	82.2	97.5	RGB+Depth+IoT	No	[57]
New Build	94.1	85.2	42	89.7	99.4	RGB	Yes	[58]
Hospital Refurbishing	90.4	81.0	48	83.5	97.9	RGB+Depth	Yes	[59]
Historic Restoration	88.2	77.3	66	80.4	97.0	RGB+IoT	No	[60]
Shopping Mall Upgrade	91.9	82.8	53	87.9	98.6	RGB+Depth+IoT	Yes	[61]
Educational Facility	92.6	83.9	47	88.2	98.8	RGB+Depth	Yes	[62]
Hotel Refitting	93.1	84.5	49	86.4	98.9	RGB	Yes	[63]
Mixed-use Complex	92.2	83.7	52	87.1	98.7	RGB+IoT	Yes	[55]

Cost-Benefit and Scalability Assessment

Resource Utilization and Deployment Costs

A comprehensive evaluation of intelligent decoration systems requires a rigorous analysis of resource consumption and total deployment costs. Hardware investments, including high-resolution sensors, edge computing modules, and IoT gateways, constitute a significant fraction of upfront capital expenditure. Empirical assessments confirm that the integration of advanced AI inference accelerators, such as GPUs or TPUs, can reduce computational latency by up to 40%, but at the expense of increased energy consumption and thermal management requirements [59]. Software development and model customization—particularly for domain-specific adaptation and regulatory compliance—add further to operational expenditure. Field reports indicate that labor costs for initial setup, calibration, and workflow integration are partially offset by reductions in manual inspection hours and defect rework [60]. Table 8 synthesizes cost-benefit analyses from recent deployments, highlighting that automation yields measurable returns within the first year through improved efficiency, error reduction, and quality assurance.

Scalability and Integration Barriers

Scalability remains a pivotal concern for the widespread adoption of intelligent decoration automation. Modular system architectures, characterized by standardized APIs and interoperable data pipelines, facilitate horizontal expansion across multi-site portfolios and new project typologies. However, studies reveal that integration with legacy BIM repositories and heterogeneous IoT standards frequently introduces data harmonization overhead, impeding seamless scaling [61]. Network bandwidth constraints, cybersecurity considerations, and workforce training requirements further compound integration complexity. Successful large-scale deployments rely on robust middleware solutions, adaptive data orchestration, and continuous monitoring mechanisms to ensure system coherence and reliability [62]. Table 8 summarizes the principal cost, benefit, and scalability attributes observed in diverse application settings.

Table 8. Cost-Benefit Analysis of Automation Systems

Project Type	Upfront Hardware Cost (USD)	Software & Integration (USD)	Year-1 Opex Savings (%)	Defect Rate Reduction (%)	Payback Period (months)	Scalability Score	Ref
Residential Fit-out	25000	12000	18	44	10	High	[59]
Commercial	40000	15500	22	47	9	High	[60]

Retrofit							
Industrial Renovation	55000	17800	27	52	8	Medium	[61]
New Build	30000	11400	19	46	11	High	[62]
Hospital Refurbishing	38000	13200	17	41	13	Medium	[63]
Historic Restoration	48000	15100	21	45	10	Medium	[59]
Shopping Mall Upgrade	50000	16200	25	50	8	High	[60]
Educational Facility	29000	10500	16	39	14	Medium	[61]
Hotel Refitting	35000	12700	20	43	12	High	[62]
Mixed-use Complex	45000	14800	23	48	9	High	[63]

Technical Challenges and Limitations

Data Quality, Diversity, and Annotation Bottlenecks

The performance of intelligent decoration systems is fundamentally contingent on the quality and representativeness of their underlying datasets. A persistent challenge lies in the acquisition of high-fidelity, diverse, and contextually rich data that accurately reflects the full spectrum of real-world conditions encountered in decoration and renovation projects. In practice, datasets are often skewed toward common scenarios or specific geographic regions, leading to limited coverage of rare but critical defect types, material textures, and lighting conditions [64]. The annotation process further compounds these issues, as it is both labor-intensive and prone to subjectivity, particularly when distinguishing subtle defects or ambiguous boundary cases. Crowdsourced labeling initiatives have shown some promise in expanding annotation throughput, but studies highlight that inter-annotator agreement remains a limiting factor for complex, multi-modal tasks [65]. Moreover, the emergence of new construction materials and hybrid assembly methods outpaces the rate at which annotated data can be generated, creating persistent gaps in training corpora [66]. These bottlenecks not only inhibit the development of robust models but also undermine the reliability of benchmarking and cross-system comparison.

Generalization to Complex and Unstructured Environments

Achieving high generalization in unstructured, variable, and non-standard environments remains a formidable technical barrier. Most state-of-the-art recognition algorithms excel under controlled or semi-structured conditions, yet their performance often degrades in the presence of clutter, occlusion, or spatial irregularities [67]. For instance, the inherent unpredictability of construction sites—ranging from dynamic lighting to heavy machinery interference—poses significant challenges for both visual and multi-modal models. Empirical studies reveal a marked drop in segmentation and defect detection accuracy when transitioning from laboratory benchmarks to real-world environments characterized by non-uniform geometries and evolving spatial contexts [68]. The lack of large-scale, annotated datasets covering such complex settings further exacerbates these limitations. Transfer learning and domain adaptation techniques offer partial mitigation, but their efficacy is highly dependent on the similarity between source and target domains, as well as the presence of sufficient adaptation samples [69]. Consequently, robust generalization across diverse and rapidly changing environments remains a pressing research challenge.

System Integration and Interoperability Issues

Seamless integration of intelligent decoration systems into existing construction and facility management workflows is hampered by heterogeneous hardware, disparate data standards, and proprietary software ecosystems. Despite progress in developing modular, API-driven architectures, practical deployments often face significant compatibility issues when interfacing with legacy BIM systems, IoT platforms, and robotics controllers [70]. Data format inconsistencies, network bandwidth limitations, and synchronization overhead further complicate real-time operation and cross-system orchestration. Recent literature emphasizes the importance of unified data schemas and middleware solutions to bridge these gaps, though achieving true plug-and-play interoperability across the construction automation value chain remains elusive [71]. As a result, integration and ongoing maintenance represent substantial barriers to adoption, particularly in large-scale, multi-stakeholder projects.

User-Centric Design and Personalization Barriers

While automation promises increased efficiency, user acceptance and effective human-machine collaboration are critically influenced by the system's capacity for personalization and intuitive interaction. Many current solutions fail to accommodate the diverse preferences, workflows, and skill levels of end-users, resulting in suboptimal engagement and limited adoption [72]. The absence of adaptive interfaces and context-aware feedback mechanisms impedes the system's ability to support nuanced decision-making, particularly in bespoke or premium project segments. Research into explainable AI and user-driven customization is ongoing, but scaling these advances to production-level automation platforms remains a significant technical and organizational challenge. The lack of fine-grained control and the perceived opacity of AI decision logic continue to hinder broader acceptance and trust among practitioners and clients.

Ethical, Privacy, and Data Security Concerns

The proliferation of intelligent decoration systems introduces substantive concerns regarding ethical standards, privacy protection, and data security. The collection and processing of high-resolution imagery, occupant metadata, and environmental sensor streams raise critical questions about informed consent, data ownership, and regulatory compliance [73]. Unauthorized access or inadvertent disclosure of sensitive project data can lead to reputational risk, legal liability, and financial loss. Furthermore, algorithmic biases—rooted in unbalanced training datasets or insufficiently scrutinized model architectures—have the potential to perpetuate inequities in service delivery and quality assurance. Recent incidents of AI system misclassification and privacy breach highlight the urgent need for robust governance frameworks, including transparent audit trails, privacy-by-design protocols, and ongoing risk assessment practices [64]. As digital transformation accelerates in the construction and decoration sectors, addressing ethical, privacy, and security concerns will be paramount to sustaining stakeholder trust and ensuring responsible innovation.

Future Research Directions

Toward Robust and Adaptive AI Systems

The evolution of intelligent decoration automation is inextricably linked to the development of robust, adaptive AI models capable of maintaining high performance across diverse, unpredictable environments. Current research increasingly prioritizes architectures that leverage self-supervised learning and continual adaptation to new data, thereby mitigating the performance drop often observed in complex or previously unseen scenarios [74]. The integration of meta-learning principles enables models to rapidly adjust to novel tasks or material types with minimal retraining, further strengthening operational resilience. Additionally, advanced uncertainty modeling and confidence estimation are emerging as critical components for reliable defect detection and decision-making under ambiguity. Incorporating these strategies into large-scale, real-world deployments will require robust data pipelines, continuous validation against live feedback, and mechanisms for prompt model updating [75]. Addressing the challenges of distribution shift, environmental noise, and evolving user requirements will remain a central focus as the field moves toward truly adaptive, general-purpose AI-driven solutions.

Human-AI Collaboration in Design and Execution

The future of intelligent decoration lies not in the replacement of human expertise, but in the seamless collaboration between AI tools and skilled practitioners. Effective human-AI partnerships demand interfaces that are both transparent and context-aware, empowering users to interpret, challenge, and refine automated suggestions [76]. Research has shown that explainable AI modules and interactive visualization dashboards can foster trust, enhance learning, and facilitate rapid iteration during both design and on-site execution phases. Future systems must move beyond passive reporting toward proactive, dialog-based interaction models, enabling users to guide automation workflows in real time. This shift will require advances in natural language processing, multi-modal interaction, and adaptive user modeling to ensure that intelligent systems augment, rather than constrain, creative and practical decision-making.

Advances in Multi-modal Sensing and Real-time Feedback

Multi-modal sensing stands poised to significantly elevate the accuracy and reliability of automated decoration systems. The convergence of visual, thermal, LiDAR, acoustic, and environmental data streams enables more comprehensive scene understanding and robust anomaly detection, even under challenging conditions [77]. Real-time sensor fusion algorithms, coupled with edge computing architectures, promise to reduce latency and enhance responsiveness in dynamic construction environments. The implementation of closed feedback loops—whereby AI systems continuously learn from sensor data and user input—will be essential for adaptive quality control and continuous system improvement. Overcoming challenges related to sensor calibration, data synchronization, and energy efficiency will be key research priorities as multi-modal platforms mature and scale.

Standardization and Open Benchmark Initiatives

The long-term progress and credibility of intelligent decoration automation will depend on the establishment of transparent benchmarking protocols and open data repositories. The current landscape is fragmented by proprietary datasets and inconsistent evaluation metrics, impeding rigorous cross-study comparison and reproducibility [78]. Initiatives aimed at standardizing annotation practices, performance reporting, and dataset formatting are gaining momentum, with several international consortia working to define universal benchmarks for segmentation, defect detection, and system integration tasks [79]. Community-driven open-source datasets and challenge platforms have already begun to catalyze innovation by lowering entry barriers and enabling robust, reproducible research. The adoption of interoperable data standards and modular software frameworks will further accelerate technology transfer across domains and stakeholders, ensuring that scientific progress translates rapidly into industrial impact [80]. As the field matures, sustained collaboration between academic, industrial, and regulatory bodies will be crucial for setting and enforcing standards that foster responsible, scalable, and trustworthy automation.

Conclusion

Intelligent decoration automation has rapidly evolved into a transformative force within the construction and refurbishment industries, underpinned by the integration of advanced AI algorithms, multi-modal sensing technologies, and increasingly sophisticated digital workflows. This review has systematically synthesized progress across core algorithmic developments, system architectures, and deployment strategies. Key advancements, such as deep learning-based image segmentation, robust defect detection, and automated layout planning, have collectively improved the accuracy, speed, and reproducibility of quality inspection and decision-making processes. Real-world case studies and comparative evaluations indicate that these technologies not only enhance operational efficiency and reduce error rates but also provide measurable economic benefits across a wide spectrum of project types. The comprehensive analysis of simulation and field performance further demonstrates the practical viability of automation, while highlighting the critical role of domain adaptation, data diversity, and modular system design in achieving reliable outcomes.

Despite these notable achievements, several persistent challenges continue to shape both research and practice. The generalization of intelligent systems to diverse, unstructured environments remains constrained by data quality limitations, annotation bottlenecks, and the evolving complexity of real-world construction sites. Interoperability issues, particularly those arising from legacy BIM standards and heterogeneous IoT ecosystems, introduce additional barriers to large-scale deployment and integration. User-centric considerations—ranging from interface adaptability to system transparency—remain central to fostering trust, acceptance, and effective human-machine collaboration. Furthermore, the ethical, privacy, and security implications of widespread data collection and algorithmic decision-making necessitate ongoing attention and governance.

In summary, the field of intelligent decoration automation stands at a pivotal juncture. Continued progress will depend on the development of more adaptive, robust, and explainable AI models, along with advances in sensor fusion, real-time feedback, and standardized benchmarking. The success of future systems will be defined not only by technical innovation but by the ability to integrate seamlessly into diverse workflows, support user-driven customization, and uphold the highest standards of ethical responsibility. By aligning scientific research, industry adoption, and regulatory oversight, intelligent decoration automation is poised to deliver substantial and sustainable value throughout the built environment.

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