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Exploring the Utility and Challenges of AI Interpretation of Construction Blueprints

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ABSTRACT

Blueprints are intricate technical documents designed to convey essential information crucial to the building construction process. They encompass text, symbols, and lines, all of which relate to structural and design details. The complexity of the data in these documents can pose challenges for manual interpretation, particularly in larger projects, leading to potential errors or delays. Recent advancements in artificial intelligence present a promising solution by enabling the automated processing of blueprints through computer vision, optical character recognition, and natural language processing. This paper examines the challenges associated with implementing AI in construction blueprint analysis from the perspective of a current construction industry professional. It also evaluates existing datasets and research related to the application of AI in interpreting construction blueprints, using a set of innovative classifications based on complexity. Finally, the paper highlights areas for future research.

Keywords **- artificial intelligence, blueprint analysis, computer vision, natural language processing, optical character recognition**

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1. INTRODUCTION

Blueprints play a pivotal role in the construction process and are essential for the successful erection of buildings. These comprehensive documents are typically the result of collaborative efforts between architects and engineers, incorporating critical information on design specifications, dimensions, materials, and more. Blueprints feature a combination of symbols, textual descriptions, and drawings, each serving distinct purposes. Symbols denote external features like doors and windows, as well as internal elements such as sinks and bathtubs. Text provides descriptions of dimensions, labels elements, highlights structural information, and references different sections within the blueprint. Various drawings illustrate different facets of the building: floor plans display spatial layout; elevation drawings show exterior features like siding; structural drawings convey details about elements such as beams; mechanical drawings outline systems like HVAC; and electrical drawings map out the electrical system and outlets.

While blueprints for small-scale projects are relatively simple and easy for humans to read, larger projects bring increased complexity that is mirrored in their blueprints. For instance, a multi-story apartment building might require hundreds of detailed pages to fully encapsulate all necessary construction information. In such scenarios, manually interpreting blueprints becomes a laborious and inefficient task, raising the chances of human error, construction delays, and added costs.

The advent of artificial intelligence (AI) offers the potential to revolutionize blueprint interpretation, addressing the challenges of complexity and enabling significant time savings for construction professionals. Research in computer vision (CV), optical character recognition (OCR), and natural language processing (NLP) has identified key challenges in AI's application within the construction industry. Progress has been made in addressing components of this issue, from symbol recognition to text parsing.

This paper investigates existing research on construction blueprint interpretation through the lens of a construction industry practitioner. This practical perspective provides valuable insights into the challenges and opportunities associated with AI implementation in this domain, aiming to contribute a fresh viewpoint and suggest possible future directions.

The paper is organized as follows: Section 2 outlines the paper's methodology. Section 3 discusses challenges encountered in implementing AI in construction. Section 4 reviews existing datasets used in research and introduces a novel classification system related to the data. Section 5 explores existing AI applications in construction, proposing a novel classification scheme based on the complexity of the information. Section 6 discusses the future work needed to achieve fully AI-interpreted blueprints, and Section 7 provides a concluding summary.

2. METHODOLOGY

The research for this paper was conducted using a sprint-based approach to ensure efficient and organized progress. Within this overall framework, two specific sub-processes were undertaken: a detailed blueprint analysis to identify common features and challenges, and a comprehensive literature survey to refine the list of relevant research. These processes are elaborated upon as follows:

2.1 Sprint-Based Approach to Research

This research was structured into sprints, inspired by the Scrum agile methodology used in software development. Given time constraints, this adaptable yet disciplined approach was essential for maintaining consistent progress while allowing adjustments as needed. The project was divided into four sprints, each with a specific focus:

1. Sprint 1: Planning Phase - This initial sprint involved examining blueprint features and surveying existing literature. Preliminary notes were also made on key topics.
2. Sprint 2: Design Phase - During this phase, additional research was conducted, classification systems were developed, and the initial project outline was completed.
3. Sprint 3: Implementation Phase - This sprint focused on finalizing the research list, classifying existing research and datasets, and drafting the initial manuscript.
4. Sprint 4: Feedback Phase - The final sprint involved refining and completing the final draft based on feedback.

2.2 Blueprint Research and Analysis

Prior to the literature review, a thorough analysis of blueprints was conducted. An anonymous contributor provided access to a collection of real-world construction blueprints for academic purposes [1]. This analysis involved manually examining these documents to identify how information is conveyed, thereby guiding subsequent research. Despite variations among plans, several common features were identified:

1. Text Elements:
   - Text elements (font, size, spacing) are not standardized across plans.
   - Text may be oriented vertically or horizontally and may include dimensions, room information, code references, or other data.
   - Text can reference other sheets and areas within the blueprints and may be linked to structural elements or interior features using lines or arrows.
   - Text may appear inside symbols, boxes, or tables, and may include scale information and abbreviations.
2. Symbol Elements:
   - Symbols lack standardization across plans and can represent beams, structural components, wall elements, interior features, and exterior details.
   - Symbols may also be integrated with text to reference other locations within the blueprint.
3. Line Elements:
   - Lines vary in thickness and continuity, where solid and dashed lines hold different meanings.
   - Lines can be straight or curved, and arrows are used to connect structural elements or interior features.
   - Lines, often in conjunction with text, denote dimensions, and lines compose walls which may be shown as hollow "boxed" lines or solid lines.
   - Doors and windows typically appear as interruptions in lines.

In addition to these descriptions, it is crucial to understand the issue of noise. Blueprints often contain overlapping informational overlays, such as dimensions and element numbering, which, while essential, act as noise when training models to identify specific features as shown in figure 1. Addressing this noise is critical for training effective models and ensuring accurate AI interpretation of blueprints.

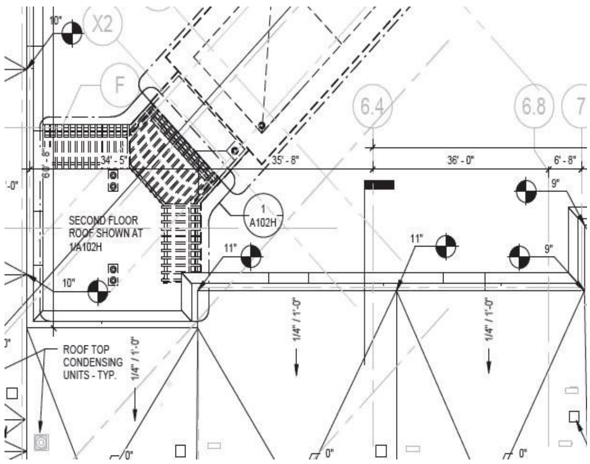

Fig. 1. An excerpt from a floor plan showing a variety of information causing noise [1]

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Additionally, contextual information within a blueprint is often distributed across multiple areas of the plan. It is common practice to use symbols and text callouts, as illustrated in Fig 2, to reference expanded details located elsewhere in the document. This interconnected information provides essential context for accurately interpreting elements within the blueprint. Failing to identify these connections could lead to the omission of critical information, which is crucial for a comprehensive understanding and accurate analysis of the blueprint

Fig. 2. Three examples of a text and symbol callout referring to another location within a blueprint [1]

In reviewing the features of blueprints, this paper suggests that the central tasks for implementing AI-based interpretation include symbol recognition and the semantic understanding of text. Addressing these tasks necessitates the use of a combination of computer vision, optical character recognition (OCR), and natural language processing (NLP).

Computer vision serves as the overarching technology for processing image-based information [2]. It facilitates the recognition of symbols and architectural elements within blueprints, which is a fundamental aspect of blueprint interpretation.

OCR and NLP provide essential complementary functions in this process. OCR enables the system to recognize and extract textual characters from the documents [3]. NLP is then required to deliver a semantic understanding of this text [4]. The overlap in required functionalities has been explored in previous research [5], making this a promising area for further investigation.

2.3 Process for Literature Survey

Based on the blueprint analysis, it was determined that blueprint features can be simplified into three major categories: text, symbols, and lines. Given these common features, the fields of optical character recognition (OCR), computer vision, and natural language processing (NLP) were identified as the primary focus areas for this paper. Once these areas of study were established, a multi-step approach to the literature survey was employed, as illustrated in Fig. 3.

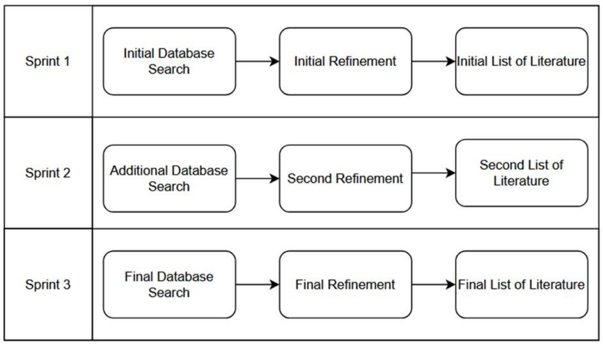

Fig. 3. The process for the literature survey relative to each sprint [1]

In Sprint 1, an initial search was conducted across various databases, including IEEE, Springer, and Science Direct. This search targeted research related to "construction," "blueprints," and "blueprint analysis." Due to minimal results, the search was broadened to incorporate terms like "floor plan" and "floor plan analysis." From these expanded results, the most pertinent papers on optical character recognition (OCR), computer vision (CV), and natural language processing (NLP) were chosen for the initial literature list.

In Sprint 2, the initial literature list was thoroughly reviewed. During this reading, additional relevant references cited within these papers were incorporated, expanding the pool of literature. The most applicable papers concerning OCR, CV, and NLP from all encountered sources were added to form a second literature list.

In Sprint 3, further literature was sourced specifically about available datasets used for AI model training. With the inclusion of these sources, a final refinement process was undertaken, resulting in a comprehensive list of 51 literature sources.

No new sources were added during the final sprint. It is important to note that while an extensive body of literature exists on OCR, CV, and NLP, this paper only includes those contributions directly related to construction research.

Here is a representation of the methodology section styled as an algorithm. This algorithmic format aims to clearly convey the sequence of steps and processes involved in the research:

Algorithm: Research Methodology for AI in Blueprint Analysis

Begin

1. Initialize Sprint-Based Research Process
   a. Sprint 1: Planning Phase
      i. Conduct initial research on blueprint features.
      ii. Perform initial literature survey on "construction," "blueprints," and "blueprint analysis."
      iii. If insufficient results, expand search to include "floor plan" and "floor plan analysis."

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b. Sprint 2: Design Phase
i. Read initial literature list.
ii. Expand literature list by reviewing references from selected papers.
iii. Develop classification systems based on findings.
iv. Complete initial outlining of research paper.

c. Sprint 3: Implementation Phase
i. Finalize list of research articles and sources.
ii. Classify existing research and datasets relevant to AI model training.
iii. Draft initial manuscript based on the classified research.

d. Sprint 4: Feedback Phase
i. Incorporate feedback to refine the manuscript.
ii. Complete the final draft of the research paper.

2. Conduct Blueprint Research and Analysis
a. Obtain access to a collection of real-world blueprints.
b. Manually examine blueprints to identify common features:
i. Text Elements
ii. Symbol Elements
iii. Line Elements
c. Address the issue of noise in training models:
i. Identify contextual information distributed across multiple blueprint areas.
ii. Link related information to preserve context and accuracy.

3. Perform Literature Survey
a. Step 1: Initial Database Search
i. Compile papers on focused areas: OCR, CV, NLP in construction.

b. Step 2: Expand Literature Pool
i. Incorporate relevant references from selected papers.

c. Step 3: Finalize Literature List
i. Include additional sources on datasets for AI training.
ii. Refine to a final list of key literature sources.

End

This algorithm outlines the structured approach to the research, highlighting the sprint phases and specific tasks involved in blueprint analysis and literature review.

3. CHALLENGES FOR AI IN CONSTRUCTION

Implementing AI in the construction industry presents several significant challenges, which can be categorized into human, technical, and data challenges. These are elaborated upon in this section and the subsequent one.

3.1 Human Challenges

The construction industry is a highly technical field that relies heavily on the expertise of its professionals. The design process, in particular, is a knowledge-intensive task that demands extensive expertise from architects and engineers who determine structural features based on their specialized knowledge [6]. Capturing this level of expertise within an AI model is challenging, necessitating close collaboration between software developers and construction industry professionals to ensure effective implementation [7].

Beyond the challenges of knowledge capture, organizational issues further complicate AI adoption in the industry. Many AI tools require some degree of human intervention to minimize errors [8]. Given the significant responsibility for ensuring safety in construction projects, there is often hesitation to adopt AI tools unless their performance can be thoroughly assessed and understood by the users [6]. This apprehension can result in resistance to implementing AI tools that are not completely transparent to those expected to use them.

3.2 Technical Challenges

Despite their critical role in construction, there is no universal standard for drawing blueprints. As a result, the same architectural element, like a staircase, can be depicted in numerous ways across different blueprints [9]. This variability complicates the task of training AI models to recognize these features, as they must accurately identify a multitude of representations. Additionally, blueprints often contain an extensive amount of overlapping information, further complicating element identification for AI systems [10].

To illustrate these challenges, Fig. 4 presents five examples from full construction blueprints [1]. These examples showcase staircase depictions in real-world construction projects, ranging from simple line drawings to complex illustrations with extraneous information. It becomes evident that even a single aspect of a blueprint can pose significant challenges for AI interpretation, as no two examples are identical. Any AI model intended for blueprint interpretation must be adaptable to these diverse depictions.

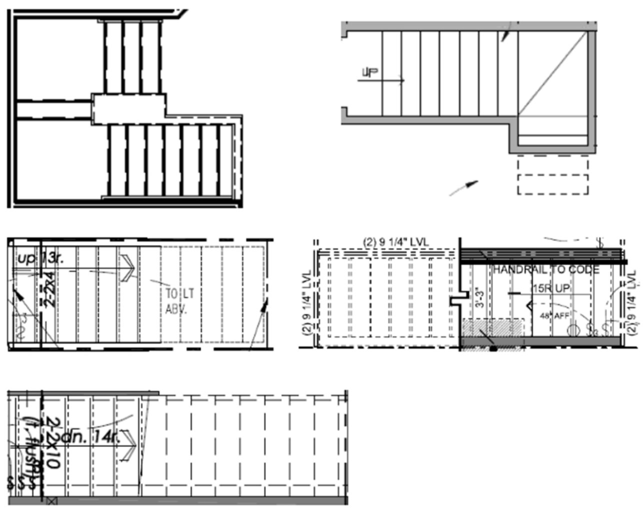

Fig. 4. Examples of Varying Staircase Depictions in Real-World Projects [1]

Beyond the challenges of inconsistent rendering of architectural elements, large-scale projects pose additional

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obstacles due to their sheer complexity. A survey of 15 large-scale construction projects conducted between 2018 and 2024 revealed that 9 projects submitted combined architectural and structural blueprints ranging from 69 to 99 pages, while 6 projects submitted blueprints ranging from 127 to 311 pages [1]. It is important to note that these figures only account for architectural and structural plans, excluding other types of blueprints typically associated with a construction project, which suggests that the total page count is likely higher in all cases.

The vast amount of information contained in a complete set of blueprints represents a significant challenge for effective AI implementation. A fully automated AI system must not only recognize graphical elements, understand dimensions, and interpret textual information, but it also needs to comprehend and track relationships between these items across potentially hundreds of pages. Developing an AI capable of handling all aspects of complex blueprints effectively remains a unique and substantial challenge in leveraging AI within the construction industry

3.3 Data Challenges

One of the most critical challenges in implementing AI for blueprint interpretation is the availability of suitable training data. While the authors of this paper had the rare opportunity to access hundreds of blueprints for academic purposes, this is not a common scenario. There is a general lack of fully research-ready data, particularly when it comes to complex blueprints. Although several datasets are available that address specific aspects of the interpretation problem—these will be briefly outlined in the next section—no comprehensive datasets exist that cover all necessary elements. This scarcity of data hampers the development and training of AI models capable of effectively understanding and interpreting blueprints in a holistic manner.

Table 1 organizes the challenges by category and provides a concise description of the key issues, along with references to the supporting literature.

Table 1. Challenges Categories

Category	Challenge Description	Key Issues	References
Human Challenges	- **Expertise Requirement**: AI must capture complex expertise of architects and engineers.	- Requires close collaboration between developers and industry experts. - Hard to encode expert knowledge into AI models.	[6], [7]
	- **Organizational Resistance**: Hesitation to adopt AI due to safety and performance concerns.	- Human intervention needed to reduce errors. - Lack of trust if AI performance is not fully transparent.	[6], [8]
Technical Challenges	- **Inconsistent Blueprint Standards**: No universal standards for blueprint rendering.	- Different depiction of the same element across blueprints. - Model must adapt to various representations.	[9]
	- **Complex Blueprint Analysis**: Overlapping information complicates element recognition.	- Extensive and variable information across many pages. - AI must track relationships over large datasets.	[10], [1]
Data Challenges	- **Lack of Comprehensive Datasets**: Insufficient training data for AI in blueprint interpretation.	- Few research-ready datasets, especially for complex blueprints. - Limited availability hampers AI training.	[1]

4. EXISTING DATASETS

To illuminate gaps in AI implementation coverage, this section briefly discusses some of the most referenced existing datasets used in research across various computer vision (CV), optical character recognition (OCR), and natural language processing (NLP) projects. A more detailed examination of this topic is provided by Pizarro et al. [11]. Moreover, these datasets are classified by the level of complexity relative to the scope of a full blueprint.

It is essential to note that the images used in existing datasets are often referred to as floor plans. These are not comprehensive architectural blueprints but rather simplified representations with limited information. Such images are more accessible than architectural blueprints, which are often proprietary and thus are frequently used in research.

1. **CVC-FP Dataset**: Created by de las Heras et al., this dataset contains 122 images annotated for features like rooms, walls, doors, and windows. However, it does not capture the full complexity of blueprints [12].
2. **Rent3D**: Developed by Liu et al., this dataset includes floor plans for 215 apartments, annotated for room outlines, room types, and structural elements. It is focused solely on apartment layouts, with relatively simple features [13].
3. **ROBIN**: This dataset comprises 510 synthetic apartment layouts for automated analysis and retrieval of floor plans, focusing on simple features [14].
4. **CubiCasa5K**: With 5000 images annotated across over 80 categories, this dataset represents a step toward comprehensive blueprint complexity, but still features simple plans [15].
5. **BRIDGE**: Created by Goyal et al., it includes over 13,000 images annotated for region types and object classifications like windows, doors, and walls, with moderate complexity [16].
6. **BTI**: Consisting of 700 images focusing on segmentation under various lighting conditions, this dataset lacks object annotation [17].
7. **HouseExpo**: Developed by Li et al., it includes 35,126 floor plans limited to interior wall schematics, excluding objects like windows and sinks, offering minimal complexity [18].
8. **EAIS**: Used by Jang, Yu, and Yang, this dataset contains 319 floor plans annotated for walls and doors but lacks detail on interior features [19].
9. **RUB**: Created by Simonsen et al. using university and concert hall floor plans, it includes 74 plans annotated primarily for door presence [20].
10. **RFP**: A dataset of 7,000 floor plans annotated for structural elements and room types, reflecting simplistic features [21].
11. **ZSCVFP**: Created by Dong et al., this dataset includes 10,800 color images with annotations for room types and some objects. The representations offer basic information [22].
12. **MLSTRUCT-FP**: Developed by Pizarro, Hitschfeld, and Sipiran, this dataset includes 954 images with multi-floor building complexity, annotated for structural components [23].
13. **SESYD**: A synthetic dataset by Delalandre et al., containing 1,000 images of simple floor plans, annotated for structural and basic elements [24].

These datasets make substantial contributions to AI research in the construction industry. However, the focus is predominantly on floor plans. There remains a significant need for complex, highly annotated blueprints to achieve detailed and effective AI interpretation in this field.

Table 2 shows compares the datasets discussed in terms of their features, complexity, and type of annotations. It summarizes the datasets, highlighting their size, type of images, key annotated features, and their relative complexity levels. It serves to illustrate the variety of datasets available and their respective focus areas within AI research for blueprint analysis.

Table 2. A comparison of the Datasets

Dataset	Number of Images	Type of Images	Key Features Annotated	Complexity Level
CVC-FP	122	Floor Plans	Rooms, walls, doors, windows, parking doors	Basic
Rent3D	215	Apartment Floor Plans	Room outlines, room types, walls, doors, windows	Simple, focused on apartments
ROBIN	510	Synthetic Layouts	Apartment layouts	Simple
CubiCasa5K	5000	Floor Plans	Over 80 categories (e.g., walls, windows, doors)	Moderate, but still simple plans
BRIDGE	13000+	Floor Plans	Region types, object classifications (e.g., windows, doors)	Moderately complex
BTI	700	Segmented Images	No useful object annotations	None - Focus on segmentation
HouseExpo	35126	Floor Plans	Interior wall schematics only	Very simple
EAIS	319	Floor Plans	Walls, doors, background	Simple
RUB	74	Floor Plans	Doors	Limited annotations

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Dataset	Number of Images	Type of Images	Key Features Annotated	Complexity Level
RFP	7000	Floor Plans	Walls, doors, windows, room types	Simple
ZSCVFP	10800	Color Floor Plans	Walls, doors, windows, room types, some objects	Simple information
MLSTRUCT-FP	954	Multi-floor Plans	Walls, slab contours	Complex
SESYD	1000	Synthetic Floor Plans	Walls, doors, windows, some objects	Basic

To assess the current state of datasets in blueprint analysis and identify areas needing improvement, a classification system is proposed based on two criteria: floor plan complexity and annotation complexity. Here's an overview of the proposed classification system:

4.1 Floor Plan Complexity Criteria

This category evaluates datasets based on the complexity of floor plans, with two types (simple and complex) and five tiers of classification:

1. **Tier 1**:
   - Simple floor plans, typically representing single apartments, single-family homes, or other small-scale layouts.
   - Usually depicted on a single page.
   - Includes basic representations: walls, windows, and doors.
2. **Tier 2**:
   - Similar to Tier 1: single-page, small-scale layouts.
   - Includes additional features like bathtubs, sinks, and dishwashers.
   - Typically includes text explaining room types, dimensions, and other information.
3. **Tier 3**:
   - Complex floor plans, involving large or multi-floor buildings.
   - Incorporates basic representations: walls, windows, and doors.
4. **Tier 4**:
   - Builds on Tier 3 with additional features (bathtubs, sinks, dishwashers).
   - Contains text explaining room types, dimensions, and other information.
5. **Tier 5**:
   - Full architectural blueprints for large or multi-floor buildings.
   - Includes comprehensive representations: walls, windows, doors, and multiple additional features.
   - Detailed text with room types, dimensions, and object relationships (e.g., electrical outlet placements).

Note: Tier 5 represents the ideal complexity level, not yet achieved in current research.

4.2 Annotation Complexity Criteria

This category classifies datasets based on the completeness and detail of their annotations, with five tiers:

1. **Tier 1**:
   - No annotations or minimal notations for a singular feature (e.g., walls or room type).
2. **Tier 2**:
   - Annotations describe walls and basic wall features (doors, windows).
3. **Tier 3**:
   - Builds on Tier 2 with annotations for room/region descriptions.
   - Includes some object descriptions.
4. **Tier 4**:
   - Comprehensive for walls, features, and room/region descriptions.
   - Provides some structural or text annotations.
5. **Tier 5**:

- Complete annotations for room types, walls, wall features, all objects, structural relationships, and text.

Note: Tier 5 represents the ideal annotation complexity, not yet achieved in current research.

This classification system provides a framework to evaluate the current state of datasets used in construction AI research, highlighting the areas where improvement is needed to handle complex blueprint interpretation effectively.

4.3 Summary

Table 3 provides a comprehensive summary of the dataset classifications under this proposed system.

Table 3. Dataset Floor Plan Complexity and Annotation Complexity -*Highest tier is bolded

Dataset	Floor Plan Type	Floor Plan Complexity	Annotations	Annotation Complexity
CVC-FP	Simple	Tier 2	Rooms, Walls, Doors, Windows, Parking Doors, Room Separations, Structural Relations	**Tier 4**
Rent3D	Simple	Tier 2	Rooms, Room Outline, Walls, Doors, Windows	Tier 2
ROBIN	Simple	Tier 1	Room Size, Room Type	Tier 1
CubiCasa5K	Simple	Tier 2	Walls, Doors, Windows	Tier 2
BRIDGE	Simple	Tier 2	Region Types, Walls, Doors, Windows, Text Descriptions	**Tier 4**
BTI	Simple	Tier 1	None	Tier 1
HouseExpo	Simple	Tier 1	Walls	Tier 1
EAIS	Simple	Tier 2	Walls, Doors, Background	Tier 2
RUB	Complex	**Tier 3**	Doors, Not Doors	Tier 1
RFP	Simple	Tier 2	Room Types, Walls, Doors, Windows, Some Objects, Text	**Tier 4**
ZSCVFP	Simple	Tier 1	Room Types, Walls, Doors, Windows, Some Objects	Tier 3
MLSTRUCT-FP	Complex	**Tier 3**	Walls, Slab Contours	Tier 1
SESYD	Simple	Tier 2	Walls, Doors, Windows, Some Objects	Tier 3

In terms of floor plan complexity, the RUB and MLSTRUCT-FP datasets reach Tier 3 complexity, which is currently the highest level available. This indicates that existing datasets lack the comprehensive scope of full architectural blueprints. Achieving higher complexity would involve incorporating complex, full architectural blueprints into datasets. However, this presents significant challenges due to issues like data availability, proprietary restrictions, and the need for alignment with real-world construction intricacies.

Regarding annotation complexity, the CVC-FP, BRIDGE, and RFP datasets achieve Tier 4 complexity. These datasets represent the most significant advancements towards the required annotation complexity but still fall short of providing a fully annotated, comprehensive architectural blueprint dataset. To reach Tier 5 complexity, datasets would need to consist of fully annotated, large or multi-floor blueprints, containing detailed, multiple-page information. Accomplishing this level of complexity poses challenges related to the volume of data, the necessity for detailed expertise, and the considerable time and resources required to annotate such intricate datasets comprehensively.

Both the creation and usage of these highly complex datasets necessitate a collaborative effort from architects, engineers, AI researchers, and data scientists to overcome these challenges and further enhance the field of AI in construction blueprint analysis.

5. STATE OF THE ART

This section provides an overview of notable research related to the interpretation of construction blueprints, focusing on computer vision (CV), optical character recognition (OCR), and natural language processing (NLP). The research is outlined chronologically to highlight advancements over the past 25 years, with a focus on studies from 2019 to 2024. The section concludes with a classification of datasets used in each research paper based on the floor plan complexity scale discussed previously, as well as the type of research and complexity relative to full blueprint interpretation.

5.1 Literature Survey

Let's explore each of the papers mentioned in greater detail to better understand their methodologies, contributions, and the advancements they have achieved in the field of construction blueprint interpretation.

Dosch et al. (2000) [25]:

Focus: Tackled 3D reconstruction challenges from 2D floor plans.

Method: Floor plans were divided into smaller tiles to manage image size. Text and graphics were processed separately—text was converted to strings, and graphics were vectorized to identify features like walls and doors. Innovative arc detection helped in identifying door locations.

Contribution: Provided foundational techniques for handling large-scale images by segmenting and focusing separately on text and graphics.

Barducci and Marinai [26]:

Focus: Object detection using a graph-based approach.

Method: Employed a region adjacency graph to represent components and their relationships, using histogram and contour descriptors to define object boundaries.

Contribution: Demonstrated the need for preprocessing by removing text and extraneous lines to enhance object detection accuracy.

de las Heras et al. [27]:

Focus: Evaluated an unsupervised wall detection method.

Method: Used preprocessing to filter out text and applied a wall detector that evaluated wall segment candidates with ranked scoring.

Contribution: Illustrated the challenges and comparative limitations of unsupervised methods versus supervised methods in accurate wall detection.

Ahmed et al. [28]:

Focus: Integrated analysis for feature retrieval from floor plans.

Method: Utilized image segmentation to isolate text from graphics and completed structural and semantic analyses to detect and interpret building features.

Contribution: Highlighted the importance of associating text with structural elements for improved blueprint analysis.

de las Heras, Ramos Terrades, and Lladós [29]:

Focus: Developed an attributed graph grammar for building structure representation.

Method: Applied graph grammar rules combined with a greedy algorithm to parse floor plans and identify rooms.

Contribution: Provided a novel grammar and algorithm combination demonstrating how structural relationships can be determined and parsed.

Beach et al. [30]:

Focus: Examined regulatory compliance using NLP.

Method: Used a semantic framework to extract and map regulation-related information, involving domain experts for rule control.

Contribution: Established a framework to incorporate complex regulatory needs within the blueprint analysis process.

Dodge, Xu, and Stenger [31]:

Focus: Developed an R-FP dataset for multi-faceted processing.

Method: Combined wall segmentation using a fully convolutional network and object recognition via Faster R-CNN.

Contribution: Demonstrated a high mean accuracy in wall segmentation, underscoring the efficacy of integrated processing approaches.

Guo and Peng [32]:

Focus: Classification of floor plans with CNNs.

Method: Applied extensive preprocessing, including grayscale conversion and filtering, followed by feature map extraction with VGG-Net and classification using a multi-layer perceptron.

Contribution: Showed effective feature extraction strategies, though noted for longer processing times compared to alternative methods.

Zeng et al. [33]:

Focus: Advanced room boundary detection within floor plans.

Method: Utilized CNN with VGG encoders/decoders to differentiate boundary from room-type pixels, integrated with spatial contextual modeling.

Contribution: Achieved accurate room, wall, and boundary identification by integrating text and graphical assessments.

Ravagli, Ziran, and Marinai [34]:

Focus: Enhanced text extraction for accessibility.

Method: Produced XML output with text information and annotations, employing bounding boxes and classification for detected text.

Contribution: Improved blueprint text extraction accuracy, though faced challenges with text quality and orientation.

Wu et al. [35]:

Focus: Emphasized augmentation in CNN-based floor plan analysis.

Method: Introduced rotation augmentation to improve wall detection, utilizing boundary simplification to process rotations.

Contribution: Remarkable improvement with challenging elements like walls and presented clear methods for handling orientation variations.

Lu et al. [36]:

Focus: Introduced RuralHomeData and a predictive deep learning framework.

Method: Employed joint DNN architectures, VGG-16 for feature mapping, and U-Net for room segmentation.

Contribution: Established a thorough data collection methodology and a robust analytical model for more accurate floor plan interpretation.

Goyal, Chattopadhyay, and Bhatnagar [37]:

Focus: Explored NLP for image captioning in floor plans.

Method: DSIC and TBDG techniques utilized hierarchical RNN and transformer-based methods for descriptive generation.

Contribution: Highlighted superior precision and coherence achieved with NLP techniques in floor plan analysis.

Cai et al. [38]:

Focus: Developed method for geometric prior-based floor plan reconstruction.

Method: Processed input point clouds, identifying super-boundary-points (SBPs) connected into refined floor plans.

Contribution: Offered one of the most effective methods for corner and edge identification, enhancing floor plan geometry detection.

Moon, Lee, and Chi [39]:

Focus: Applied NLP to process construction specifications.

Method: Constructed a semantic thesaurus with Word2Vec, developed NER models for recognizing keywords.

Contribution: Showed substantial time savings in specification retrieval, emphasizing the benefits of NLP integration in construction documentation.

Karthik, Safvan, and Abraham Samuel [40]:

Focus: Differentiated floor plans from other images.

Method: Analyzed color, saturation, contour, and line metrics to classify image types.

Contribution: Provided utilities to remove non-floor plan content from blueprint processing, aiding in preprocessing optimization.

Urbieta et al. [41]:

Focus: Explored BIM model creation from simpler plans.

Method: Utilized Mask R-CNN, FPN, and ResNet101 for classification and feature extraction alignment.

Contribution: Advanced progress in using AI to convert CAD designs into detailed BIM models.

Wen et al. [42]:

Focus: Developed a segmentation methodology using two complementary branches.

Method: Integrated OCR embeddings with segmentation results for improved contextual insights.

Contribution: Pioneered the use of heatmaps for text integration, pushing forward understanding in blueprint analysis.

Wang et al. [43]:

Focus: Proposed RC-net for enhanced floor plan parsing.

Method: Employed room and text branches for precise boundary specification.

Contribution: Suggested new methods for precise room and label processing through rectangular constraints.

Huang et al. [44]:

Focus: Introduced MuraNet for floor plan feature extraction.

Method: Utilized attention mechanisms and multi-head processing for enhanced doorway and window detection.

Contribution: Improved processing speed through a new model fitting technique, boosting feature detection accuracy.

Upadhyay, Dubey, and Kuriakose [45]:

Focus: Targeted thorough segmentation with FPNet.

Method: Merged encoder-decoder attention approaches to target low- and high-level features.

Contribution: Achieved impressive accuracy in room detection, underlining attention networks' versatility.

Wu and Ma [46]:

Focus: Addressed safety info retrieval using NLP.

Method: Extracted keywords and evaluated semantic word tendencies

Contribution: Proposed methods applicable to blueprint retrieval tasks, leveraging comprehensive NLP techniques.

Xu et al. [47]:

Focus: Enhanced single-page floor plan interpretation with ArchNetv2.

Method: Expanded backbone modules and refined mid-level processing for wall object detection.

Contribution: Set precedence for deep parsing techniques in complex high-detail single-page layouts.

Chen and Wang [48]:

Focus: Dual-stage comprehensive floor plan analysis.

Method: Integrated segmentation data with architectural features for improved semantic labeling.

Contribution: Created strong architectural-symbol integration, essential for interpretation advancements.

Xu et al. [49]:

Focus: FloorNet aimed to address both simple and complex blueprint challenges.

Method: Developed a CNN-based process for thorough semantic segmentation.

Contribution: Tackled complex blueprint processing challenges, focusing on accuracy in diverse plan types.

Goyal, Chattopadhyay, and Bhatnagar [50]:

Focus: Developed FloorCaps using a CapsNet framework.

Method: Utilized VGG19 for preliminary processing, and CapsNet for classification.

Contribution: Presented a new CapsNet-based classification method for blueprint regions.

Saparamadu, Jayasena, and Eranga [51]:

Focus: Leveraged NLP for construction compliance processes.

Method: Building a knowledge repository to streamline data handling.

Contribution: Demonstrated the potential for increasing efficiency and accuracy in handling regulatory constraints using AI [52].

These detailed presentations highlight the innovative methods employed by researchers over the years to tackle the complexity of blueprint interpretation. Significant progress has been made, but the journey toward fully automated and comprehensive solutions continues to present exciting opportunities for further development in AI and construction technology.

Table 4 summarizes the literature survey, highlighting the key focus, methodologies, and contributions of each paper discussed. The table provides a concise overview of each study, focusing on key research areas and advancements they contribute to the field of AI-based blueprint interpretation.

Table 4. A Summary of the Literature Survey

Study	**Focus**	**Key Methodologies**	**Contributions**
Dosch et al. (2000) [25]	3D reconstruction from 2D floor plans	Segmentation into smaller tiles, arc detection for doors, recurring patterns for stairs	Provided foundational techniques for segmenting large-scale images

Study	Focus	Key Methodologies	Contributions
Barducci and Marinai [26]	Object detection in floor plans	Region adjacency graph with histogram and contour descriptors	Highlighted preprocessing importance for enhancing object detection accuracy
de las Heras et al. [27]	Unsupervised wall detection	Preprocessing, special detector for walls, scoring system for segmentation candidates	Demonstrated unsupervised methods' limitations, insights into automated systems
Ahmed et al. [28]	Multi-faceted floor plan interpretation	Image segmentation, structural and semantic analysis	Demonstrated value of text association with structural elements
de las Heras, Ramos Terrades, and Lladós [29]	Graph grammar for structure representation	Graph grammar rules and greedy algorithm for room identification	Innovatively addressed structural relationships using graph-based parsing
Beach et al. [30]	Regulatory compliance using NLP	Semantic framework, regulation extraction, industry expert control	Provided a framework for integrating compliance into blueprint interpretation
Dodge, Xu, and Stenger [31]	Dataset creation and analysis	Fully convolutional network for wall segmentation, Faster R-CNN for object detection	Showed high accuracy in wall segmentation; emphasized integrated processing benefits
Guo and Peng [32]	Floor plan classification	Extensive preprocessing, VGG-Net for feature extraction, multi-layer perceptron for classification	Highlighted the role of preprocessing in improving classification output
Zeng et al. [33]	Room boundary detection	CNN with VGG encoders/decoders, spatial contextual modeling	Achieved accurate room and boundary identification through joint graphical and textual evaluation
Ravagli, Ziran, and Marinai [34]	Text extraction for accessibility	XML output generation, text detection and classification	Improved performance in text detection, faced challenges with text quality and orientation
Wu et al. [35]	Augmentation in wall detection	CNN-based analysis with rotation augmentation, boundary simplification	Provided novel augmentation techniques to enhance wall and architectural feature detection
Lu et al. [36]	RuralHomeData dataset and learning framework	Joint DNN architectures for room segmentation, VGG-16, U-Net duplex framework	Established robust data and model frameworks for accurate plan interpretation
Goyal, Chattopadhyay, and Bhatnagar [37]	Image captioning in floor plans	DSIC and TBDG methods using hierarchical RNN and transformer-based techniques	Demonstrated NLP improvement for descriptive context in floor plans
Cai et al. [38]	Geometric prior-based reconstruction	Input point clouds, super-boundary-point identification	Advanced corner and edge detection methodologies
Moon, Lee, and Chi [39]	Construction specification interpretation	Semantic thesaurus with Word2Vec, NER models for industry terminology	Streamlined specification retrieval, highlighted NLP application benefits

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Study	Focus	Key Methodologies	Contributions
Karthik, Safvan, and Abraham Samuel [40]	Floor plan image differentiation	Analyzed color, saturation, contour, line metrics	Provided preprocessing insights for filtering non-floor plan content
Urbieta et al. [41]	BIM model creation from CAD designs	Mask R-CNN, FPN, object detection for architectural features	Enabled conversion of CAD plans to detailed BIM models, aiding in complex blueprint handling
Wen et al. [42]	Dual-context floor plan analysis	Visual and textual segmentation, text embedding as heatmaps	Enhanced contextual accuracy in blueprint analysis
Wang et al. [43]	RC-net for parsing floor plans	Dual branches for room and text processing, rectangular processing for textual metadata	Provided detailed methodologies for structured processing of blueprint sections
Huang et al. [44]	MuraNet for feature extraction	Multi-scale attention, enhanced model fitting	Improved processing efficiency in detecting features like doors and windows
Upadhyay, Dubey, and Kuriakose [45]	FPNet segmentation network	Encoder-decoder attention network for segmentation accuracy	Demonstrated high segmentation accuracy for rooms, objects
Wu and Ma [46]	NLP for construction process	Semantic analysis, keyword extraction, document matching	Extended blueprint information retrieval, emphasized NLP's potential in construction contexts
Xu et al. [47]	ArchNetv2 for detailed plan analysis	Comprehensive processing modules for wall detection on single-page plans	Set precedents for detailed single-page blueprint interpretations
Chen and Wang [48]	Two-stage floor plan recognition	Integrated architectural symbols into semantic data processing	Advanced integration techniques for graphical and semantic blueprint interpretation
Xu et al. [49]	FloorNet for complex blueprint analysis	CNN-based framework for semantic segmentation across floor plan types	Tackled challenges in handling complex floor plans
Goyal, Chattopadhyay, and Bhatnagar [50]	FloorCaps classification framework	VGG19 features with Capsule Network for classification	Introduced CapsNet for floor plan region classification
Saparamadu, Jayasena, and Eranga [51]	NLP for compliance processes	Developed blueprint for efficient NLP integration in compliance checks	Highlighted AI's potential in improving compliance accuracy and efficiency through NLP applications

5.2 Summary of Existing Research

The literature survey highlights several contributions to the use of AI in interpreting construction blueprints. While a more detailed analysis will follow in the next section, two key trends emerge from the current research landscape:

1. **Focused but Fragmented Efforts**: A substantial portion of research has concentrated on tasks such as identifying walls and various architectural features using computer vision (CV) techniques, and reading text through optical character recognition (OCR) techniques. However, these efforts largely operate in isolation. There is limited integration of natural language processing (NLP) in these tasks; apart from storing text for room labeling, text often plays a minimal role in the interpretation process.

2. **Limited Scope with Single-Page Images**: The majority of studies address single-page images rather than tackling the complexity of multi-page, detailed blueprint plans. This reflects the current difficulty in processing and contextualizing the vast amount of technical data present in full construction blueprints, as discussed in Section III.

Given these observations, it is evident that a comprehensive solution for blueprint interpretation remains a challenge, as it requires the integration of multiple components and the processing of extensive textual and graphical data across numerous pages. To further understand the research complexity relative to what is necessary for effective AI blueprint interpretation, a new classification system is proposed. This system aims to assess current efforts against the broader requirements of a fully integrated and automated AI interpretation system.

5.3 Research Analysis and Classification

To assess the current complexity of state-of-the-art blueprint interpretation against the demands of complete architectural blueprints, and to pinpoint areas needing improvement, a two-part classification system is proposed. This system evaluates both floor plan complexity and the handling of blueprint features: text, symbols, and lines. The goal is to gauge how comprehensively each feature is addressed in current research. The two-part classification system is as follows:

1. Floor Plan Complexity Classification

This component builds on the previously proposed system, assessing datasets by tier (from simple single-page plans to complex multi-page types).

2. Feature Complexity Scoring System

This scoring system evaluates research papers based on their level of engagement with each type of blueprint feature—text, symbols, and lines.

Text Complexity Levels

- **No Complexity (0 points)**: The paper does not address text features.
- **Basic Complexity (1 point)**: Focuses on detecting text in images without understanding its meaning.
- **Intermediate Complexity (2 points)**: Involves text detection and some level of contextual understanding on a single page (e.g., recognizing dimensions or room labels).
- **Advanced Complexity (3 points)**: Includes text detection and interpretation in a broader context, understanding relationships across a full blueprint or construction specification document.

Symbol Complexity Levels

- **No Complexity (0 points)**: The paper does not address symbol features.
- **Basic Complexity (1 point)**: Focuses on detecting basic architectural elements like doors, windows, and stairs.
- **Intermediate Complexity (2 points)**: Involves detecting architectural elements and additional objects like furniture or fixtures, with interpretation in a narrow context.
- **Advanced Complexity (3 points)**: Encompasses detection and broad contextual interpretation of symbols across multiple pages or a full blueprint.

Line Complexity Levels

- **No Complexity (0 points)**: The paper does not address line features.
- **Basic Complexity (1 point)**: Focuses solely on the detection of walls or slab contours.
- **Intermediate Complexity (2 points)**: Involves detection and narrow contextual understanding of walls, mainly for identifying regions or rooms.
- **Advanced Complexity (3 points)**: Includes detection and broad contextual understanding, with insights into inter-room relationships and wall functionalities.

5.4 Scoring and Comparison

By applying this structured scoring system, each paper can be evaluated on how well it addresses the complexity of blueprint features relative to the ideal interpretation system, which would integrate all features across multiple connected pages. It's crucial to note that these complexity scores refer exclusively to the treatment of blueprint features, and not the inherent complexity or innovation of the research ideas themselves.

This classification system allows for objective comparison across studies, helping to map the current landscape of AI application in blueprint analysis and identify where research can be expanded or integrated to achieve more comprehensive solutions.

5.5 Results

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Table 5 summarizes the datasets based on the proposed classification system, focusing on floor plan complexity and feature complexity (text, symbols, and lines). The table illustrates current research gaps, offering a quick-glance comparison of how well datasets capture the essential elements for AI blueprint interpretation against the proposed ideal system. Further advancements in feature complexity, especially with text and lines across comprehensive multi-tiered floors, remain a critical step forward.

Table 5. A Summary of the Datasets Based on the Proposed Classification System

Dataset	Floor Plan Complexity Tier	Text Complexity	Symbol Complexity	Line Complexity	Total Complexity Score (max 9)
CVC-FP	Tier 1	1	2	1	4
Rent3D	Tier 1	1	1	1	3
ROBIN	Tier 1	0	1	0	1
CubiCasa5K	Tier 2	1	2	2	5
BRIDGE	Tier 2	1	2	2	5
BTI	Tier 1	0	0	1	1
HouseExpo	Tier 1	0	0	1	1
EAIS	Tier 1	0	1	1	2
RUB	Tier 3	0	1	2	3
RFP	Tier 2	1	2	1	4
ZSCVFP	Tier 2	0	2	1	3
MLSTRUCT-FP	Tier 3	1	3	2	6
SESYD	Tier 2	0	1	1	2

5.6 Summary of Dataset Classifications:

- **Tier 1**: Simple floor plans, often single-page for small structures. These datasets like ROBIN, BTI, and HouseExpo feature minimal complexity.
- **Tier 2**: Slightly more detailed plans with additional annotations. Datasets like CubiCasa5K and BRIDGE move towards moderate feature complexity with better annotations for symbols and lines.
- **Tier 3**: Complex, multi-floor plans as seen in RUB and MLSTRUCT-FP offer advanced handling of lines and a deeper engagement with architectural features, indicating the closest move to comprehensive blueprint representation within available datasets.

5.7 Total Complexity Score:

The **Total Complexity Score** aggregates the feature complexity scores for text, symbols, and lines, providing an overall metric of how comprehensively each dataset addresses the features within its tier classification.

Table 6 provides a comprehensive summary of the dataset classifications under this proposed system.

Table 6. Existing Research Classification Summary **-** *Highest tier is bolded

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Author	Ref. #	Floor Plan Type	Floor Plan Complexity	Research Category	Research Focus	Text Complexity (from 0 to 3)	Symbol Complexity (from 0 to 3)	Line Complexity (from 0 to 3)	Total Complexity (from 0 to 9)
Dosch et al.	25	Simple	Tier 2	CV, OCR	Room Types, Walls, Door, Windows, Some Objects, Text	2	2	2	6
Barducci et al.	26	Simple	Tier 2	CV	Rooms, Walls, Doors, Windows, Some Objects	0	2	2	4
de las Heras et al.	27	Simple	Tier 2	CV	Walls	0	0	1	1
Ahmed et al.	28	Simple	Tier 2	CV, OCR, NLP	Room Types, Walls, Text	2	0	2	4
de las Heras et al.	29	Simple	Tier 2	CV	Rooms, Walls, Doors	0	1	2	3
Beach et al.	30	N/A	N/A	NLP	Text	3	0	0	3
Dodge et al.	31	Simple	Tier 2	CV, OCR	Rooms, Walls, Text	2	0	2	4
Guo et al.	32	Simple	Tier 2	CV	Rooms, Walls	0	0	2	2
Zeng et al.	33	Simple	Tier 2	CV	Rooms, Room Types, Walls, Doors, Windows	2	1	2	5
Ravagli et al.	34	Simple	Tier 2		Text	2	0	0	2
Wu et al.	35	Simple	Tier 2	CV,	Rooms, Walls, Doors/Windows, Staircase	0	1	2	3
Lu et al.	36	Simple	Tier 2	CV, OCR, NLP	Room, Walls, Door, Window, Staircase, Slopes, Text	2	1	2	5
Goyal et al.	37	Simple	Tier 2	CV, OCR, NLP	Room, Doors, Windows, Objects, Text	2	2	2	6
Cai et al.	38	Simple	Tier 2	CV	Rooms, Walls	0	0	2	2
Moon et al.	39	N/A	N/A	NLP	Text	2	0	0	2
Karthik et al.	40	Simple	Tier 2	CV	Floor Plan or Not	0	0	0	0
Urbieta et al.	41	Complex	Tier 5	CV, OCR, NLP	Room, Walls, Door, Window, Staircase, Text	3	1	2	6
Wen et al.	42	Simple	Tier 2	CV, OCR, NLP	Rooms, Walls, Door, Windows, Text	2	1	2	5
Wang et al.	43	Simple	Tier 2	CV, OCR, NLP	Room, Walls, Doors, Windows, Text	2	1	2	5
Huang et al.	44	Simple	Tier 2	CV	Room, Doors, Windows	0	1	2	3
Upadhyay et al.	45	Simple	Tier 2	CV, OCR, NLP	Room, Room Types, Walls, Doors, Windows, Objects, Text	2	2	2	6
Wu et al.	46	N/A	N/A	NLP	Text	3	0	0	3
Xu et al.	47	Complex	Tier 4	CV, OCR, NLP	Room, Room Types, Text	2	0	2	4
Chen et al.	48	Simple	Tier 2	CV, OCR, NLP	Room, Room Types, Walls, Door, Windows, Text	2	1	2	5
Xu et al.	49	Simple	Tier 2	CV, OCR, NLP	Room, Room Types, Walls, Doors, Windows, Objects, Text	2	2	2	6
Goyal et al.	50	Simple	Tier 2	CV, OCR	Room, Room Types	2	0	2	4
Saparamadu et al.	51	N/A	N/A	NLP	Text	0	0	0	0

When examining the datasets used in research, most papers align with Tier 2 complexity, focusing on single-page or less intricate floor plans. However, it's important to highlight that two studies have ventured into tackling more complex floor plans, indicating progress towards dealing with greater complexity [41, 47]. As technological advancements continue, the integration of multiple facets may become more feasible, potentially paving the way for addressing new levels of complexity.

Regarding research complexity, in relation to a complete blueprint's demands, the highest complexity score observed was 7, achieved by studies such as [25, 37, 41, 45, 49]. These studies reached this level by incorporating text analysis alongside symbol and line interpretations. Nonetheless, it is common for research to specialize in one or two features, typically lines and symbols, without fully integrating all three. Text features were often used at lower complexity levels alongside symbols and lines, predominantly for room labeling rather than comprehensive interpretation.

Lines, on the other hand, were typically understood only up to Tier 2 complexity. This limited approach lacks a broader understanding of how lines integrate with other blueprint components, such as symbols and text. Achieving true comprehension in this area requires the effective implementation of symbol and text recognition to ascertain how walls correlate with additional relevant information throughout a more extensive document. Thus, full blueprint interpretation necessitates significant advancements in integrating text, symbols, and lines into a cohesive analytical framework.

In summary, the state-of-the-art research in AI-driven blueprint interpretation reveals a landscape where progress is being made, albeit with certain limitations. Many studies have concentrated on isolated tasks, such as identifying walls and architectural features through computer vision (CV) or reading textual elements using optical character recognition (OCR). However, there often remains a lack of integration between these features, with text predominantly used for basic labeling, rather than deeper contextual understanding. While most studies focus on simple, single-page designs, some have extended their reach to more complex, multi-page blueprints, highlighting incremental progress toward greater complexity. The highest complexity achieved by some research reflects efforts to incorporate both symbols and text, although full integration across all blueprint features is still an emerging challenge. This underscores the need for comprehensive datasets and frameworks that account for the intricate relationships between text, symbols, and lines within diverse blueprint plans.

6. FUTURE WORK

Despite the progress made in AI-driven blueprint interpretation, significant opportunities for advancement remain. Addressing these will enhance the field's applicability and robustness.

1. **Development of Comprehensive Datasets**: There is an urgent need to create large-scale, publicly accessible datasets with fully annotated, multi-page blueprints. These datasets should be developed in collaboration with industry professionals to ensure they are accurate and relevant. Current research is limited by the lack of such comprehensive datasets,

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which hinders the development of more sophisticated AI models capable of handling complex blueprints.

2. **Collaboration with Industry Experts**: The intersection of academic research and practical application necessitates closer collaboration with industry professionals. As exemplified by Moon, Lee, and Chi [39], engaging with experts can facilitate the development of tools like semantic thesauri, which are grounded in practical knowledge. Such collaborations can bridge the gap between theoretical research and real-world application, leading to more effective AI solutions.
3. **Holistic Feature Integration**: Future research should explore how to simultaneously address text, symbols, and lines in blueprints. This might involve integrating methods such as semantic thesauri, captioning techniques, and object detection into a cohesive framework. Such integration could enable AI models to create descriptive frameworks that capture the complexity of entire pages, enhancing the understanding of structural and contextual elements.
4. **Innovative Approaches to Data Annotation**: Developing efficient and accurate methods for annotating large datasets is crucial. This might involve crowdsourcing annotations or employing AI-assisted annotation tools, which can expedite the process while maintaining accuracy.
5. **Enhancements in Interdisciplinary Research**: Encouraging interdisciplinary research collaborations will infuse construction expertise into AI development, fostering innovative solutions tailored to industry needs. These collaborations could focus on developing AI models that are not only technologically advanced but also aligned with construction practices and standards.

6.1 CHALLENGES

Several challenges persist in the journey toward advanced AI-powered blueprint interpretation:

1. **Complexity and Standardization**: The diversity and lack of standardization in blueprint designs across the industry present significant hurdles for AI models that rely on pattern recognition. Efforts to establish more consistent standards or adaptable AI systems need to be prioritized.
2. **Integration of Features**: While many studies focus on one or two elements of blueprint analysis, such as lines or symbols, integrating all features into a coherent analysis remains challenging. Developing systems that can seamlessly process text, symbols, and lines simultaneously will be critical.
3. **Scalability of Solutions**: As projects and data size grow, the scalability of AI solutions becomes a pressing issue. Ensuring that AI models can function efficiently across a range of project sizes, from small residential builds to expansive commercial developments, is a key challenge.
4. **Accuracy and Reliability**: Ensuring the accuracy and reliability of AI-generated interpretations is vital, particularly given construction's impact on safety and costs. Continuous improvement in algorithms and validation against real-world scenarios are necessary to build trust in AI solutions.
5. **Ethical and Privacy Concerns**: As data collection and processing intensify, addressing ethical and privacy concerns becomes important. Developing protocols for data use that respect privacy while enabling robust AI training is essential.

By tackling these challenges and focusing on future work directions, the field can move toward fully realizing AI's potential in blueprint interpretation, ultimately transforming the construction industry

7.CONCLUSION

The integration of artificial intelligence into blueprint interpretation stands as a transformative opportunity for the construction industry, promising to revolutionize processes with enhanced efficiency, accuracy, and insight. Despite its potential, the path to full implementation is hindered by several formidable challenges encompassing human, technical, and data-related issues.

Human challenges involve the need for deep collaboration between AI developers and construction professionals to capture the nuanced expertise required for effective blueprint interpretation. Only through a partnership with industry experts can AI solutions be refined to meet real-world demands.

Technical challenges are largely due to the diverse and non-standardized nature of blueprints, which vary widely in complexity and presentation. These variations necessitate sophisticated AI systems capable of flexibly adapting to and learning from diverse datasets, an area where current technology still falls short.

Data challenges are perhaps the most critical. There is a significant deficit in comprehensive, publicly available datasets—particularly multi-page, fully annotated blueprints. Such datasets are essential for training AI models to handle the intricacies of full-scale construction documents. Developing these would require substantial interdisciplinary cooperation and resource allocation, yet they are vital to advancing research.

This paper has introduced a novel classification system, crafted from the perspective of an industry professional. This system is designed not only to offer a construction-centric viewpoint but also to appreciate the technological intricacies required for a comprehensive blueprint interpretation system. By categorizing research relative to the complexity of blueprints, this system brings clarity to the existing challenges and outlines a structured framework for progress.

The classification system serves to illuminate the gaps in current research and can guide future efforts to bridge these divides, pushing the boundaries toward fully autonomous AI interpretation. By highlighting both the challenges and opportunities, this paper aims to stimulate further research, collaborations, and innovations, thereby accelerating the journey toward leveraging AI for blueprint interpretation.

In conclusion, the journey toward AI-enhanced blueprint interpretation is a complex but rewarding endeavor. Addressing current barriers will require significant advancements in technology, an influx of robust data, and the sustained synergy of industry and academic partnerships. However, the potential rewards—streamlined construction processes, reduced errors, and heightened project outcomes—make this pursuit not only necessary but imperative for the future of construction.

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