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From Floor Plans to Cost Estimates: A Deep Learning Approach for Room Segmentation and Material Quantification

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Abstract: Architectural floor plans are widely used to represent spatial layouts and structural details of buildings, but their availability in raster formats limits automated analysis due to the loss of semantic and geometric information. This paper presents a deep learning based approach for room level semantic segmentation and its application to material quantity and cost estimation. A transformer U-Net architecture is employed to accurately segment room regions and structural elements from floor plan images. The segmentation outputs are further processed to extract geometric features such as room area and wall length. These measurements are combined with semantic information to estimate material quantities, including flooring, paint, tiles, and lighting, and to compute room wise and overall construction costs. Experimental results demonstrate strong segmentation performance and effective downstream analysis. The proposed approach highlights the potential of integrating computer vision techniques with construction oriented tasks, enabling automated interpretation of floor plans for practical applications in building design and cost estimation.
Keywords: Floor Plan Analysis, Semantic Segmentation, Deep Learning, Construction Cost Estimation, Computer Vision, Building Information Modeling

I. INTRODUCTION

Architectural floor plans play a fundamental role in the design and construction of buildings, providing detailed representations of spatial layouts, structural components, and functional zones. They serve as an essential communication medium between architects, engineers, and stakeholders throughout the design and execution process. Although modern floor plans are typically created using Computer Aided Design (CAD) tools, they are often shared in raster formats such as scanned images or photographs. This conversion leads to the loss of important semantic and structural information, making automated interpretation challenging. As a result, extracting useful information from such drawings remains largely manual, time consuming, and prone to errors.

The need for automated floor plan analysis has grown significantly with the increasing adoption of Building Information Modeling (BIM), digital twin technologies, and intelligent construction workflows. Early approaches relied on rule based methods and handcrafted features, including geometric heuristics and morphological operations. However, these methods often lack robustness and struggle to generalize across diverse architectural styles, variations in drawing quality, and inconsistencies in annotations.

Recent advancements in deep learning have substantially improved performance in visual understanding tasks. Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in semantic segmentation, enabling pixel level classification of architectural elements such as walls, doors, and room regions. More recently, attention mechanisms and transformer based architectures have been introduced to better capture global context and long range dependencies in complex layouts. Despite these developments, existing research has largely focused on segmentation accuracy as an end goal, with limited emphasis on translating segmentation outputs into practical, quantitative insights.

A key limitation in current approaches is the lack of integration between semantic understanding and downstream analytical applications. In particular, the use of segmented floor plans for deriving geometric measurements and supporting material quantity estimation and cost analysis remains underexplored. Additionally, challenges such as high inter-class similarity among room types and the scarcity of large scale annotated datasets further complicate reliable room level interpretation.

To address these challenges, this work investigates a deep learning based approach for room level semantic segmentation of floor plan images and explores its application in enabling quantitative analysis. By leveraging modern segmentation architectures, the study aims to accurately capture spatial structures within floor plans and utilize the resulting representations for geometric feature extraction. These features form the basis for estimating material quantities and supporting cost evaluation at the room level. The proposed framework thus bridges the gap between visual floor plan understanding and practical construction oriented analysis.

The proposed approach is evaluated on a large scale floor plan dataset, demonstrating its effectiveness in room segmentation and supporting downstream estimation tasks. This work contributes toward automated floor plan interpretation for construction and cost analysis.

II. LITERATURE REVIEW

Floor plan drawings are fundamental to the architectural, engineering, construction, and operations industry, serving as essential communication tools between engineers, architects, and clients [1-2]. These drawings provide critical details about building components such as walls, doors, windows, and room layouts, which are indispensable for Building Information Modeling creation and design automation [3-4]. Traditionally, extracting information from these plans has been a manual, labor intensive, and error prone process, often requiring experts to interpret raster images or scanned paper documents [5]. As the industry moves toward digital twins and automated structural design, the development of robust, automated methods for floor plan semantic segmentation and feature extraction has become a primary research focus [6].

Traditional approaches to floor plan analysis typically relied on handcrafted rules and low level computer vision techniques such as morphological filtering, Hough transforms, and Voronoi-graph-based segmentation [7-8]. While these methods were pioneered for identifying basic primitives like lines and arcs, they often struggled with the high variability in architectural notations, line thicknesses, and symbols across different firms [9]. These rule based systems were frequently sensitive to noise and lacked the flexibility to generalize across diverse architectural styles [10]. Furthermore, early methods treated wall and room segmentation as separate, sequential steps, which could lead to accumulated errors in the final spatial representation [11].

The advent of deep learning has revolutionized this field, with convolutional neural networks (CNNs) demonstrating superior performance in capturing spatial hierarchies and extracting complex features from raster images [12]. Standard architectures such as U-Net, Fully Convolutional Networks (FCN), and DeepLabv3+ are now widely employed for pixel level classification of walls and rooms [13-14]. Recent research has shifted toward multitask learning frameworks, such as DeepFloorPlan (DeepFP), which jointly segment rooms and boundaries to leverage their inherent spatial relationships [12]. However, these shared-feature-space models often encounter feature entanglement, where room types and boundary cues interfere with one another, potentially causing fragmented or inconsistent segmentation results in complex layouts.

To address these limitations, researchers have introduced advanced attention mechanisms and transformer based architectures. Transformers, such as the Swin Transformer, utilize self-attention to model long range global dependencies, which is crucial for distinguishing between rooms with similar textures but different functions [15]. The Multi-Branch and Multi-Attention (M&M) framework explicitly separates room segmentation from boundary recognition, using cross-branch attention to align structural boundaries with room labels without the need for handcrafted priors [2]. Additionally, Offset-Guided Attention networks have been proposed to improve room level semantic consistency by predicting the offset of each pixel to its room center, ensuring that large or irregularly shaped rooms receive unified classifications [12].

A significant challenge remains the scarcity of large scale labeled datasets, as annotating floor plans for segmentation is a time consuming process requiring expert knowledge [16]. This has motivated the exploration of semi-supervised and few-shot learning techniques [16]. Frameworks like FixMatch leverage unlabeled data through consistency regularization to refine decision boundaries with limited training samples [17]. Furthermore, vision foundation models like the Segment Anything Model (SAM), combined with large multimodal models like GPT-4, have demonstrated impressive zero-shot or few-shot capabilities in segmenting and classifying architectural elements without extensive task specific training.

While significant progress has been made in floor plan segmentation for tasks like 3D reconstruction, indoor navigation, and accessibility analysis, a critical gap exists in directly linking segmentation outputs to material quantification and cost estimation. Automated segmentation provides the geometric foundation necessary for retrospective BIM modeling, allowing for the precise estimation of surface areas and building components [15]. Integrating semantic room information with geometric data enables the generation of comprehensive bills of materials and life cycle cost analyses [18-19]. By automating the transition from 2D raster floor plans to structured material data, deep learning approaches can significantly reduce the bottlenecks in building simulation and financial planning workflows.

III.DATASET

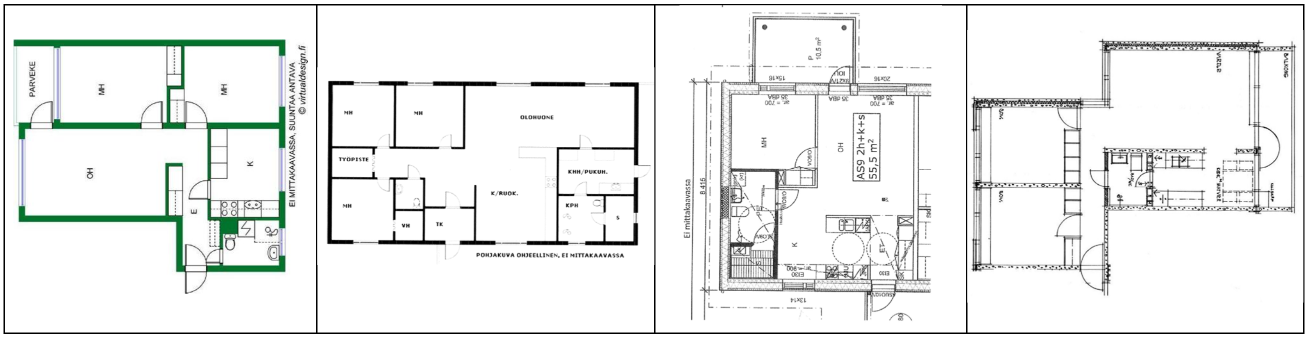

Fig. 1. Sample floor plan images from the CubiCasa5K dataset.

The proposed segmentation model is trained and tested using the CubiCasa5K dataset [20], a large scale dataset designed for floor plan understanding tasks. CubiCasa5K contains 5,000 floor plan images collected from real architectural drawings and annotated with detailed structural and semantic information. The dataset provides dense polygon based annotations for more than 80 floor plan object categories, including architectural components such as walls, doors, and windows, as well as different room regions.

Each floor plan sample includes high quality vector annotations stored in SVG format, enabling accurate pixel level segmentation of architectural elements and room areas. For the room segmentation task in this study, the annotations are grouped into multiple room categories such as kitchen, living room, bedroom, bathroom, storage, garage, and entry spaces.

The dataset is divided into predefined training, validation, and test splits, which are used for model training, hyperparameter tuning, and performance evaluation. Sample floor plan images from the dataset are shown in Figure 1.

IV.METHODOLOGY

This section presents the proposed framework for automated analysis of architectural floor plan images. The objective of the system is to extract structural and semantic information from floor plans and utilize it to estimate room geometry, material quantities, and overall construction cost. The proposed pipeline integrates architectural symbol detection, text recognition, room segmentation, geometric feature extraction, and cost estimation. First, architectural symbols and textual annotations are detected from the floor plan image. Next, a semantic segmentation model identifies room regions and structural elements such as walls. The resulting segmentation masks are then processed to extract room geometry, including room boundaries, areas, and wall lengths. Finally, these geometric measurements along with detected architectural objects are used to estimate material quantities and construction costs.The overall workflow of the proposed system is illustrated in Figure 2.

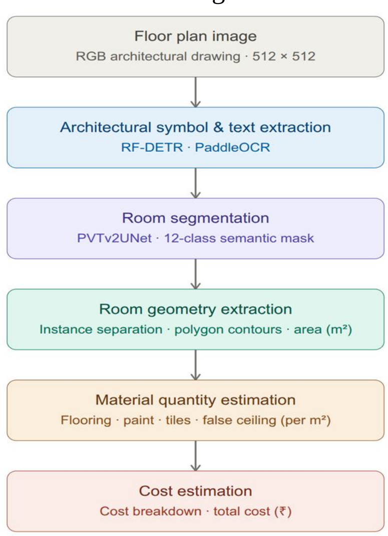

Fig. 2 Overview of the proposed floor plan analysis framework integrating symbol detection, room segmentation, geometric feature extraction, and cost estimation.

A. Architectural Symbol Detection and Text Extraction

Architectural symbols and textual annotations are first extracted from the floor plan image to obtain semantic information about building components. In our previous work [21], a transformer based object detection model, RF-DETR, was employed to detect symbols such as doors, windows, furniture, and sanitary fixtures from floor plan images. The model was trained on the FloorPlanCAD dataset containing annotated floor plan drawings across multiple symbol categories. In addition, textual annotations such as room labels and measurements are extracted using an optical character recognition (OCR) module. The detected symbols and recognized text provide semantic information about objects present in the floor plan, which is subsequently used in later stages for room interpretation and cost estimation.

B. Room Segmentation

Room regions are identified using a semantic segmentation network that assigns a class label to each pixel of the floor plan image. The segmentation model follows a transformer–U-Net architecture, where a Pyramid Vision Transformer v2 (PVTv2-B4) encoder extracts hierarchical multi-scale visual features from the input floor plan and a U-Net style decoder progressively reconstructs the segmentation map through multi-scale feature fusion. The overall architecture of the proposed segmentation network is illustrated in Figure 3. These features are then processed by attention-gated skip connections, which progressively upsample the feature maps and combine low level spatial information with high level semantic representations.

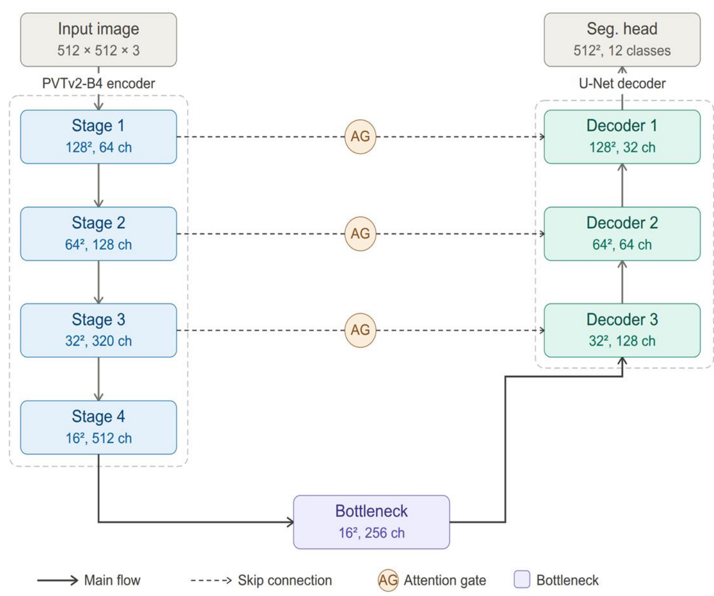

Fig. 3 Architecture of the proposed PVTv2-UNet based room segmentation network.

The model is trained on the CubiCasa5K dataset, which provides pixel level annotations for multiple room categories such as kitchen, living room, bedroom, bathroom, storage, garage, and entry spaces. To improve robustness to layout variations, data augmentation techniques including flipping, rotation, scaling, and color perturbation are applied during training. The network is optimized using a combined cross-entropy and Dice loss, balancing pixel wise classification accuracy with region level segmentation quality.

The output of this stage is a semantic segmentation mask where each pixel corresponds to a specific room category or structural element. This mask serves as the input for the subsequent room geometry extraction stage, where individual room instances and their spatial properties are computed.

C. Room Geometry Extraction

After obtaining the semantic segmentation mask, the geometric properties of individual rooms are extracted to enable quantitative spatial analysis. This stage converts the pixel wise segmentation output into structured geometric representations of rooms, including their boundaries, areas, and wall lengths. The process involves room instance separation, polygon boundary generation, and geometric measurements derived from the detected room regions.

1) Room Instance Extraction

The semantic segmentation mask assigns a class label to each pixel; however, multiple rooms of the same category may exist within a floor plan. To distinguish individual room regions, connected component analysis is applied to the binary mask corresponding to each room category. Small regions caused by noise or segmentation artifacts are removed using morphological filtering and area thresholds. Each connected component is then treated as an individual room instance and assigned a unique room identifier along with its semantic class label.

2) Polygon Boundary Generation

For each detected room instance, the boundary of the region is extracted from the binary mask using contour detection. The resulting contour points are converted into a polygon representation, which provides a compact geometric description of the room boundary. This polygonal representation enables accurate geometric computations and facilitates visualization or further spatial analysis of room layouts.

3) Area Calculation

The area of each room is initially computed in pixel units by counting the number of pixels belonging to the corresponding room instance. To convert this value into real world units, a pixel-to-meter scale factor is estimated. When dimensional annotations are available in the floor plan, optical character recognition is used to extract measurement information and determine the scale. If such information is unavailable, a heuristic estimation based on typical room dimensions is applied. Using the estimated scale factor, the pixel area is converted into square meters (m^2).

The real world area is computed as:

$$A_{room} = \frac{A_{pixels}}{s^2} \tag{1}$$

where A_{pixels} denotes the number of pixels belonging to the room region and s represents the pixel-to-meter scale factor (pixels per meter).

4) Wall Length Estimation

The wall length of each room is derived from the polygon boundary obtained in the previous step. The perimeter of the polygon is computed by summing the lengths of its edges, providing an estimate of the total boundary length of the room. Similar to the area computation, the pixel based perimeter is converted into real world units using the estimated pixel-to-meter scale. The resulting wall length measurements are later used in the material quantity estimation stage for calculating construction and finishing costs.

$$L_{room} = \frac{P_{pixels}}{s} \tag{2}$$

where P_{pixels} denotes the perimeter of the room measured in pixel units and s represents the pixel-to-meter scale factor.

D. Material Quantity and Cost Estimation

Based on the geometric properties obtained from the room geometry extraction stage, the required quantities of interior finishing materials and associated costs are estimated. This stage combines spatial measurements derived from the segmented floor plan with semantic information obtained from architectural symbol detection to generate a room wise cost breakdown.

1) Material Quantity Estimation

The quantities of interior finishing materials are estimated using the geometric measurements of each detected room. The flooring quantity is directly computed from the room area, while the wall finishing materials, such as paint and wall tiles, are estimated using the room perimeter derived from the polygon boundary. Ceiling related materials, including false ceiling installations and lighting fixtures, are calculated based on the room area and predefined design assumptions for each room category.

Material requirements vary depending on the room type. For example, bathrooms and kitchens typically require wall tiles in addition to flooring, whereas living rooms and bedrooms primarily require flooring and paint. These material requirements are determined using a predefined material configuration table associated with each room category.

The material quantities are computed as follows:

$$N_{tiles} = \frac{A_{room}}{A_{tile}} \quad (3)$$

$$A_{paint} = L_{room} \times H_{wall} \quad (4)$$

$$N_{lights} = \frac{A_{room}}{A_{per\ light}} \quad (5)$$

where A_{room} denotes the area of the room, A_{tile} represents the area of a single tile, L_{room} is the room perimeter, H_{wall} denotes the wall height, and $A_{per\ light}$ represents the area covered by a single lighting unit.

2) Cost Estimation

The total interior cost is computed by multiplying the estimated material quantities with predefined unit cost rates for different construction materials. The cost for each room is calculated by summing the individual costs of flooring, wall paint, tiles, false ceiling, and lighting components based on the corresponding material rates.

In addition to material costs, detected architectural objects obtained from the symbol detection stage are incorporated into the cost estimation process. Furniture and fixture symbols such as beds, sofas, toilets, and kitchen appliances are identified within their respective rooms, and their estimated costs are added to the corresponding room level cost calculation. This integration allows the framework to account for both structural finishing materials and interior fixtures when estimating the total project cost.

The overall cost is defined as:

$$C_{total} = \sum_{i=1}^{N} Q_i \cdot P_i + \sum_{j=1}^{M} C_j^{object} \quad (6)$$

where Q_i denotes the quantity of material i, P_i its unit price, and C_j^{object} the cost of the j^{th} detected object.

The final output of this stage is a room wise cost breakdown, providing detailed estimates for each detected room along with an aggregated total cost for the entire floor plan.

V. RESULTS AND DISCUSSION

This section presents the experimental evaluation of the proposed floor plan analysis framework. The results evaluate the effectiveness of the proposed approach in accurately segmenting room regions, extracting geometric features, and enabling downstream material quantity and cost estimation. Both quantitative metrics and qualitative visual analysis are used to validate the segmentation performance and demonstrate its capability in capturing complex architectural layouts.

A. Training Performance

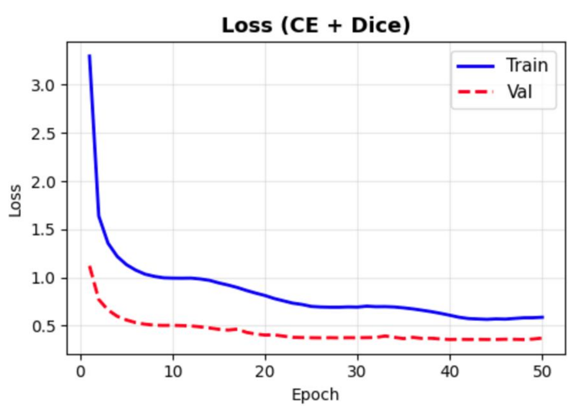

Fig. 4 Training and validation loss curves of the proposed segmentation model across epochs.

The training behavior of the proposed segmentation model was analyzed using the combined Cross-Entropy and Dice loss function. As shown in Figure. 4, both training and validation loss decrease steadily across epochs, indicating stable convergence and effective learning of spatial features from floor plan images without significant overfitting.

B. Quantitative Segmentation Performance

TABLE I
OVERALL SEGMENTATION PERFORMANCE OF THE PROPOSED MODEL

Metric	Value (%)
Mean IoU	73.60
Mean Precision	78.17
Mean Recall	84.36
Mean F1	78.24
Pixel Accuracy	88.00

The segmentation performance of the proposed model was evaluated on the test dataset using standard semantic segmentation metrics including mean Intersection over Union (mIoU), mean F1-score (mF1), pixel accuracy, mean precision, and mean recall. The overall results presented in Table 1 demonstrate strong segmentation performance, indicating that the model can reliably classify room regions and accurately capture their spatial boundaries within floor plan layouts.

C. Per-Class Segmentation Performance

TABLE III
PER-CLASS SEGMENTATION PERFORMANCE OF THE PROPOSED MODEL

Class	IoU (%)	Precision (%)	Recall (%)	F1 (%)
Background	91.85	94.50	96.82	95.65
Outdoor	86.52	89.31	92.87	91.06
Wall	90.24	92.54	95.43	93.96
Kitchen	73.21	78.14	84.68	81.28
Living Room	78.16	82.67	86.95	84.76
Bedroom	80.37	84.51	88.74	86.57
Bathroom	75.84	80.63	86.12	83.29
Entry / Hall	69.13	74.22	81.10	77.51
Railing	56.48	62.35	69.41	65.70
Storage	61.25	66.84	73.62	70.07
Garage	66.79	72.41	79.33	75.71
Undefined	54.42	59.86	67.18	63.30

To further evaluate model performance across different room categories, class wise segmentation metrics were computed for all classes in the dataset. The results shown in Table 2 report IoU, F1-score, precision, and recall for each room class, demonstrating that the model achieves consistent segmentation accuracy across major room types while maintaining balanced performance across multiple categories.

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D. Qualitative Segmentation Results

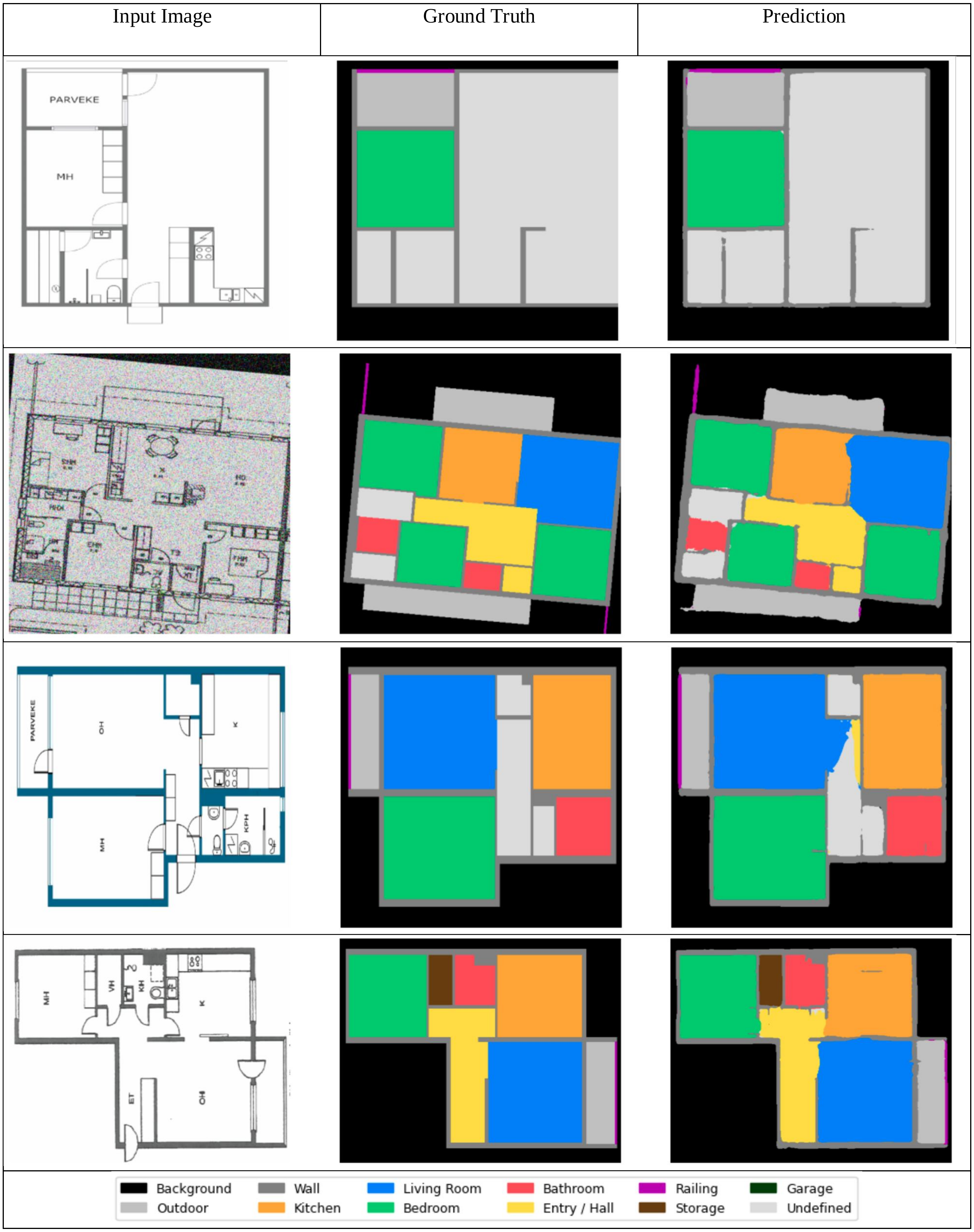


Fig. 5 Qualitative segmentation results illustrating the input floor plan, ground truth annotation, and predicted room segmentation produced by the proposed model.

To visually assess the segmentation capability of the proposed model, qualitative results were generated for several test samples. Figure 5 presents representative examples showing the input floor plan image, the corresponding ground truth mask, and the predicted segmentation output. The results demonstrate that the model accurately captures the spatial layout of rooms and correctly identifies major room categories while preserving structural boundaries within the floor plan.

E. Material Quantity and Cost Estimation

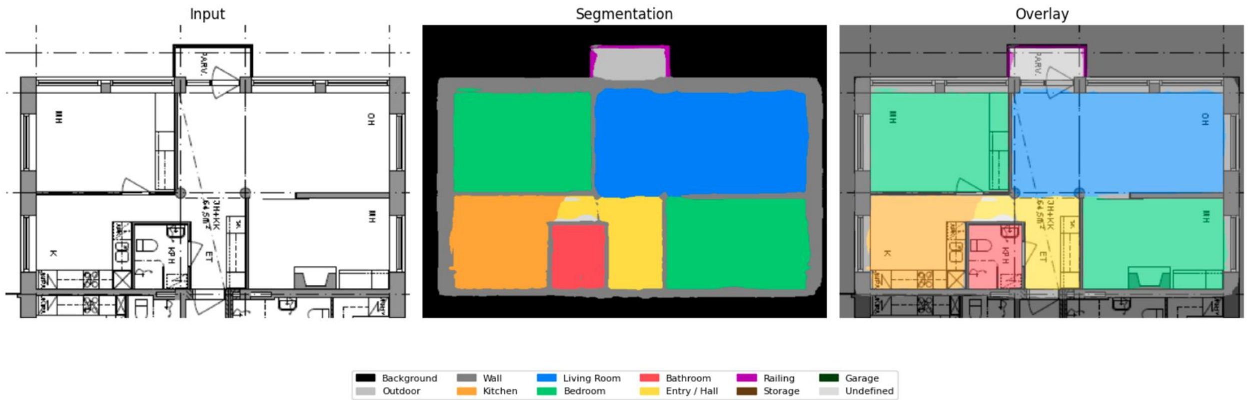


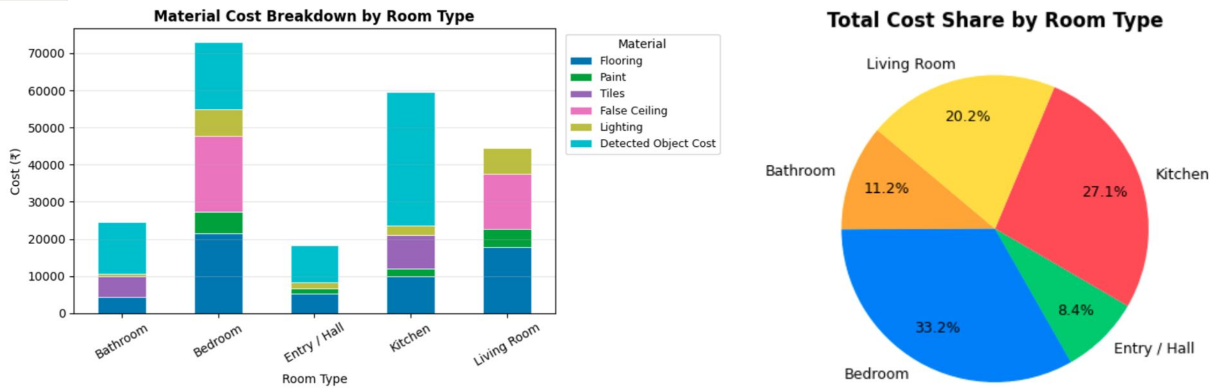
Fig. 6 Input floor plan, predicted room segmentation, and overlay visualization showing detected room regions used for quantity and cost estimation.

To demonstrate the practical applicability of the proposed framework, material quantity and cost estimation were performed based on the segmented room regions. Figure 6 illustrates the output of the complete pipeline, including the input floor plan, the predicted room segmentation, and the overlay visualization highlighting the detected room regions. This visualization shows how the segmentation results can be used to extract spatial information required for further analysis.

TABLE IIIII
ESTIMATED MATERIAL QUANTITIES AND TOTAL COST PER DETECTED ROOM BASED ON PREDICTED ROOM AREAS

Room ID	Room Type	Area (m^2)	Flooring (₹)	Paint (₹)	Tiles (₹)	False Ceiling (₹)	Lighting (₹)	Detected Object Cost (₹)	Total (₹)
0	Kitchen	8.31	9,972	1,994.40	9,141	0	2,493	36,000	59,600.40
1	Living Room	19.85	17,865	4,764	0	14,887.50	6,947.50	0	44,464
2	Bedroom	12.41	11,169	2,978.40	0	10,548.50	3,723	6,000	34,418.90
3	Bedroom	11.59	10,431	2,781.60	0	9,851.50	3,477	12,000	38,541.10
4	Bathroom	3	4,500	0	5,400	0	720	14,000	24,620
5	Entry / Hall	5.38	5,380	1,291.20	0	0	1,721.60	10,000	18,392.80
TOTAL	—	60.54	59,317	13,809.60	14,541	35,287.50	19,082.10	78,000	**220,037.20**

Based on the segmented room instances, the area of each room was computed and used to estimate the quantities of construction materials required for different room types. Table 3 presents the room level estimation results, including the room identifier, room type, calculated area, and estimated costs for flooring, paint, tiles, false ceiling, lighting, and detected symbols, along with the total cost for each room.



(a) (b)

Fig. 7 Material cost analysis across room types: (a) stacked bar chart showing the material wise cost breakdown for each room type, and (b) pie chart showing the percentage contribution of each room type to the total estimated construction cost.

To provide a clearer understanding of the cost distribution across different room types and material categories, additional visual analysis was performed. Figure 7(a) presents a stacked bar chart illustrating the material cost breakdown for each room type, while Figure 7(b) shows a pie chart representing the overall cost distribution among room categories. These visualizations highlight how the proposed framework can assist in analyzing construction cost allocation across different parts of the building layout.

VI. CONCLUSION

This paper presented a deep learning based framework for automated interpretation of architectural floor plan images, emphasizing room level semantic segmentation and its direct application to material quantity and cost estimation. The approach demonstrates that accurate segmentation, when coupled with geometric feature extraction, can move beyond visual understanding to enable practical, data-driven construction analysis. The experimental results validate the effectiveness of the method in capturing complex spatial layouts and producing reliable room wise cost estimates from raster floor plans.

By bridging the gap between computer vision and construction analytics, this work highlights the potential of intelligent systems to streamline traditionally manual and error prone processes in building design and planning. Future research can focus on enhancing robustness across diverse architectural styles, improving scale inference, and extending the framework toward 3D reconstruction and real time BIM integration, enabling more comprehensive and industry ready automated solutions.

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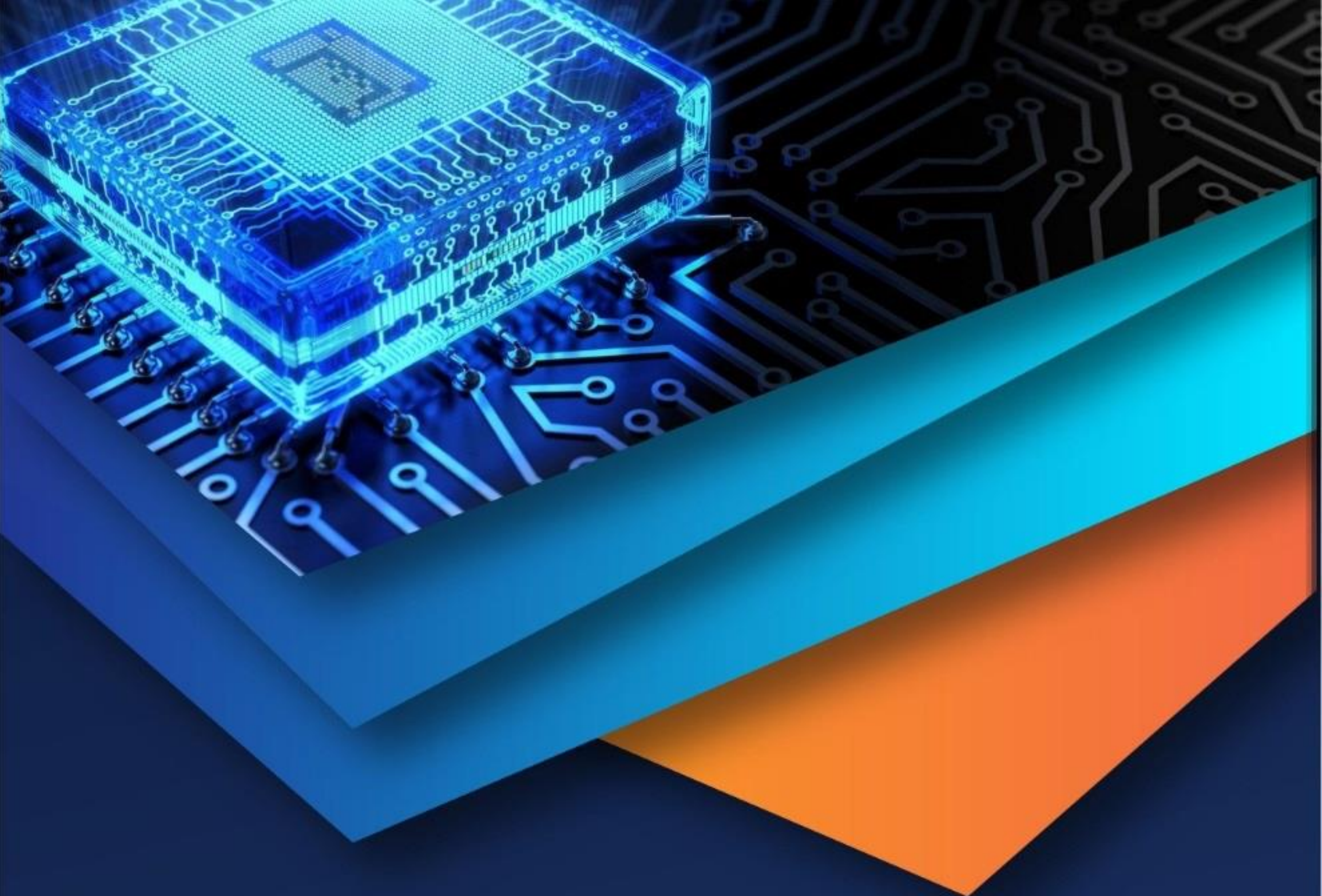

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