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Automated 3D Visualization from 2D Design Plans

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Abstract: *The increasing shift toward digital design in architecture and engineering has created a strong need to convert old 2D blueprints into usable 3D models. Manually turning these drawings into 3D structures is slow, depends heavily on expert skill, and often leads to mistakes. To address these issues, this project introduces an automated system that uses deep learning to convert 2D architectural plans into structured 3D models.*

The workflow begins with cleaning the input blueprint through noise removal, binarization, and scale adjustments. A CNN-based segmentation model then identifies key elements such as walls, windows, doors, and other markings present in the drawing. These identified components are transformed into a layout graph, which helps the system understand the spatial arrangement of the structure. A reconstruction model then predicts height, dimensions, and geometric details required to generate a 3D model.

The final output is produced as a 3D mesh or a CAD-friendly model that can be edited and visualized using existing design tools. Tests conducted on various floor plans show that the system can create consistent and accurate 3D structures with much less manual effort, making it a practical solution for modern design workflows.

Keywords: *2D blueprints*

I. INTRODUCTION

Even today, many engineering and architectural projects rely on 2D drawings for planning and communication. However, modern design processes increasingly require 3D models for tasks such as visualization, walkthroughs, simulation, and BIM integration. Creating these 3D models manually from older or hand-drawn blueprints is time-consuming and requires highly skilled CAD professionals.

With recent advancements in deep learning and computer vision, systems can now interpret visual patterns from blueprint images automatically. Convolutional neural networks can detect building layouts, identify walls and openings, and extract useful information directly from 2D plans.

This project builds a fully automated pipeline that takes a 2D architectural blueprint as input and produces a corresponding 3D model. The pipeline focuses on three major tasks:

- **Preprocessing** the blueprint to ensure clarity and standardization
- **Semantic segmentation** to detect architectural features
- **3D reconstruction** to generate a usable 3D structural model

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II. LITERATURE REVIEW

Research on converting 2D architectural drawings into 3D models has grown significantly due to improvements in deep learning and computer vision. One of the earliest approaches involved preprocessing the blueprint to remove noise and refine contours so that the drawing could be interpreted by a model. Later, CNN-based segmentation methods became popular because they were able to distinguish structural elements such as walls, doors, windows, and symbols with good accuracy.

Recent studies have combined deep learning with geometric reasoning to achieve better reconstruction results. For example, graph-based structural analysis helps the system understand how different building components relate to one another, which is especially useful for complex floor plans. Some researchers have also explored using Generative Adversarial Networks (GANs) to enhance 3D realism by learning features such as wall thickness, height variations, and relative spatial organization.

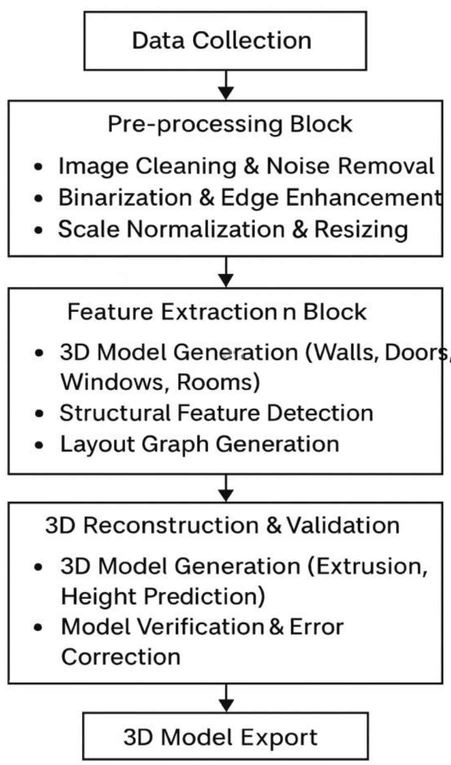
Large datasets like Structured3D and RPLAN have supported these advances by providing diverse examples of annotated floor plans. However, challenges remain—particularly with low-quality scans, faded drawings, and missing labels. Multi-storey buildings also add complexity because the system must infer vertical relationships from limited 2D information.

Overall, the literature highlights the importance of accurate segmentation combined with strong geometric reasoning. These insights guide the design of the proposed system for reliable 2D-to-3D visualization.

III. METHODOLOGY

The flowchart represents the end-to-end process of converting a 2D architectural blueprint into a 3D structure.

The pipeline begins when a blueprint image is uploaded. The first step is **preprocessing**, where the image is cleaned through noise removal, binarization, and resizing. These steps ensure that the blueprint is readable and consistent. If the processed image remains unclear, the system repeats additional cleaning steps before moving forward.



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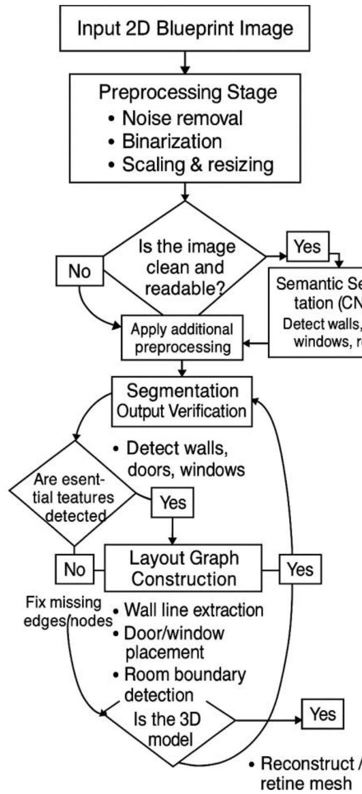
Once the blueprint is clear, the next stage is **semantic segmentation**, where a CNN or U-Net model identifies structural components such as walls, doors, windows, and room areas. If the system detects missing or incomplete features, it applies corrective steps such as filling gaps or defining edges, then checks the output again.



The **3D reconstruction module** converts this layout into a three-dimensional model through height estimation, extrusion, and mesh generation. The reconstructed model is validated, and if errors are found—such as missing walls or incorrect connections—the system automatically adjusts them.Finally, the completed 3D model is exported in a standard format for visualization or further architecturaldesign.

The block diagram outlines the complete workflow used in the proposed 2D-to-3D blueprint conversion model. The process begins with **Data Collection**, where the system receives the input architectural blueprint. This can be a scanned plan, a digital drawing, or any 2D floor layout that needs to be converted into a 3D representation.The next stage is the **Pre-processing Block**, where the blueprint image is cleaned and prepared for analysis. This involvesremoving unwanted noise, improving the visibility of structural lines through binarization or edge enhancement, and normalizing the scale of the image sothat all elements are interpreted correctly.

Resizing and cleaning ensure that the blueprint is consistent enough for reliable extraction of architectural features.

After preprocessing, the workflow moves into the **Feature Extraction Block**. At this point, the system identifies key structural components within the blueprint—such as walls, windows, doors, and room boundaries.

These elements are then used to create alayout graph that represents the underlying spatial structure of the building. This graph becomes the foundation for building the 3D model.

Once the essential features have been extracted, the system proceeds to the **3D Reconstruction and Validation** stage. Here, the extracted layout is converted into a 3D model through processes like extrusion, height prediction, and volumetric construction. The generated model then goes through a verification step to ensure accuracy. Any inconsistencies—such as missing walls or incorrect dimensions—are corrected automatically.

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Finally, the completed model moves to the **3D Model Export** stage, where it is saved in a usable format for visualization, simulation, or further architectural design work.

Overall, the diagram represents a structured pipeline that cleans the input blueprint, extracts meaningful architectural features, reconstructs them into a 3D structure, validates the output, and exports a ready-to-use 3D model.

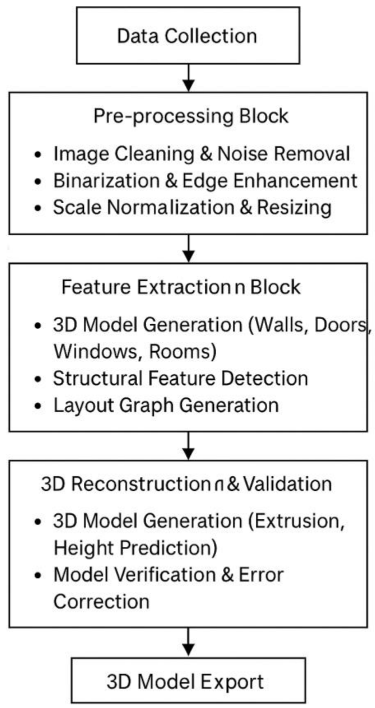
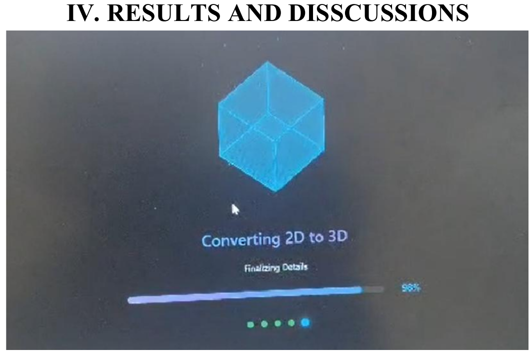
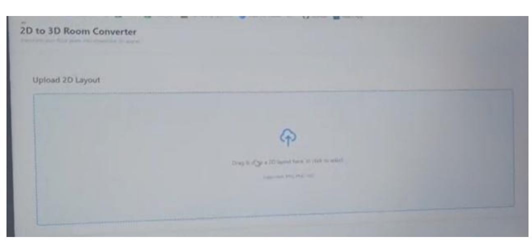
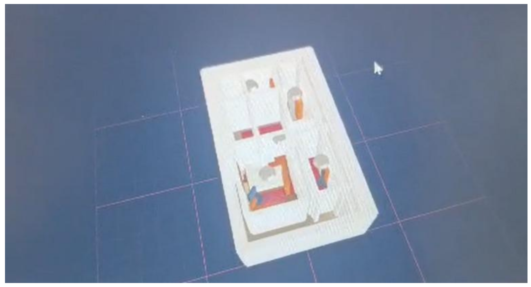


Fig 2. Block Diagram of Proposed 2D-to-3D Blue-print Conversion Model.

IV. RESULTS AND DISSCUSSIONS







V. COMPARSION BETWEEN PROPOSED 2D-3D MODEL AND TRADITIONAL MODELS

Traditional architectural workflows rely heavily on manual interpretation of 2D drawings, where designers recreate the structure in CAD software step by step. This approach, although precise when performed by experts, has several drawbacks. It is time-consuming, demands deep technical knowledge, and becomes increasingly difficult when dealing with old, damaged, or low-quality blueprints. Even small errors or misinterpretations during manual drafting can lead to major inconsistencies in the final 3D model. Moreover, manual reconstruction lacks scalability—producing a large number of models requires significant manpower, making the process impractical for organizations handling bulk architectural data.

In contrast, the proposed deep learning–based pipeline automates most of the interpretation work. The system reads the blueprint, identifies walls and openings, constructs structural relationships, and generates a 3D model with minimal human input. Instead of depending on the user's skill, the model relies on learned patterns from training data, which makes the results more consistent. The pipeline also handles common issues found in old or unclear floor plans by applying preprocessing and corrective steps automatically, something traditional manual methods cannot do efficiently.

Another advantage of the proposed system is its **speed**. Tasks that traditionally take hours can be completed within minutes, making it suitable for large-scale digitization projects. The system also improves **accuracy** by eliminating human bias and reducing the likelihood of overlooking structural elements. Although manual CAD modelling offers precise control and customization, it cannot match the efficiency, consistency, and scalability provided by an automated deep learning approach.

Overall, the automated method provides a modernized workflow that bridges the gap between conventional blueprints and today's demand for detailed 3D representations. It supports faster decision-making, reduces labour costs, and creates a reliable foundation for BIM and visualization tools.

method modernizes the blueprint conversion process and improves efficiency for architectural visualization

VI. CONCLUSION

This project demonstrates a practical and efficient approach to converting traditional 2D architectural blueprints into structured 3D models using deep learning. By integrating preprocessing techniques, semantic segmentation, and graph-based reconstruction, the proposed system successfully automates a process that has historically required extensive manual effort. The results show that the model can interpret common floor plan elements—such as walls, doors, and windows—with a high level of consistency, even when the input drawings vary in clarity or format.

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The generated 3D models provide designers, engineers, and clients with a clearer understanding of spatial layouts, making the system valuable for visualization, documentation, and early-stage design review. The automated pipeline also reduces dependency on skilled CAD operators, improves turnaround time, and decreases the chances of human error.

However, the project also opens several avenues for future development. Enhancing the segmentation accuracy for complex layouts, including support for multi-level structures, predicting material properties, and improving geometric refinement would make the system even more robust. Expanding the training dataset with a wider variety of architectural styles would also support better generalization.

Despite these challenges, the work confirms that AI-driven techniques offer a powerful alternative to traditional workflows. As deep learning continues to evolve, automated blueprint-to-model systems like this one are likely to become standard components in architectural and construction industries, enabling faster, smarter, and more reliable digital design processes.

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