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AI-Driven Design: Using Generative Models for Floor Plan Automation

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Abstract:- The project explores the use of advanced AI technologies and generative models to automate the creation of floor plans. This initiative leverages tools such as ComfyUI and models like Stable Diffusion, LoRA, ELLA, and ControlNet to streamline the design process by translating textual prompts and boundary inputs into detailed floor layouts. This proof of concept establishes a foundation for future work, including the integration of generative outputs into CAD workflows, enhanced dataset training, and the development of user-friendly interfaces for real-time customization. The study also compares the approach with existing tools like Maket.ai and Revit Generative Design, underscoring the competitive edge of AI-driven methodologies in automating floor plan design.

I. INTRODUCTION

This proof of concept aims to leverage generative AI models to automate the creation of floor plans, reducing costs and saving time in the context of applications like **Planon**, a widely used workspace management tool within Organizations.

Planon is an integrated workspace management software that enables workspace management by recognizing 2D architectural floor plans with annotated features such as seating areas, meeting rooms, and open spaces. These annotations, often in the form of colored poly lines, allow employees to book spaces efficiently via a mobile application or Outlook mail.

Currently, many organizations utilize third-party services to create these 2D architectural floor plans, which are later processed to add color-coded poly lines that categorize areas such as seats, meeting rooms, and floors. This manual process is time-intensive and costly, presenting a clear need for automation.

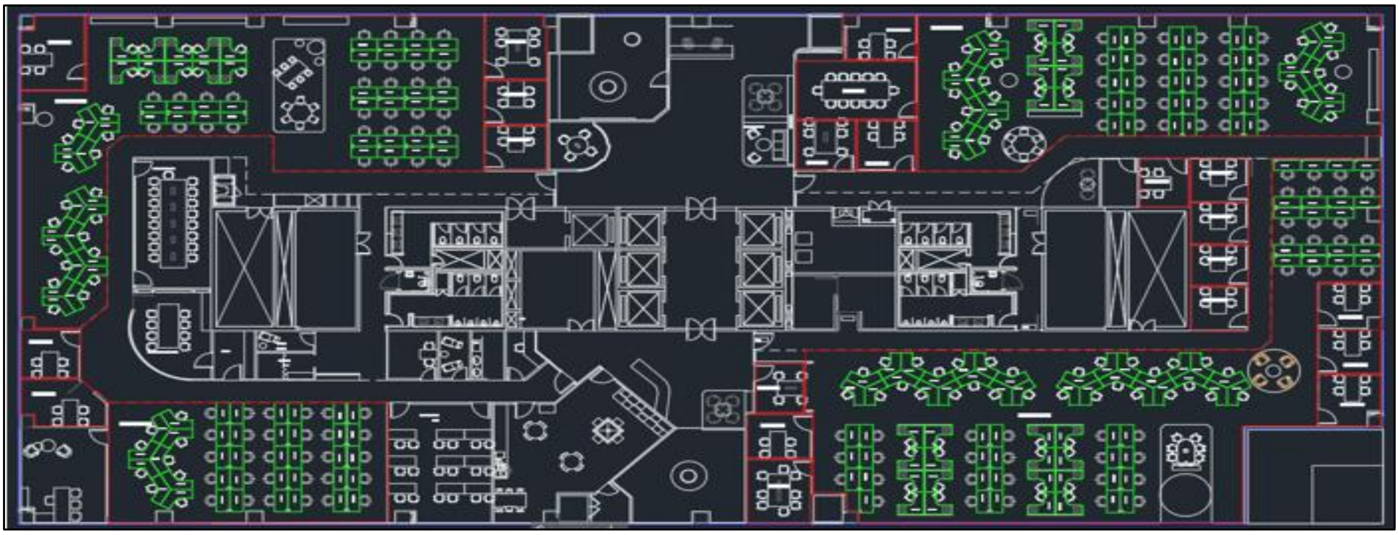

Fig 1: A Finished Floor Plan Design with Color Coded Polyline Annotations

This project investigates how to expedite this process by combining cutting-edge models like Stable Diffusion, LoRA, ControlNet, and ELLA with open-source generative AI tools like ComfyUI. The goal of the project is to produce annotated, Planon-compatible layouts with less manual involvement by automating the development of floor plans based on textual prompts and boundary images.

The method offers scalable architectural design solutions by integrating contemporary AI operations to improve spatial accuracy and layout refinement. By transitioning from manual creation to AI-driven generative processes, this proof of concept lays the groundwork for automated floor plan annotation and integration, directly supporting Planon's functionality and improving employees' booking experience.

II. APPROACHES & METHODOLOGY

This project experimented with a variety of approaches and tools to achieve efficient generative design for floor plans. Below is a detailed explanation of each approach, the challenges encountered, and how the techniques were refined over time.

➢ *Manual Master Dataset Creation and Initial Tests*

- Build a custom dataset of office furniture and layout requirements.
- Test the ability of AI models to generate floor plans based on text prompts.

A. Process:

➢ *Dataset:*

- Furniture types: desks, meeting tables, lounges, etc.
- Dimensions and capacities, adhering to ergonomic and BOMA standards.
- Examples: L-shaped desks (75 sq. ft.), 2-table combos (150 sq. ft.).

	Furniture Type	Typical Size (sq ft)	Capacity
0	Workspace (Standard)	50	1
1	L-shaped Desk	75	1
2	2 Table Combo	150	2
3	Personal Cabin	125	1
4	Meeting Table (Small)	65	6

Fig 2: Sample Master Data for Testing Stable Diffusion Model.

```
# Example usage
master_data = {
    'Furniture Type': pd.Series(['Workspace (Standard)', 'L-shaped Desk', '2 Table Combo', 'Personal Cabin', 'Meeting Table (Small)']),
    'Typical Size (sq ft)': pd.Series([50, 75, 150, 125, 65])
}
```

Fig 3: Sample User Prompt

➢ *Challenges:*

- Lack of Detail: Generated images lacked functional layouts.
- Limited Customization: Text prompts alone were insufficient for controlling precise spatial layouts.

➢ *Outcome:*

- Established baseline results, proving the feasibility of integrating generative models for design.

B. Generative Models for Improved Results

- Enhance image outputs using generative models fine-tuned for architectural styles.
- Introduce structured boundary input for spatial control.

➢ *Process:*

- *Model Used:*

✓ **Stable Diffusion:** Pre-trained generative model for text-to-image synthesis.
✓ **LoRA** (Low-Rank Adaptation): Used for fine-tuning Stable Diffusion on domain-specific architectural data.
✓ **ControlNet**: Integrated spatial boundary images to guide floor plan generation.
✓ **ELLA**: Advanced model for creative generative tasks.

➢ *Tool:*

- *ComfyUI: Workflow-based UI for Managing Generative Pipelines*

✓ Allowed integration of text prompts, pre-trained models, and boundary images in a modular way.

➢ *Workflow:*

- Input textual description:

" Generate a detailed 2D top view floor plan of a modern corporate office, designed in a technical, architectural style resembling an AutoCAD blueprint. The layout should include six meeting rooms, each furnished with a central table and eight chairs. Additionally, incorporate a reception area equipped with a modern desk and seating for visitors. The office should also contain 25 individual work desks, arranged to optimize space and workflow. Ensure that the design is clear and precise, suitable for professional architectural presentation."

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- Generate initial layouts using Stable Diffusion.
- Apply boundary constraints using ControlNet to refine spatial placement.
- Enhance results using LoRA to adapt architectural nuances.

➤ *Challenges:*

- Model Compatibility: Tensor mismatches between ControlNet and other components required debugging.
- Compute Limitations: Even with an NVIDIA RTX 3600+ GPU, generating high-resolution images was resource intensive.

➤ *Outcome:*

- Significantly improved design quality.
- Process large, detailed prompts as input from user.
- Introduced flexibility in integrating boundary images for more precise control.

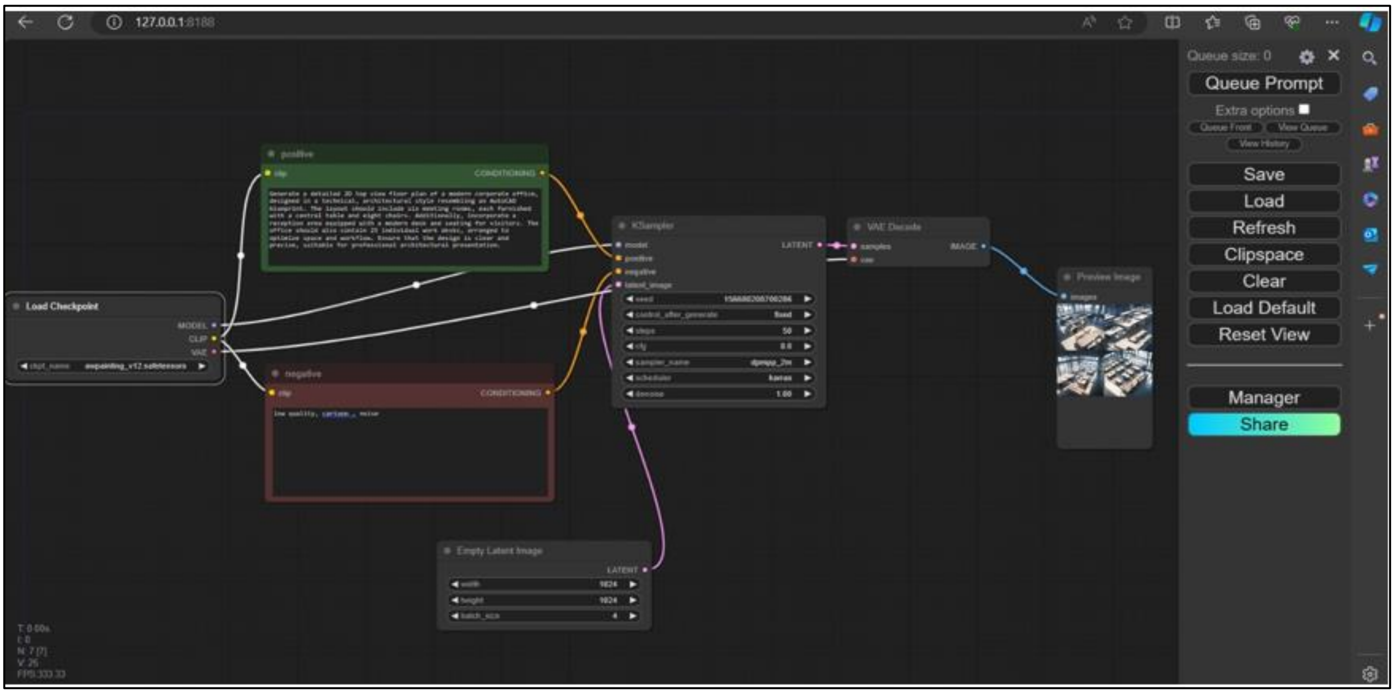

Fig 4(a)

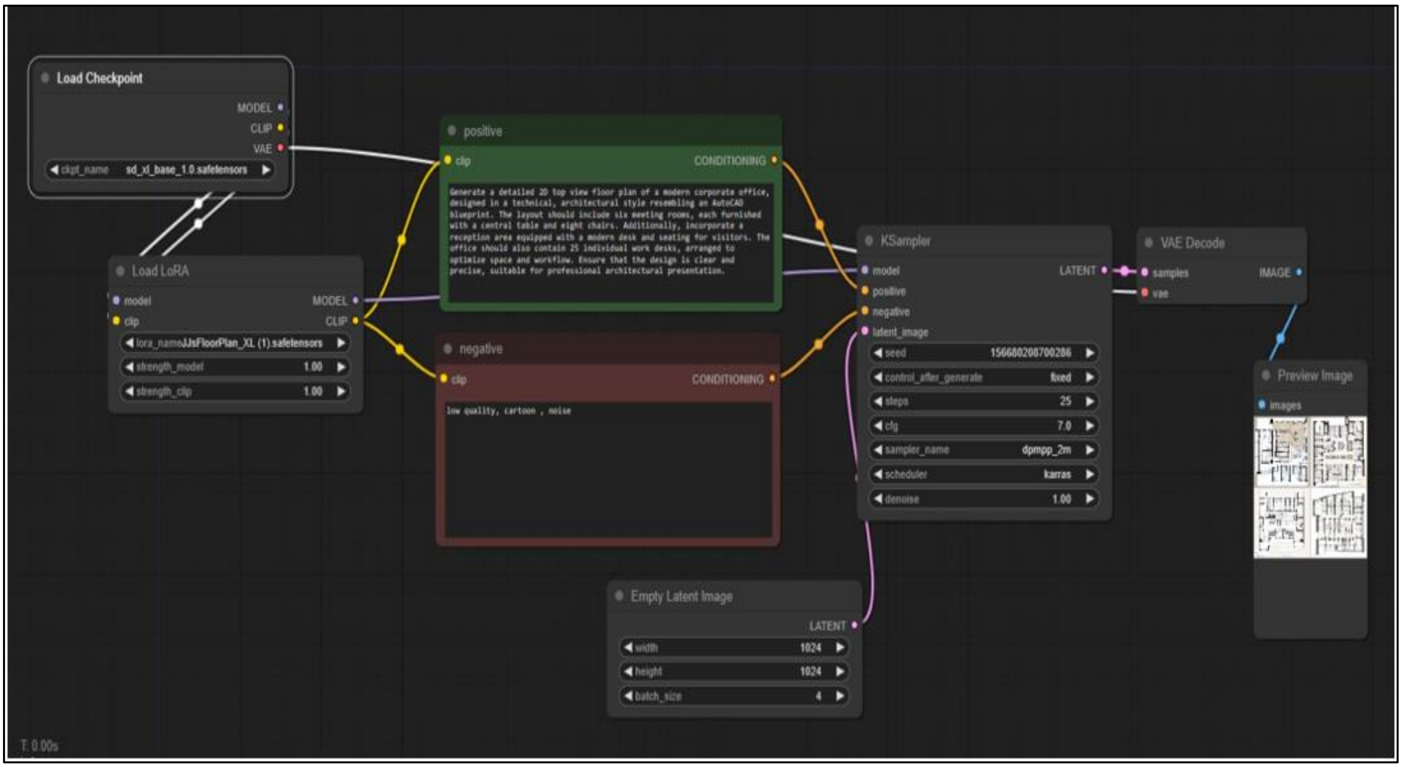

Fig 4(b)

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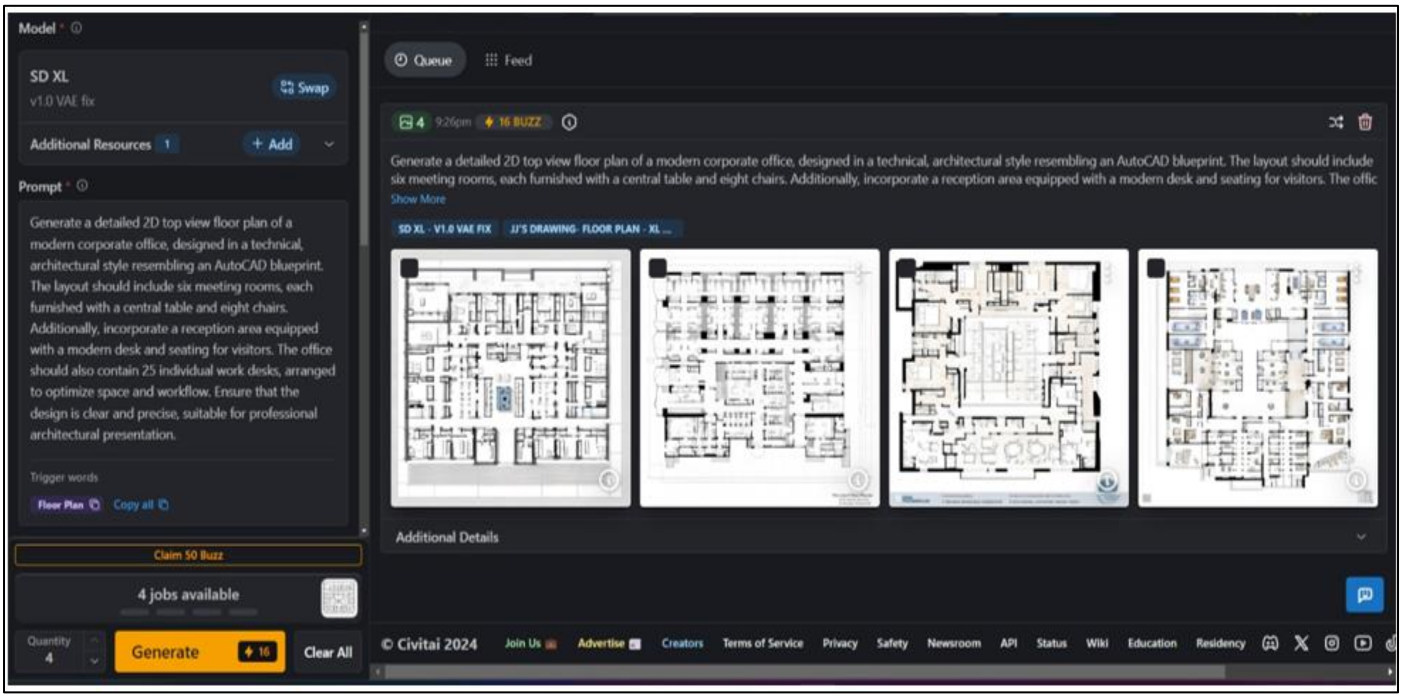

Fig 4(c)

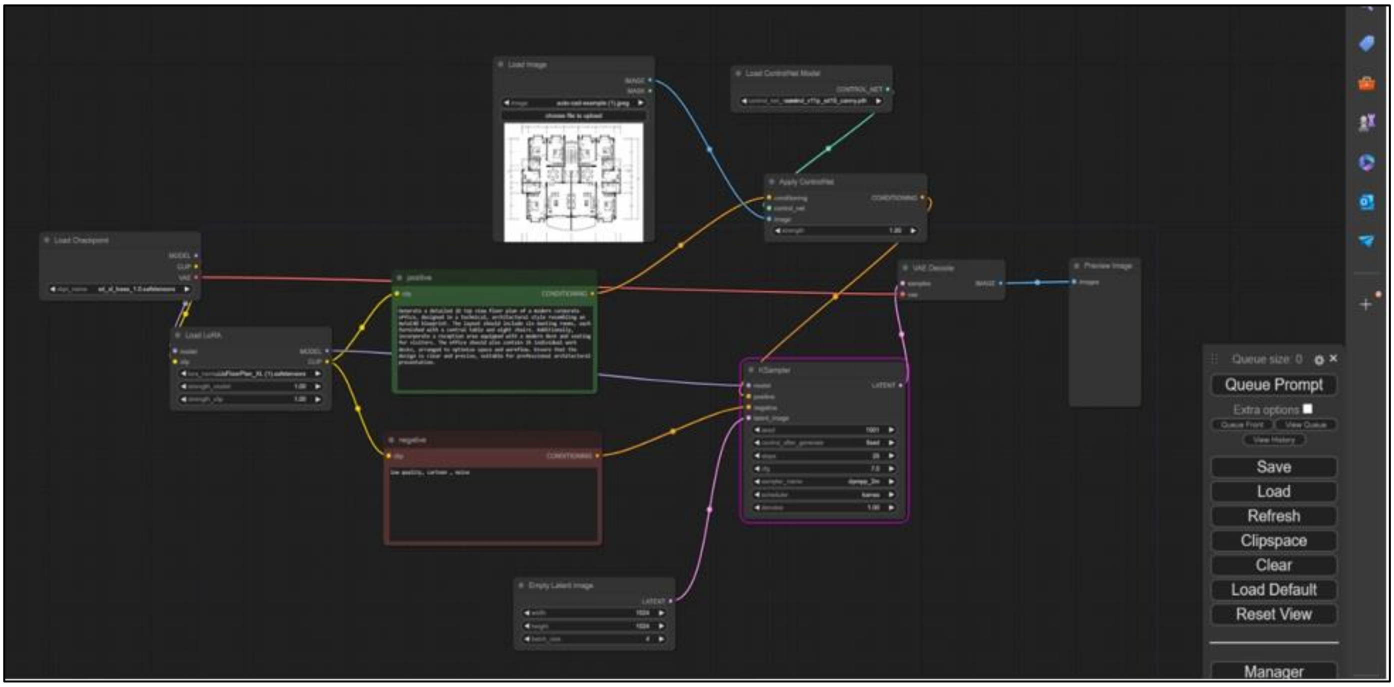

Fig 4(d)

Fig 4: Checkpoints with Different Scenarios as Input Models
4(a)Stable Diffusion; 4(b): Stable Diffusion & LoRA; 4(c): Stable Diffusion xl & LoRA;
4(d): Stable Diffusion, LoRA and ControlNet

Table 1: Techstack used Throughout the Project

Component	Technology/Tool	Purpose
Models	Stable Diffusion	Text-to-image generation
	LoRA	Domain-specific fine-tuning
	ControlNet	Spatial control for layouts
	ELLA	Creative generative design tasks
Framework	ComfyUI	Node-based Modular UI for model workflows.
	Google Collab	Run python scripts
Hardware	NVIDIA RTX 3600+ GPU	Accelerated image generation.

III. BENCHMARKING & RESULTS

To evaluate the performance and effectiveness of the generative AI models and workflows, the project used several metrics focused on computation time, layout quality, and applicability to Planon requirements as depicted in **Table 1**.

Table 2: Breakdown of Time, Quality and Resolution by using Generative AI Approach

Aspect	Metric	Result
Computation Time	Avg. time/floor plan	3-5mins/image
Quality	Spatial Accuracy	Improved with ControlNet boundary inputs
Resolution	Max resolution supported	1024x1024 pixels

A. Insights

- Initial tests use only textual prompts lacked spatial precision, resulting in incomplete or overlapping layouts.
- Integrating ControlNet significantly improved spatial accuracy, especially for complex office layouts.
- The NVIDIA RTX 3600+ GPU handled the tasks efficiently, with minor slowdowns during high-resolution processing.

B. Comparison with Existing Tools

The project's integration with generative AI outperformed other tools in terms of adaptability and generation time. Particularly for office-specific layouts.

Table 3: Comparison with Different Tools

Tool/Model	Feature	Comparison
Maket.ai	Generative design for residences	Highly specialized for residential use. Limited for office spaces.
Revit generative design	Parametric design	Robust, but requires expertise. Lacks AI-driven generative features.
Planner 5D	Interactive floor planning	Simplified. Not generative or AI-based.

C. Future Directions

The aim of this proof of concept provides a strong foundation for advancing the application of generative AI models in architectural automation. The following future directions focus on refining the workflow, enhancing automation capabilities, and integrating enterprise-level functionality:

➢ *Full Integration with CAD Software- enable seamless export of AI-generated floor plans into CAD tools like AutoCAD and Revit.*

- *Approach:*

✓ Develop scripts or APIs to translate AI outputs into CAD-compatible formats such as DWG or DXF.
✓ Automate annotation within CAD, including the creation of colored poly lines for seats, meeting rooms, and other spaces directly recognized by Planon.

➢ *Improved Dataset Creation and Model Training- Build domain-specific datasets tailored to office floor plans and enhance the adaptability of generative models.*

- *Approach:*

✓ Use automated web scraping or partnerships with architectural firms to collect large-scale datasets of office layouts.
✓ Fine-tune models like Stable Diffusion and LoRA with this dataset to improve the realism and functionality of generated outputs.

➢ *Automation of Annotation for Planon Compatibility- Remove the need for manual post-processing of AI-generated floor plans for Planon integration.*

- *Approach:*

✓ Develop custom algorithms to automatically assign colored poly lines to areas of the generated floor plans (e.g., red for meeting rooms, green for workspaces, blue for floor).
✓ Train AI models to recognize and apply predefined Planon standards during image generation.

➢ *Real-Time User Interaction- Create a user-friendly interface for real time customization of floor plans.*

- *Approach:*

✓ Develop a web-based frontend using frameworks like React or Angular, where users can input specifications (e.g., number of seats, meeting rooms, room dimensions).
✓ Integrate real-time feedback mechanisms that allow users to view and adjust AI-generated plans interactively.

- *Exploring 3D Floor Plan Generation- Transition from 2D layouts to 3D floor plans for a more comprehensive view of spatial arrangements.*

- *Approach:*

✓ Utilize 3D generative models like NVIDIA's Omniverse or Blender for AI-driven 3D floor plan creation.
✓ Generate 2D and 3D outputs simultaneously for better visualization.

IV. CONCLUSION

This research effectively exhibits the ability of generative AI models, such as Stable Diffusion, LoRA, ControlNet, and ELLA, to automate the development of 2D floor designs. By moving from manual dataset production to advanced workflows with ComfyUI, the project demonstrates the scalability and efficiency of generative approaches.

Despite initial difficulties in automating floor plan production with AutoCAD scripts due to component unpredictability, the addition of AI models resulted in considerable gains in spatial accuracy and adaptability. Using text prompts and border pictures, the system generated floor designs in an average of 3-5 minutes each arrangement.

It also performs well versus existing tools such as Maket.ai and Revit Generative Design, demonstrating faster generating times and adaptability to office layouts.

While current results require further post-processing for Planon compatibility, the foundation established here paves the way for future developments.

Moving forward, further enhancements can include integrating generative outputs with CAD software, refining datasets for domain-specific designs, and automating annotation for full compatibility with Planon. This proof of concept underscores the transformative potential of AI-driven design and lays the groundwork for scalable, enterprise-level solutions in architectural automation.

ABOUT THE AUTHOR

Khushboo Nijhawan works as an Application Analyst in Digital Governance COE She finished her bachelor’s degree in computer science and engineering with Rank 7 from Vellore Institute of Technology. During which she has been part of various Tech competitions and public forums. Previously, published a research paper on “Sanitization & Temperature Based Auto Unlocking System” for SIET 2023. With the help of her technical skills across domains like Machine Learning, Deep Learning, Data Science, Web Development, and various programming languages, she aims to build empowering communities and explore new frontiers in technology.

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