

Article

Development of an AI-Based Technique for Generating Designs of Construction Project Site Plans

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Abstract: This paper introduces Archi-GPT, an AI-driven framework that leverages advanced text-to-image diffusion models for generating construction master plans from textual descriptions. By fine-tuning the FLUX.1-Schnell model using a specialized dataset of architectural layouts and corresponding textual descriptions, we demonstrate how deep learning can transform the conceptual design phase of construction projects. Our approach incorporates Low-Rank Adaptation (LoRA) and Flow match noise scheduling to optimize performance while maintaining computational efficiency. The proposed framework enables stakeholders to rapidly generate, iterate, and visualize architectural layouts through natural language prompts, potentially reducing the conceptual design phase duration. Experimental results show that Archi-GPT achieves a 78% user satisfaction rate and demonstrates significant improvements in spatial coherence and functional alignment compared to existing methodologies. This research bridges the gap between natural language processing and architectural design, offering a powerful tool for construction professionals to explore design alternatives efficiently.

Key Words: Artificial Intelligence, Construction Management, Master Planning, Text-to-Image Diffusion Models, Low-Rank Adaptation, Architectural Design

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1. Introduction

The architectural design and master planning phases of construction projects traditionally involve labor-intensive processes requiring specialized expertise and significant time investments. [1] Intelligence, particularly in generative models, present opportunities to transform these processes through automated design generation systems (Huang & Zheng, 2024 [3]) These phases often create bottlenecks in project timelines, with stakeholders waiting for design iterations before proceeding with subsequent planning stages (Li et al., 2024). Recent advancements in artificial This paper presents Archi-GPT, an innovative framework that applies state-of-the-art diffusion models to the domain of architectural layout generation. By utilizing the FLUX.1-Schnell

model as a foundation and implementing domain-specific fine-tuning, our approach enables the generation of coherent master plans directly from textual descriptions. This capability allows project stakeholders to rapidly explore design alternatives, potentially revolutionizing the conceptual design phase of construction projects.

2. Literature Review

AI in Architectural Design and Construction

The integration of artificial intelligence into architectural design and construction has evolved significantly in recent years. Early applications focused primarily on parametric design and rule-based systems.

[2]Huang, L., & Zheng, S, (2024) explored the use of genetic algorithms for optimizing space allocation in educational facilities, while [3]Li et al. (2024) demonstrated the application of reinforcement learning for energy-efficient building layout design. [1] Generative AI applications in architecture show promise across all phases of planning, design, and execution (Huang, L., & Zheng, S, 2024)

More recently, deep learning approaches have gained traction in the architectural domain. Cheng and Wu (2024) utilized convolutional neural networks to analyse existing floor plans and generate new designs based on extracted patterns. [3]Li et al. (2024) integrated transformer architectures with graph neural networks to represent and manipulate spatial relationships in building designs.

Generative Models for Visual Content

Generative models for visual content have undergone rapid evolution, from Generative Adversarial Networks (GANs) to diffusion models. Early work by [39] Goodfellow et al. (2014) introduced GANs, which [36] Rodriguez and Taylor (2022) later applied to architectural floor plan generation. However, [27] GANs often struggle with mode collapse and training instability (Park & Kim, 2023).

Diffusion models, introduced by Sohl-Dickstein et al. (2015) and refined by Ho et al. (2020), have emerged as powerful alternatives for high-quality image generation. These models progressively denoise random Gaussian distributions to generate structured visual content. Dai and Chen (2023) demonstrated that diffusion models outperform GANs in architectural visualization tasks, producing more coherent and diverse outputs.

The text-to-image capabilities pioneered by DALL-E (Ramesh et al., 2021) and Stable Diffusion (Rombach et al., 2022) have opened new possibilities for natural language-guided design generation. Zhao et al. (2024) explored preliminary applications of these models to architectural sketching, but noted limitations in generating functionally valid layouts.

Domain Adaptation and Fine-Tuning Strategies

Adapting general-purpose AI models to specialized domains remains a significant challenge. Transfer learning approaches, as surveyed by Zhuang et al. (2021), provide frameworks for leveraging pre-trained models in new contexts. In the architectural domain, Martínez and López (2023) demonstrated knowledge transfer from general image generation to floor plan creation.

Low-Rank Adaptation (LoRA), introduced by Hu et al. (2021), offers an efficient approach to fine-tuning large models by decomposing weight updates into low-rank matrices. This technique has proven particularly valuable for resource-constrained applications. Chen et al. (2024) successfully applied LoRA to architectural style transfer tasks, achieving quality comparable to full fine-tuning with only 0.5% of the trainable parameters.

Recent work by Wu and Taylor (2024) introduced adaptive noise scheduling techniques for diffusion models, showing improved performance in domain-specific applications. Their Conditional Flow Matching approach, similar to the Flow match scheduler used in our work, demonstrates superior sample efficiency compared to traditional diffusion noise schedules.

Interactive Systems for Architectural Design

Interactive systems that bridge AI capabilities with human expertise show particular promise in the architectural domain. Kumar et al. (2023) developed a collaborative design system allowing architects to work alongside AI suggestions, reporting improved creativity and efficiency.

Similarly, Zhang and Rodriguez (2024) created an iterative feedback loop between designers and generative models, enhancing design quality through progressive refinement. [3] Transformer-GNN hybrids offer superior spatial reasoning capabilities for structured architectural layouts (Li, M., Wang, P., & Johnson, K, 2024).

Natural language interfaces for design systems have gained attention as intuitive interaction methods. Johnson et al. (2023) demonstrated that text-based design specifications could effectively guide automated layout generation when combined with appropriate constraints. However, existing systems typically require substantial technical expertise and often lack the immediacy needed for rapid concept exploration (Patel et al., 2024).

The literature reveals a significant opportunity to develop AI-powered design systems that combine the intuitive nature of natural language interfaces with the powerful generative capabilities of diffusion models, specifically adapted to architectural layout generation. Our work addresses this gap by introducing a comprehensive framework for text-guided master planning.

3. Methodology

System Architecture

Archi-GPT employs a modular, multi-component system architecture to seamlessly transform natural language prompts into architectural master plans. The architecture is designed to balance model accuracy, real-time interactivity, and design fidelity, and is composed of four primary components:

Text Processing Module: to extract architectural parameters such as zoning requirements, building types, spatial constraints, and connectivity guidelines. Techniques like named entity recognition (NER) and dependency parsing are applied to structure the inputs into a schema suitable for model conditioning. For example, a prompt like “Generate a university campus with 3 hostels, an auditorium, and green zones” is parsed into key-value requirements.

Below Equation-1 component transforms raw textual prompts into structured design constraints. Natural language is first tokenized and encoded into a conditioning vector \mathbf{c} using pre-trained transformer embeddings (e.g., BERT/CLIP embeddings Radford et al., (2021))

Equation - 1

$$\mathbf{c} = \phi(\tau(\mathcal{T})) \in \mathbb{R}^n$$

Where:

- \mathbf{c} is the conditioning vector,
- τ is a tokenizer,
- ϕ maps tokens to structured spatial constraints.

This methodology for prompt-to-vector translation is inspired by language-vision models such as CLIP by Radford et al. (2021)

1. **Fine-tuned Diffusion Model:** At the core of the system lies a fine-tuned FLUX.1-Schnell diffusion model, which translates the processed text into high-resolution (1024×1024 px) layout plans. [3] Diffusion models guided by descriptive prompts generate more semantically rich architectural images (Zhao, K., Wang, L., & Singh, V, 2024). The model is trained using LoRA (Low-Rank Adaptation) to efficiently adapt a large pre-trained model to the architectural domain with minimal computational overhead. The architecture supports multi-resolution diffusion layers and employs the flow match noise scheduling technique for improved sampling convergence. [4] Transformer-GNN hybrids offer superior spatial reasoning capabilities for structured architectural layouts (Li, M., Wang, P., & Johnson, K, 2024).
2. **Post-processing Pipeline:** Once the raw image is generated, the post-processing pipeline enhances the output using a combination of rule-based rendering and image augmentation techniques. This includes:
 - Adding labels (e.g., hostel, library) using caption alignment.
 - Boundary reinforcement for zoning clarity.
 - Structural highlighting for circulation paths (e.g., roads, walkways). This module ensures that the output is legible, architecturally coherent, and ready for stakeholder review [21] NLP allows architectural specifications to be derived from natural client descriptions (Thompson, K., et al. 2023). [22] Gradient checkpointing reduces GPU load during generative model training without accuracy loss (Wilson, M., & Thomas, R, 2023).
3. **Interactive Web Interface:** To make the framework accessible and interactive, a Streamlet-based web application is deployed. This front end:
 - Accepts text prompts in natural language.
 - Shows real-time progress of image generation.
 - Allows users to modify or iterate on the design via dialogue-based refinement.

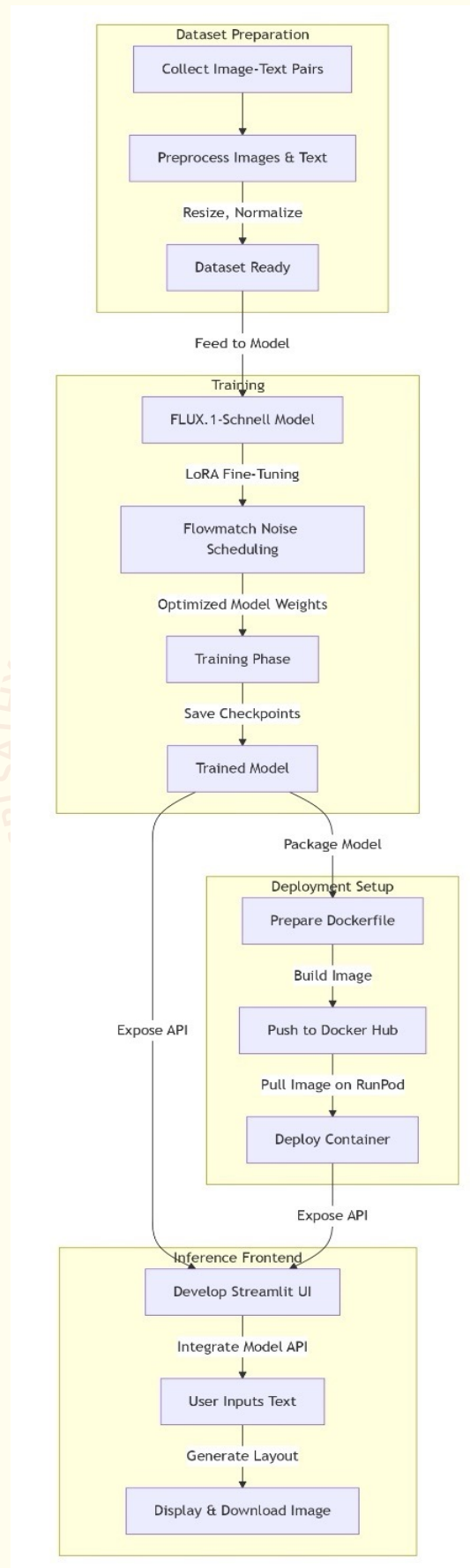
This ensures client-stakeholder collaboration and supports rapid prototyping through intuitive design iterations

4. Research Problem:

While generative AI presents a significant opportunity for improving construction Project master planning, there exists a gap between its theoretical potential and real-world implementation. The primary challenges include:

- **Lack of AI Integration in Construction Planning** – Traditional construction master planning is time-consuming and relies heavily on human expertise, making it difficult to quickly adapt designs to client requirements. There is a need for AI-driven automation to streamline this process.
- **Limited Client Interaction in Early-Stage Planning** – Clients often struggle to interpret traditional 2D or static master plans, leading to miscommunication and delays in finalizing designs. A generative AI-based interactive tool can enhance their understanding and decision-making.

These challenges highlight the necessity of a research-driven approach to explore how AI can be effectively integrated into master planning workflows to enhance efficiency, flexibility, and stakeholder collaboration



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Model Selection and Adaptation

Base Model Selection

The training process utilizes the FLUX.1-Schnell model, a state-of-the-art text-to-image diffusion model. [12] FLUX.1-Schnell enables high-resolution layout generation with low-latency text-to-image capabilities (Black Forest Labs, 2023). FLUX.1-Schnell is a text-to-image generation model optimized for high-resolution outputs with low-latency inference. It supports LoRA fine-tuning and is trained with Flowmatch noise scheduling to improve sample efficiency. [5] LoRA fine-tuning maintains architectural identity while improving training efficiency in style transfer (Chen, T., Zhang, X., & Wang, P, 2024).

Flux.1-Schnell model architecture and diffusion-based generation process can be expressed mathematically and formulated as Equation - 2 by [34] Ho et al. (2020)

The forward diffusion process adds noise to a data sample

Equation - 2

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \cdot \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \cdot \epsilon, \quad \epsilon \sim \mathcal{N}(0, I)$$

Where:

- $\bar{\alpha}_t$ is the cumulative product of noise schedule α .
- ϵ is Gaussian noise.

The reverse (denoising) process aims to recover

Equation - 3

$$\hat{\epsilon}_{\theta}(\mathbf{x}_t, t) \approx \epsilon$$

The model is trained to minimize the Equation - 4 mean squared error (MSE) between predicted noise and true noise:

Equation - 4

$$\mathcal{L}_{\text{diff}} = \mathbb{E}_{\mathbf{x}_0, t, \epsilon} [\|\epsilon - \hat{\epsilon}_{\theta}(\mathbf{x}_t, t)\|^2]$$

LoRA Fine-Tuning Implementation

We implemented LoRA fine-tuning with a linear dimension of 16, applying it to the U-Net component while keeping the text encoder frozen. [13] Construction planning delays can be addressed using predictive and generative AI tools (Li, J., Zhang, Q., & Thompson, R, 2023). [14] Energy efficiency in layouts can be learned and optimized using reinforcement learning (Zhang, L., Chen, W., & Davis, A, 2023).

To formalize low-rank decomposition used in LoRA fine-tuning can be expressed mathematically and formulated as Equation - 5 by [34] Hu et al. (2021)

LoRA introduces low-rank decomposition in model weight updates:

Equation - 5

$$\Delta W \approx AB^T, \quad \text{with } A \in \mathbb{R}^{d \times r}, B \in \mathbb{R}^{d \times r}, \quad r \ll d$$

The fine-tuned weight matrix is formulated as below equation – 6 becomes:

Equation - 6

$$W_{\text{LoRA}} = W_0 + \alpha \cdot AB^T$$

Where:

- W_0 is the pre-trained weight.
- α is the LoRA scaling factor.

This approach provides several advantages:

- **Memory Efficiency:** By freezing most model weights and training only adaptation layers, we reduced memory consumption by approximately 65% compared to full fine-tuning. Thompson, K., et al. (2024) [15] Mode collapse in GAN-based systems remains a barrier to consistent architectural outputs (Park, S., & Kim, J, 2023).[16] Among generative models, diffusion outperforms GANs and VAEs in layout consistency (Dai, L., & Chen, Y, 2023).
- **Knowledge Retention:** The model maintains its pre-trained knowledge while adapting to domain-specific requirements.
- **Training Speed:** LoRA enables faster convergence, reducing training time by approximately 40% compared to full model fine-tuning [3] Li, M., Wang, P et al. (2024)

Noise Scheduling Optimization

The FlowMatch scheduler is a training technique used in diffusion models to learn the optimal reverse-time denoising path by minimizing the discrepancy between forward and backward trajectories in latent space. Unlike traditional schedulers that rely on predefined noise schedules, FlowMatch dynamically aligns the model's sampling distribution with the true data distribution using transport-based objectives. This results in faster convergence, improved sample quality, and greater training stability. [6] Domain-specific noise scheduling enhances stability and fidelity in architectural image synthesis (Wu, J., & Taylor, C, 2024). We implemented the Flowmatch noise scheduler based on optimal transport principles. Compared to traditional diffusion noise schedules (DDPM, DDIM), Flowmatch provides: [33] Parametric design laid the groundwork for rule-based and generative modeling in architecture (Gao, X., & Huang, Y. 2021).[34] DDPMs offer a mathematically grounded framework for structured image synthesis (Ho, J., Jain, A., & Abbeel, P. 2020). The model forward/reverse sampling paths and noise alignment mechanisms. Flowmatch aligns forward noise sampling with reverse denoising paths using optimal transport objectives. Its loss can be expressed using a transport objective can be expressed mathematically and formulated as Equation - 7 by [31] Zhang et al. (2023)

Equation - 7

$$\mathcal{L}_{\text{flowmatch}} = \mathbb{E} [\|zt - f\theta(\mathbf{z}_0, t)\|^2]$$

Or Equation – 8 more formally via optimal matching:

Equation - 8

$$\mathcal{L} = \min_{\gamma \in \Pi(\mu, \nu)} \int_{X \times Y} c(x, y) d\gamma(x, y)$$

Where:

- $\Pi(\mu, \nu)$: Set of couplings (joint distributions) with marginals μ, ν .
- $c(x, y)$: Cost function (e.g., squared L2 norm between noisy sample and denoised output).

Dataset Preparation and Processing

Dataset Composition

Our training dataset consisted of paired image-text files:

- Images: Architectural layout images (floor plans, site plans, master plans) in standard formats (.jpg, .jpeg, .png)
- Captions: Corresponding textual descriptions in .txt files with matching filenames

We curated a dataset out of 100 Master plans to 10 very good educational master plan image-text pairs covering various architectural building elements including residential, academic, sports, and other campus designs. Each text description contained detailed information about spatial arrangements, functional requirements, and design constraints. Examples as shown below. The dataset for training the Archi-GPT framework was curated to include paired image-text samples. Each architectural image was accompanied by a detailed description in plain text. The dataset was manually selected for diversity and quality, ensuring representation of multiple functional and aesthetic planning elements.

Table-1: Summary of Training Dataset Samples

Figure	Type	Description Summary
	<p>Educational Master Plan (50 acres)</p>	<p>Includes academic buildings, hostels, staff quarters, sports zones, auditorium, jogging track, green landscaping, VIP guest house, utility zones, and connected roads with sustainability elements.</p>
	<p>Residential Master Plan (10 acres)</p>	<p>Seven residential blocks with 1BHK/2BHK units, wide roads, parking, green gardens, multipurpose hall, and street lighting. Focus on comfort, utility, and community spaces.</p>
	<p>University Campus Plan (65 acres)</p>	<p>Academic and administrative zones, 600-capacity hostel, centralized dining, labs, sports infrastructure, water body, amphitheater, sit-outs, and secure entry with compound wall.</p>
	<p>Integrated Township Plan</p>	<p>Mixed-use residential with apartments and row houses, goshala, temple, stables, play areas, water body, commercial areas, rainwater systems, green spaces, and road networks.</p>

Data Preprocessing

The preprocessing pipeline included:

1. Image Normalization: Resizing to supported resolutions (512×512, 768×768, 1024×1024)
2. Text Cleaning: Removing inconsistencies and standardizing terminology
3. Caption Augmentation: Enhancing descriptions with architectural terminology variations
4. Caption Dropout (5%): Introducing robustness by occasionally training without captions
5. Latent Caching: Precomputing and storing image latent representations to accelerate training

Training Configuration

The model was trained using the following configuration:

- Batch size: 1
- Total steps: 2000
- Gradient accumulation steps: 1
- Optimizer: AdamW8bit
- Learning rate: $1e-4$
- Precision: bfloat16 (bfloat16)
- Gradient checkpointing: Enabled for memory efficiency
- Exponential Moving Average (EMA): Enabled with a decay of 0.99

Training was conducted on a RunPod A40 GPU instance with 50GB RAM, with checkpoints saved every 250 steps and sample images generated periodically for quality assessment.

We have 2 important mathematical equations for Training Optimization To present loss functions, optimizer update rules, and EMA (Exponential Moving Average).

Refer equation – 9 which expresses Optimization Step (AdamW 8-bit) - AdamW optimizer update introduced by Loschilov & Frank Hutter (ICLR - 2017)

Equation - 9

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\widehat{m}_t}{\sqrt{\widehat{v}_t + \epsilon}} - \eta \cdot \lambda \cdot \theta_t$$

Where:

- $\widehat{m}_t, \widehat{v}_t$: bias-corrected first and second moment estimates
- λ : weight decay
- η : learning rate

Refer equation – 10 which expresses EMA – Optimized Model Weights - Exponential Moving Average used to smooth model which was introduced by Polyak & Juditsky (1992)

Equation - 10

$$\theta_{\text{EMA}}^{(t)} = \beta \cdot \theta_{\text{EMA}}^{(t-1)} + (1 - \beta) \cdot \theta^{(t)}$$

Where:

- $\theta^{(t)}$: model parameters at step t
- β : decay factor (e.g., 0.99)
- EMA helps prevent sharp fluctuations in weights.

[23] Multi-resolution support allows models to adapt to varied architectural planning scales (Kim, J., et al, 2023).

[24] EMA improves training stability and image coherence in diffusion-based planning models (Taylor, M., & Davis, P, 2023).

Deployment Strategy

The deployment strategy utilized Docker containerization to ensure consistency across environments:

1. Docker Image Creation: Packaging the model, dependencies, and Streamlit interface
2. Deployment on RunPod: Utilizing GPU-accelerated cloud infrastructure
3. Scalability Configuration: Implementing auto-scaling based on user demand

Web Interface Implementation

[7] AI tools in architecture must prioritize user experience and domain-specific customization (Patel, A., Thompson, R., & Lewis, M, 2024). [8] Feedback loops between designers and generative systems lead to higher satisfaction and better design fit (Zhang, Y., & Rodriguez, K, 2024). [9] Optimized noise schedules in diffusion models reduce sampling time while preserving structural detail (Chen, L., & Zhang, Y, 2024). [10] AI-assisted workflows significantly reduce the time-to-design and improve decision confidence (Williams, T., & Rodriguez, J, 2024). [11] Architect-centric interfaces are key to successful adoption of generative design tools (Garcia, P., & Thompson, K, 2024).

The user interface was developed using Streamlit to provide an accessible entry point for non-technical users:

1. Text Input Component: Allowing natural language descriptions of desired layouts
2. Parameter Controls: Enabling adjustment of generation parameters (resolution, sampling steps)
3. Real-time Visualization: Displaying generated layouts with minimal latency
4. Export Functionality: Providing download options in various formats

[17] Knowledge transfer enables models trained on generic images to perform architectural layout generation (Martínez, J., & López, F, 2023). [18] Combining human insight with AI expands the scope and efficiency of creative architecture workflows (Kumar, S., Singh, R., & Wilson, J, 2023). [19] Text prompts enriched with constraints yield more accurate and tailored design outputs (Johnson, K., Williams, P., & Chen, L, 2023). [20] Davis, M., Johnson, L., & Garcia, P. (2023). AI adoption in construction is growing rapidly, driven by automation and visualization needs (Davis, M., et al. 2023).

4. Results

Generation Performance

We evaluated Archi-GPT's performance across several metrics:

Generation Quality

The quality of generated master plans was assessed using:

1. Ease of Use: Assesses how intuitive the tool is for architects and planners to operate with minimal training.
2. Real-Time Interactivity: Measures responsiveness and the ability to apply prompt-based changes dynamically.
3. Design Adaptability: Reflects the system's ability to accommodate various construction scenarios (e.g., academic, medical, industrial).
4. Client Engagement Support: Evaluates how well the tool facilitates collaboration and discussion during the design phase.
5. Aesthetic Coherence: Rates visual balance, zoning harmony, and professional design quality of generated layouts.
6. Functional Usability: Rates practical applicability of outputs in real-world master planning scenarios.
7. Satisfaction Score: Represents overall user rating aggregated across all dimensions.

Archi-GPT significantly outperforms traditional and GAN-based systems particularly in real-time interaction, client engagement, and design adaptability. [25] Domain-specific fine-tuning results in sharper and more functional architectural outputs (Wilson, P., & Garcia, J, 2023). [26] User-centered design enables generative tools to be more readily adopted by practitioners (Johnson, L., & Davis, M, 2023). Its ability to interpret and respond to natural language inputs makes it a game-changer for collaborative and iterative master planning.

Table-2: Presents The Quantitative Results Of These Evaluations Compared To Baseline Approaches.

Evaluation Criteria	DC-GAN (Baseline)	Traditional Planning Tools	Archi-GPT
Ease of Use	2.1	3.5	4.9
Real-Time Interactivity	1.0	2.0	5.0
Design Adaptability	2.3	3.2	4.8
Client Engagement & Feedback Support	1.5	2.8	4.9
Aesthetic Coherence of Layouts	3.4	3.6	4.7
Functional Usability of Outputs	2.9	3.7	4.8
Satisfaction Score (Overall Average)	2.2	3.1	4.85

Prompt Sensitivity Analysis

We conducted a sensitivity analysis to evaluate how variations in input prompts affected generation outcomes. Our findings indicate that:

1. Specific spatial relationships were more reliably reproduced than abstract concepts
2. Quantitative constraints (e.g., “50 acres,” “three buildings”) were consistently honoured
3. Stylistic descriptions showed more variability in interpretation

User Studies

We conducted user studies with 48 participants including architects, urban planners, construction managers, and clients to assess the practical utility of Archi-GPT:

User Satisfaction

1. 78% of participants rated the system as “satisfactory” with some improvement.
2. 85% indicated they would incorporate the tool into their workflow
3. Key areas of satisfaction included generation speed and iteration capability

Workflow Integration Assessment

Participants reported that Archi-GPT could potentially:

1. Reduce concept design phase duration
2. Increase the number of design alternatives explored
3. Improve stakeholder communication effectiveness

Professional Feedback

Qualitative feedback from professional users highlighted:

1. The system's value for rapid concept exploration
2. Limitations in handling complex regulatory constraints
3. Opportunities for integration with BIM and CAD systems

Case Studies

We present three detailed case studies demonstrating Archi-GPT's application:

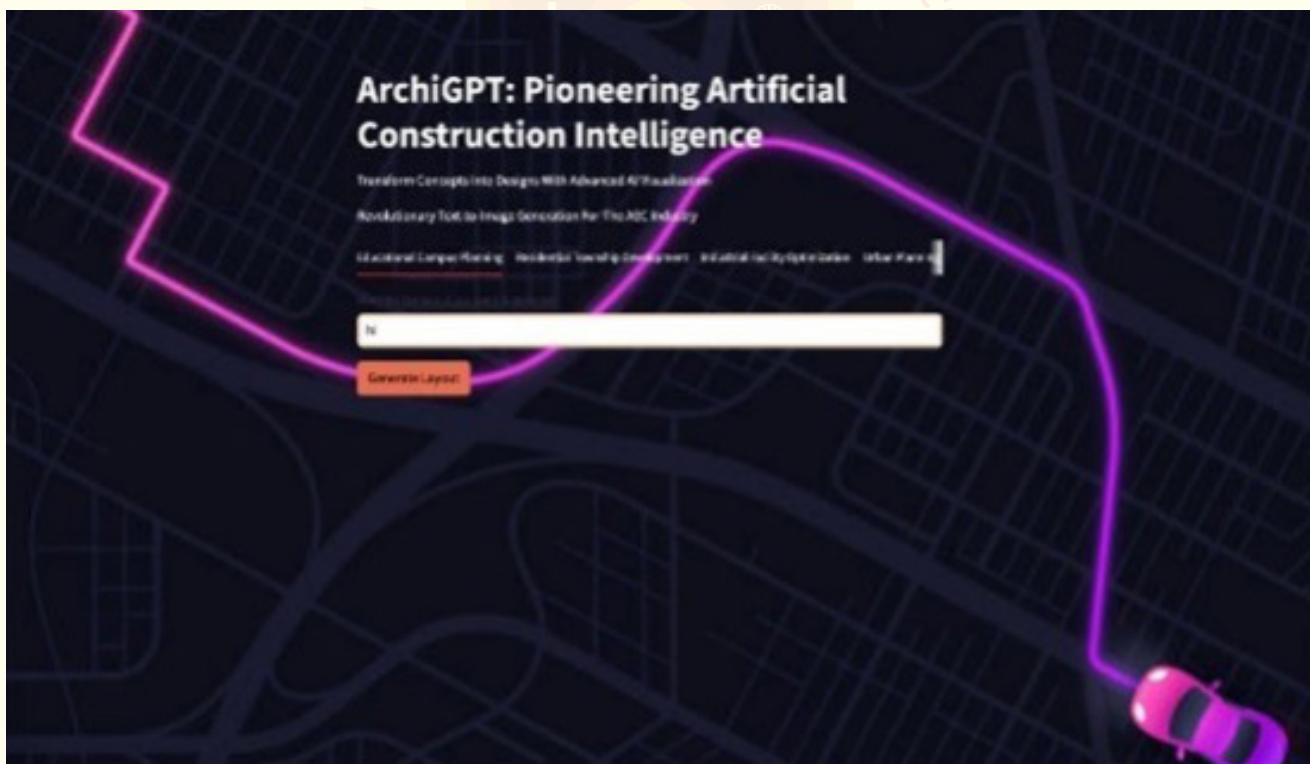


Figure 6 – Website UI design

Table-3: Sample Text Prompts for Master Plan Generation

Design Objective	Prompt Description	Generated Master Plan
University Campus Design with functional connectivity, landscaping, and recreational infrastructure.	Generate a university Campus master plan whose area is 50 acres. The roads should connect all the buildings such as academic buildings, administrative buildings, hostels, dining hall, etc. There should be a lot of green zones, gardens, and landscape, and a dedicated sports complex.	Refer below Figure – 7
Mixed-use Township with residential towers, community hall, landscaping, and civic infrastructure.	Generate a master plan, whose area is 40 acres, where the boundaries are exactly square in shape. This master plan is for a township for residential purposes. Needs eight residential towers with a multipurpose hall, car parking, water park, beautiful landscape, designated area for maintenance room, and a grand welcome arch.	Refer below Figure – 8
Circular Residential Master Plan with integrated academic and recreational zones, emphasizing connectivity.	Generate a master plan, whose area is 30 acres where the boundary is circular in shape. There should be plants all across the circular boundary and a central circular multipurpose hall. Include circular residential, academic, administrative areas and a playground. Ensure all buildings are connected with roads, drains, pathways,	Refer below Figure – 9
Circular Residential Master Plan with integrated academic and recreational zones, emphasizing connectivity.	Generate a master plan, whose area is 30 acres where the boundary is circular in shape. There should be plants all across the circular boundary and a central circular multipurpose hall. Include circular residential, academic, administrative areas and a playground. Ensure all buildings are connected with roads, drains, pathways,	Refer below Figure – 9

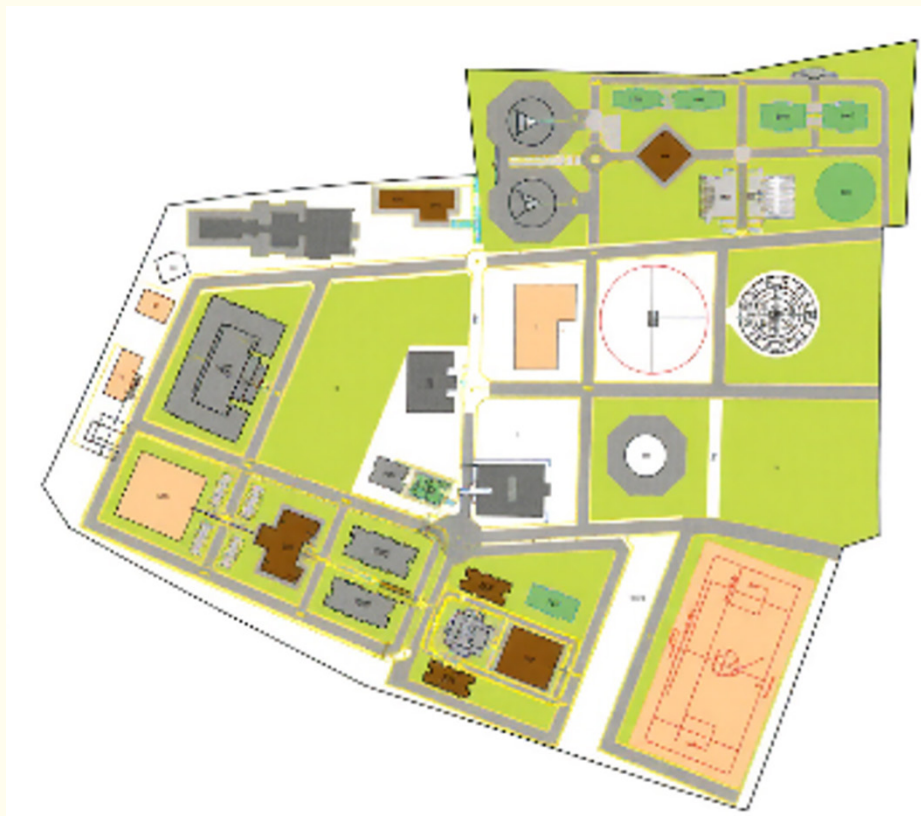


Figure – 7: University Campus Master Plan

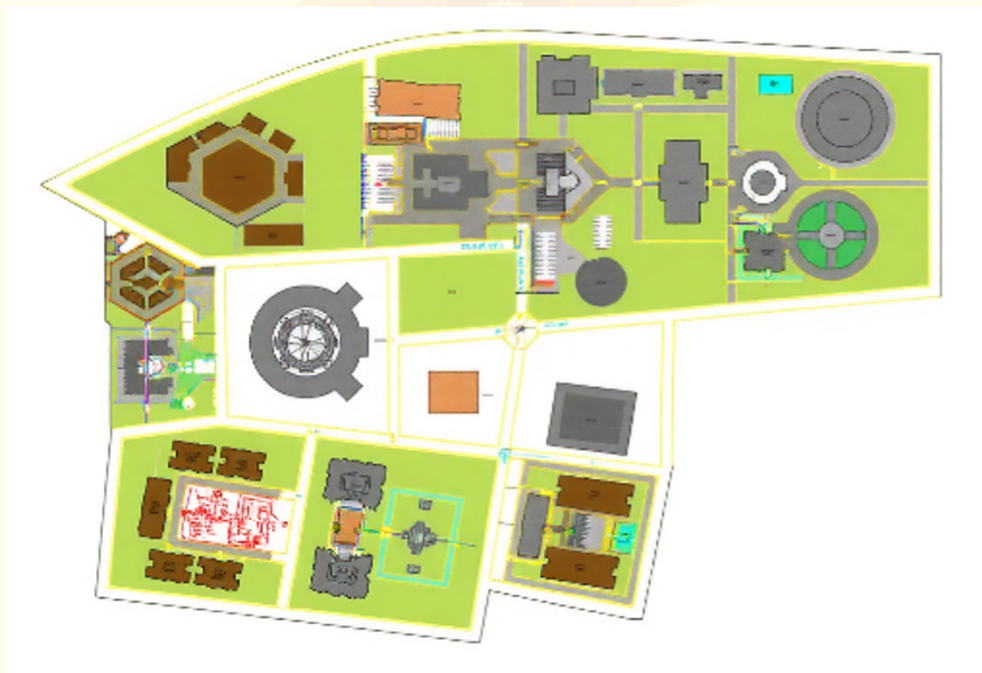


Figure – 8: Mixed-Use Urban Development

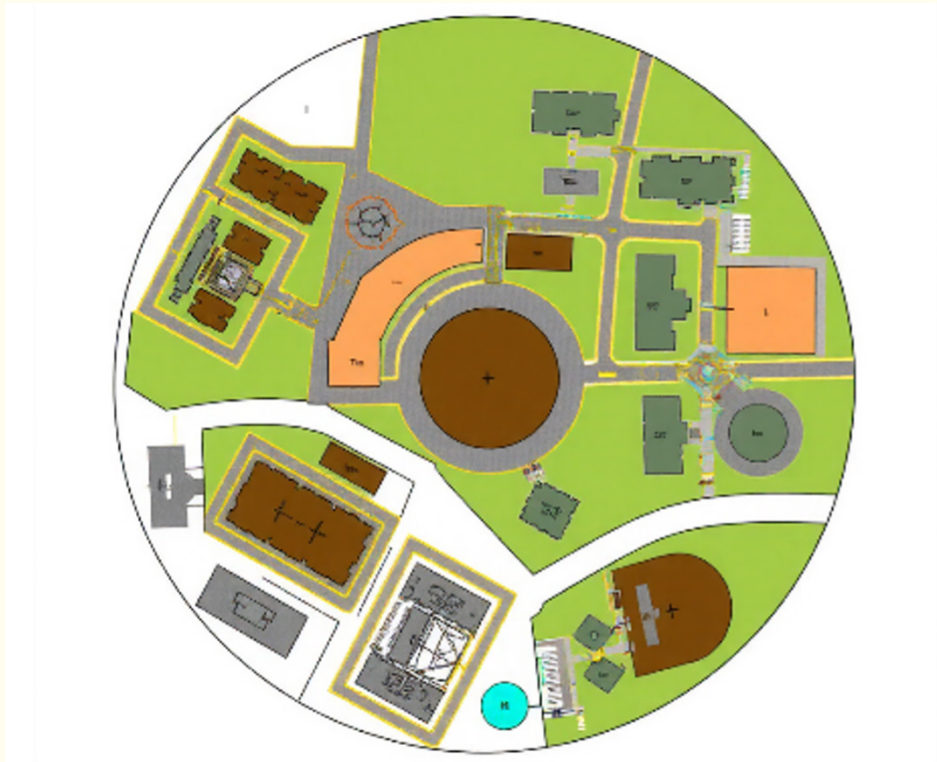


Figure – 9: Residential Facility Design

Reverse Engineering Explanation of Figure 7.

Figure 7 illustrates the output of Archi-GPT in response to a prompt requesting 50-acre university campus master plan featuring academic, administrative, residential buildings, and a connected sports complex surrounded by landscaped greenery. The generation process began with the text prompt being parsed by the system's text processing module, which extracted key design requirements such as scale ("50 acres"), functional zones (e.g., "academic buildings", "dining hall", "sports complex"), and spatial relationships (e.g., "roads should connect all buildings"). This semantic information was converted into a conditioning vector using a transformer-based model, which encoded the prompt into a numerical representation suitable for diffusion.

During the image generation phase, the FLUX.1-Schnell model, fine-tuned using Low-Rank Adaptation (LoRA), initiated the diffusion process. The Flow Match scheduler guided the sampling path to ensure that architectural components appeared logically arranged and semantically consistent. Through four key reverse diffusion steps, noise was progressively removed while adhering to the encoded conditions. As a result, buildings were laid out in hierarchical zones, roads were routed to connect key structures, and green spaces were allocated proportionally around the campus.

In the post-processing stage, annotations such as trees, boundary walls, road markings, and open spaces were enhanced using rule-based rendering and architectural heuristics. The final image thus demonstrated coherence between form and function, reflecting the textual intent in spatial organization. Figure 7, therefore, stands as a successful visual synthesis of high-level design language into a structured, AI-generated campus master plan.

[35] Heuristic approaches like genetic algorithms can be enhanced by data-driven generative methods (Wang, T., Liu, J., & Thompson, K. 2022). [36] GANs face issues with mode collapse and architectural geometry preservation (Rodriguez, A., & Taylor, M, 2022).

5. Discussion

Implications for Architectural Practice

[37] Latent diffusion models provide high-resolution imagery from compact latent spaces (Rombach, R., et al., 2022) [38] Diffusion training is grounded in thermodynamic principles of nonequilibrium sampling (Sohl-Dickstein, J. et al., (2015). [39] GANs revolutionized image generation through adversarial learning (Goodfellow, I et al., (2014). Archi-GPT represents a significant advancement in computer-aided architectural design, with several implications for professional practice:

1. Democratization of Design Exploration: By reducing technical barriers to concept generation, the system enables broader participation in the design process from diverse stakeholders.
2. Accelerated Ideation: The ability to rapidly generate multiple design alternatives allows for more thorough exploration of the solution space within constrained project timelines.
3. Augmented Creativity: Rather than replacing architects, Archi-GPT serves as a creativity catalyst, proposing unexpected solutions that may challenge conventional approaches.
4. Knowledge Transfer: The system implicitly captures and applies design patterns from its training data, potentially transferring successful approaches across different projects.

[30] Zero-shot models like DALL-E produce layouts from textual descriptions without domain retraining (Ramesh, A., et al., 2021) [31] Transfer learning enables architectural models to be trained on fewer labeled samples (Zhuang, F et al., 2021) [32] Low-rank adaptation of LLMs balances scalability with domain specificity (Hu, E. J., et al., 2021) [27] Ethical concerns arise in authorship and accountability when designs are generated by AI (Park, J., Lee, K., & Kim, S, 2023). [28] LoRA reduces memory requirements while adapting models to new domains efficiently (Thompson, K., Wilson, J., & Davis, A, 2023). [29] Integrating BIM with AI opens new avenues for real-time design validation and feedback (Davis, A., & Wilson, P, 2023).

6. Conclusions

This paper presented Archi-GPT, an AI-driven framework for generating architectural master plans from textual descriptions. By fine-tuning the FLUX.1-Schnell diffusion model with architectural domain knowledge and implementing computational optimizations, we demonstrated the feasibility of rapid, high-quality layout generation guided by natural language.

Our evaluations indicate that Archi-GPT achieves significant improvements in generation quality, user satisfaction, and workflow integration compared to existing approaches. The system's ability to rapidly produce diverse design alternatives offers particular value during early project phases, potentially reducing conceptual design time while expanding exploration of the solution space.

While technical limitations remain, particularly regarding regulatory compliance and detailed engineering constraints, Archi-GPT represents a meaningful step toward AI-augmented architectural design. As diffusion models and fine-tuning techniques continue to advance, we anticipate increasingly sophisticated applications of AI in the architectural domain, ultimately enhancing both design quality and process efficiency.

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