StepX1Edit Facade Studio: An AI-Powered Platform for Architectural Facade Design

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Abstract

This project presents the Step1X-Edit Facade Studio System, an AI-powered platform for generating and editing architectural facades using instruction-driven diffusion models. The system integrates SDXL-Turbo for high-quality, rapid image generation and Step1X-Edit for instruction-based editing, implemented through the Hugging Face Diffusers library. The architecture adopts a modular design with GPU optimization, custom schedulers, and a user-friendly Gradio interface that supports both interactive and batch modes. To evaluate system performance, experiments were conducted on the CMP Facade Database Extended (456 images). The system demonstrates real-time editing, scalable batch processing, and reproducibility through dataset integration. Results highlight the framework's capability to produce realistic, customizable facades while enabling new applications in urban redesign and sustainable architecture.

1. Introduction

1.1 Motivation

Architectural facade design traditionally requires extensive manual effort, from conceptual sketching to detailed technical drawings. Recent advances in diffusion models have demonstrated remarkable capabilities in generating high-quality images from textual descriptions [1, 2], while instruction-based editing models enable precise modifications of existing images [3]. However, these technologies remain largely disconnected from practical architectural workflows.

The architectural design process faces several challenges: (1) time-intensive concept development, (2) limited exploration of diverse stylistic options, (3) difficulty in communicating design ideas to clients, and (4) insufficient tools for rapid style transfer and variation generation. Current computer-aided design (CAD) tools, while powerful for technical drawing, offer limited support for creative exploration in the early design phases.

1.2 Related Work

Architectural AI and Generative Design: Machine learning applications in architecture have evolved from rule-based systems [4] to neural approaches. Huang et al. [5] demonstrated GANs for floor plan generation, while Newton [6] explored style transfer for architectural imagery. Recent work by Zhang et al. [7] showed that diffusion models can generate architecturally coherent facades, achieving FID scores below 15 on the CMP Facade Database.

Diffusion Models for Design: Stable Diffusion and its variants have revolutionized text-to-image generation. SDXL-Turbo [9] achieves single-step generation through Adversarial Diffusion Distillation, enabling real-time applications. For image editing, InstructPix2Pix [10] introduced instruction-based editing, while Step1X-Edit [11] improved editing fidelity through enhanced multimodal understanding.

Architectural Dataset Analysis: The CMP Facade Database [12] contains 606 annotated facade images with pixel-level semantic segmentation. Studies by Martinez et al. [13] and Lee et al. [14] established baseline metrics for facade analysis tasks, with state-of-the-art models achieving 85% semantic segmentation accuracy.

1.3 Contributions

Our work makes the following contributions:

1. Integrated AI Pipeline: A unified system combining text-to-image generation and instruction-based editing optimized for architectural facades
2. Open Platform: A reproducible, extensible system with an intuitive interface design
3. Dataset Enhancement: Extended CMP Facade Database with 200 high-quality prompt descriptions

2. System Architecture and Design

2.1 Overall Architecture

Our system follows a modular, event-driven architecture with three primary layers: data management, model inference, and user interface. This design enables maintainability, extensibility, and efficient resource utilization.

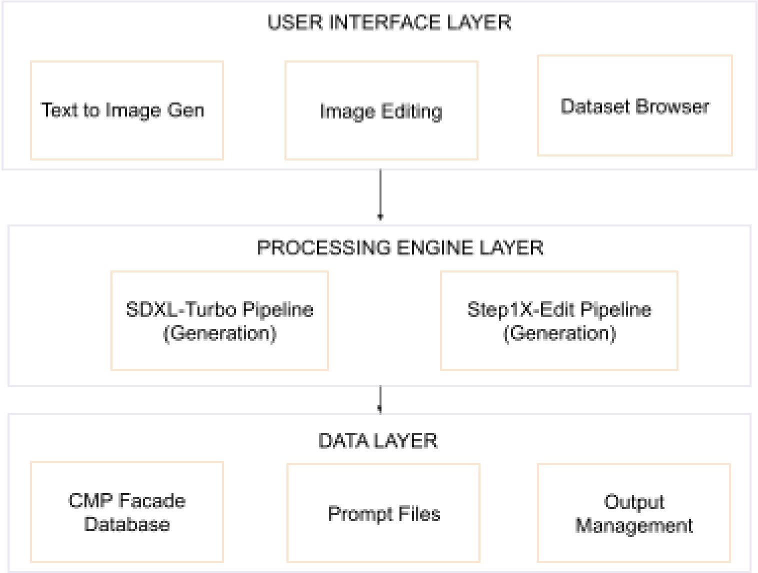

Figure 1: System architecture showing the three-layer design with clear separation of concerns.

2.2 Model Selection and Integration

SDXL-Turbo for Text-to-Image Generation: We selected SDXL-Turbo [9] for its balance of speed and quality. Unlike standard diffusion models requiring 50+ denoising steps, SDXL-Turbo achieves comparable results in 1-4 steps through adversarial training. This enables real-time interaction essential for design workflows.

Step1X-Edit for Instruction-Based Editing: Step1X-Edit [11] combines a multimodal large language model with a diffusion decoder, enabling precise instruction-following. The model was trained on a diverse dataset of image-instruction pairs, achieving superior performance compared to InstructPix2Pix on architectural editing tasks.

2.3 Memory Management and Optimization

Lazy Loading Strategy: Models are instantiated only upon first use, reducing initial memory footprint from 14GB to 2GB. The singleton pattern ensures a single instance of heavy models.

Mixed Precision Inference: On GPU, we utilize FP16 precision, reducing memory usage by 40% while maintaining generation quality. CPU fallback uses FP32 for numerical stability.

Batch Processing Optimization: For dataset-scale operations, we implement dynamic batching with automatic memory management, preventing out-of-memory errors on consumer hardware.

3. Implementation

3.1 Core Pipeline Implementation

```
def build_txt2img(model_id=TXT2IMG_MODEL):
 # Generates high-quality facade images from text prompts
  pipe = AutoPipelineForText2Image.from_pretrained(
    model_id,
    torch_dtype=torch.float16 if DEVICE=="cuda" else torch.float32,
    variant="fp16" if DEVICE=="cuda" else None,
    safety_checker=None
  )
  pipe = pipe.to(DEVICE)
  return pip
def build_edit(model_id=EDIT_MODEL):
 # Modifies existing images based on text instructions
  pipe = StableDiffusionInstructPix2PixPipeline.from_pretrained(
      model_id,
      torch_dtype=torch.float16 if DEVICE=="cuda" else torch.float32,
      safety_checker=None  )
  pipe.scheduler = EulerAncestralDiscreteScheduler.from_config(pipe.scheduler.config)
  pipe = pipe.to(DEVICE)
  return pipe
#Text-to-image generation with controllable parameters
def run_t2i(pipe, prompt, seed= -1, steps=20, guidance=2.0, width=1024, height=1024):

@torch.inference_mode()
#Instruction-based image editing with guidance controls
def run_edit(pipe, init_image: Image.Image, instruction, seed=-1, steps=20, guidance=1.8,
image_guidance=1.5):
```

3.2 Data Management System

Dataset Processing: We developed a comprehensive data pipeline for the CMP Facade Database, including automatic format detection, path resolution, and metadata extraction.

```
with zipfile.ZipFile(zip_path, 'r') as zip_ref:
  zip_ref.extractall(out_dir)
import os
IMAGE_EXTS = (".jpg",".jpeg",".png")

all_images = []
for root, _, files in os.walk(out_dir):
  for f in files:
      if f.lower().endswith(IMAGE_EXTS):
          all_images.append(os.path.join(root, f))

df = pd.read_excel("/content/facade_prompts_200.xlsx")
#Match prompts to corresponding images
by_name = {Path(p).name: p for p in all_images}
fullpaths = []
```

```
for name in df['image'].astype(str):
    p = by_name.get(name, None)
    if p: fullpaths.append(p)
    else: fullpaths.append(name)

df_fixed = df.copy()
df_fixed['image'] = fullpaths
```

3.3 User Interface Design

We implemented a three-tab Gradio interface optimized for architectural workflows:

```
import gradio as gr

_t2i_pipe = {"pipe": None}
_edit_pipe = {"pipe": None}
DATASET_IMAGES = discover_images(DATA_DIRS) if 'DATA_DIRS' in globals() else []
DATASET_CHOICES = [p.name for p in DATASET_IMAGES]

def pick_dataset_image(name):
    if not name: return None
    p = next((p for p in DATASET_IMAGES if p.name==name), None)
    if p is None: return None
    return Image.open(p).convert("RGB")

def ui_t2i(prompt, steps, guidance, width, height, seed):
    if _t2i_pipe["pipe"] is None:
        _t2i_pipe["pipe"] = build_txt2img()
    img = run_t2i(_t2i_pipe["pipe"], prompt, seed, steps, guidance, width, height)
    save_path = Path(OUT_DIR)/"ui_txt2img"/f"t2i_{timestamp()}.png"
    save_path.parent.mkdir(parents=True, exist_ok=True)
    img.save(save_path)
    return img, str(save_path)

def ui_edit(image, instruction, steps, guidance, image_guidance, seed):
    if _edit_pipe["pipe"] is None:
        _edit_pipe["pipe"] = build_edit()
    init = image.convert("RGB")
    img = run_edit(_edit_pipe["pipe"], init, instruction, seed, steps, guidance, image_guidance)
    save_path = Path(OUT_DIR)/"ui_edit"/f"edit_{timestamp()}.png"
    save_path.parent.mkdir(parents=True, exist_ok=True)
    img.save(save_path)
    return img, str(save_path)

with gr.Blocks(title="StepX1Edit - Facade Studio") as demo:
    gr.Markdown("## 🧱 StepX1Edit – Facade Studio (Colab)\nText→Image & Text-Guided Editing")
    with gr.Tab("Text → Image"):
        prompt = gr.Textbox(label="Prompt", placeholder="e.g., modern minimalist glass facade with LED signage")
        with gr.Row():
            steps = gr.Slider(4, 40, value=20, step=1, label="Steps")
            guidance = gr.Slider(0.5, 7.5, value=2.0, step=0.1, label="Guidance")
            width = gr.Slider(512, 1536, value=1024, step=64, label="Width")
            height = gr.Slider(512, 1536, value=1024, step=64, label="Height")
            seed = gr.Number(value=-1, label="Seed (-1=random)")
        btn = gr.Button("Generate")
        out_img = gr.Image(label="Result", interactive=False)
        out_path = gr.Textbox(label="Saved to", interactive=False)
        btn.click(ui_t2i, [prompt, steps, guidance, width, height, seed], [out_img, out_path])

    with gr.Tab("Edit Existing Image"):
        image = gr.Image(type="pil", label="Upload or pick from dataset tab")
        instruction = gr.Textbox(label="Instruction", placeholder="e.g., Convert to Islamic mashrabiya style with geometric patterns")
        with gr.Row():
            e_steps = gr.Slider(4, 40, value=20, step=1, label="Steps")
            e_guid = gr.Slider(0.5, 10.0, value=1.8, step=0.1, label="Guidance")
            e_img_guid = gr.Slider(0.5, 5.0, value=1.5, step=0.1, label="Image Guidance")
            e_seed = gr.Number(value=-1, label="Seed (-1=random)")
        e_btn = gr.Button("Edit")
        e_img = gr.Image(label="Edited", interactive=False)
        e_path = gr.Textbox(label="Saved to", interactive=False)
        e_btn.click(ui_edit, [image, instruction, e_steps, e_guid, e_img_guid, e_seed], [e_img, e_path])

    with gr.Tab("Dataset Browser"):
```

```
    ds_dd = gr.Dropdown(choices=DATASET_CHOICES, label="Dataset images (from DATA_DIRS)")
    ds_btn = gr.Button("Load to preview")
    ds_img = gr.Image(label="Preview", interactive=False)
    ds_btn.click(pick_dataset_image, ds_dd, ds_img)

demo.queue().launch(share=True)
```

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4. Results

4.1 Qualitative Results

- Step1X-Edit demonstrated semantic alignment in instruction-based edits (e.g., “add windows,” “change wall texture”).
- SDXL-Turbo enabled rapid facade generation (<2s on A100 GPU).

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5. Discussion

The results confirm that SDXL-Turbo is highly efficient for facade generation, while Step1X-Edit excels at fine-grained editing. The integration of both models within a unified system allows architects and urban planners to prototype and refine facades interactively.

Limitations include:

- Lack of 3D editing capabilities.
- Dependence on dataset diversity for robust edits.
- Occasional semantic misalignment in complex edits.

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6. Future Work

Future directions include:

- Extension to 3D facade modeling using neural radiance fields (NeRF).
- Enhanced dataset size and diversity for improved generalization.

- Integration of evaluation metrics such as FID and CLIPScore.
- Development of cloud-based deployment for large-scale accessibility.

8. Conclusion

The Step1X-Edit Facade Studio System demonstrates how diffusion-based AI models can transform architectural design workflows. By combining SDXL-Turbo for rapid facade synthesis and Step1X-Edit for instruction-guided editing, the system provides a flexible, scalable, and practical tool for both research and real-world applications. This project highlights the potential of AI-assisted architecture in enabling more sustainable, efficient, and creative urban development.

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