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Virtual Interior Design Using Stable Diffusion–Based Generative Models

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Abstract: This paper proposes an image-to-image interior design generation framework based on latent diffusion modeling. Given a single RGB image of an indoor space, the system formulates interior redesign as a conditional generation problem, where structural geometry is preserved while visual attributes are optimized under style-specific constraints. A Stable Diffusion backbone is employed with controlled text-conditioning and spatially consistent sampling to generate multiple décor configurations. The framework incorporates preprocessing for viewpoint normalization and semantic alignment, enabling robustness across varied room layouts. Quantitative and qualitative evaluations demonstrate improved perceptual quality, structural fidelity, and stylistic consistency compared with conventional template-based visualization methods. The results indicate that diffusion-based generative models provide an effective and scalable solution for automated interior design synthesis with minimal human intervention.

Keywords: Latent Diffusion Models; Image-to-Image Translation; Automated Interior Design; Style-Conditioned Generation; Stable Diffusion.

I. INTRODUCTION

Interior design traditionally requires a substantial amount of time, skill and expertise. It plays a big role in user comfort, room functionality and aesthetic appeal. Our system converts user provided images into visually enhanced interior layouts and also allow users to experiment with different décor themes according to their liking.

II. LITERATURESURVEY

Related Work

Karras et al. (2019) introduced Style GAN, a style-based generative adversarial network that significantly advanced high-resolution image synthesis by enabling fine-grained control over visual attributes at different levels of abstraction. By mapping latent vectors into an intermediate latent space and injecting style information throughout the generator network, Style GAN achieved highly realistic and diverse image generation with reduced feature entanglement. However, despite its strong controllability and image quality, Style GAN is primarily designed for unconditional image generation and does not natively support conditional transformations required in interior design tasks.

Rombach et al. (2022) proposed Latent Diffusion Models (**LDMs)**, introducing *Stable Diffusion* as a scalable and computationally efficient approach for high-resolution image generation. By performing the diffusion process in a compressed latent space rather than pixel space, the model significantly reduced memory and compute requirements while maintaining strong visual fidelity.

However, for interior design applications, Stable Diffusion often requires domain-specific fine-tuning to ensure consistency in room layouts, furniture styles, and structural elements, as generic pre trained models may produce visually appealing but spatially incoherent or unrealistic interior designs.

Yu etal. (2020) presented an interactive system for furniture and layout design in interior scenes, focusing on AI-assisted planning and object placement to support user-driven design workflows. The approach enables users to arrange furniture within a scene while the system provides real-time suggestions that respect spatial constraints, functionality, and ergonomic rules, thereby improving layout feasibility and design efficiency. While effective for structural organization and scene composition, the method is not a generative model and does not synthesize new visual content

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or realistic images.

Ulyanov et al. (2018) proposed Deep Image Prior (DIP), revealing that the architecture of a convolution neural network itself can serve as an implicit prior for image restoration tasks, even without any external training data. By fitting a randomly initialized network to a single degraded image, the model is able to progressively reconstruct meaningful structures while suppressing noise, leading to effective results in de-noising, super-resolution, and image inpainting.DIP exploits this property by using early stopping during optimization to preserve perceptually meaningful content. The approach challenges traditional learning-based methods by demonstrating that explicit datasets are not always necessary for restoration.

Despite its effectiveness in restoring image clarity and removing noise, Deep Image Prior has clear limitations when applied to stylistic modification or interior décor redesign. The method operates at a low-level pixel optimization stage and lacks semantic understanding of objects, layouts, or styles within an image.

III. EXISTINGSYSTEM

The existing interior design visualization system primarily dependsonmanual3Dmodeling toolssuchasAutodesk3ds Max, Sketch Up, and Blender, which offer detailed control but require significant time, expertise, and effort. Many users also rely on professional interior designers, increasing cost and reducing flexibility for rapid experimentation. Other solutions include static style templates that provide limited customization without AI-driven transformation, and AR- based furniture placement applications like IKEA Place, which allow basic object visualization but do not support full- room redesign or intelligent stylistic modification.

Request Handling via Flask Backend

After the user submits an image and selects a style, the request is transmitted to the Flask back end through a REST-based API handler. The backend performs essential tasks such as validating input data, managing session flow, and handling concurrency when multiple users access the system simultaneously. It acts as the central controller of the application, orchestrating communication between preprocessing modules, AI models, and the database while ensuring reliable and secure execution of each request.

Image Preprocessing with Open CV

Once the request is validated, the backend invokes the Open CV preprocessing module to prepare the uploaded image for AI processing. This module performs operations such as noise removal, image resizing, contrast enhancement, and normalization to standard dimensions. Proper preprocessing helps preserve important structural elements of the room, reduces visual artifacts, and ensures consistent input quality, which directly improves the reliability and visual accuracy of the generated interior design outputs.

IV. PROPOSED SYSYTEM

Our system proposes an automated AI-driven interior design visualization platform in which users upload a room image that is first pre-processed using Open CV to enhance quality and structural clarity. The processed image is then passed to a Stable Diffusion–based generative model to produce multiple interior design variations in different styles. Users can compare generated designs, save preferred outputs, and download results for future reference, while a Flask-based backend manages request handling, model inference, and system workflows.

V. SYSTEM ARCHTECTURE

The system architecture of the proposed AI-driven interior design visualization platform is designed to ensure efficiency, scalability, and ease of use. It integrates a user-friendly web interface with a robust back end to support seamless interaction and processing. The architecture follows a modular approach, allowing each component to function independently while contributing to the overall work flow. User inputs are efficiently handled and transformed into meaningful design outputs using advanced AI models. Image preprocessing ensures high- quality inputs for accurate generation. Backend services manage data flow, storage, and model inference. This structured design enables future expansion and integration of new technologies without major architectural changes.

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User Interaction and Front-End Interface

The user interacts with the system through a web-based front- end designed for simplicity and ease of use. It provides dedicated interfaces for image upload, style selection, and result visualization, enabling users to seamlessly submit room images, choose interior design styles.

AI Model Interface and Stable Diffusion Processing

The cleaned and standardized image is then forwarded to the Stable Diffusion model through a dedicated AI Model Interface. This interface decouples the model logic from the backend, enabling seamless integration and easy replacement of generative models in the future. The Stable Diffusion model applies the selected style while maintaining room structure and realism, generating multiple interior design variations. This component is responsible for the core intelligence of the system, transforming user inputs into visually compelling interior designs.

Result Delivery and Visualization

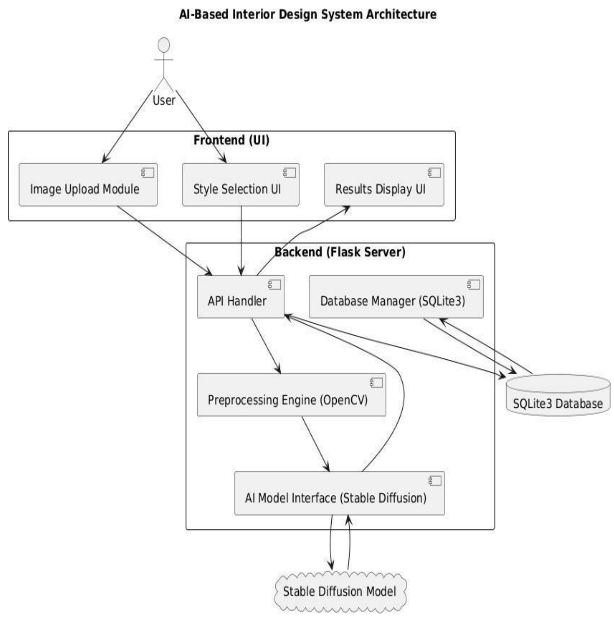
After the model completes the generation process, the redesigned images are sent back to the backend for formatting and post-processing if required. The backendthen delivers the results to the front-end UI, where users can view high-resolution outputs, compare different style variations, and analyze design details. This stage focuses on clarity and usability, ensuring that users can easily interpret the results and make informed design choices.

Database Management and System Scalability

Simultaneously, the system stores user-uploaded images, selected styles, generated outputs, and user preferences in an SQLite3 database. This enables history tracking, allowing users to revisit previous designs and maintain consistency across sessions. The overall modular and scalable architecture ensures that new interior styles, advanced preprocessing techniques or alternative generative models can be integrated in the future without requiring major changes to the existing system, supporting long-term extensibility and growth.

VI. WORKING SCENARIO

The AI-Powered Interior Design System operates as an automated image-to-image transformation pipeline that enables users to visualize interior design concepts with minimal effort. The process begins when a user uploads a room photograph through the web interface and selects a preferred design style such as modern, minimalist, Scandinavian, or luxury.



The uploaded image is first preprocessed using image enhancement techniques to normalize resolution, reduce noise, and preserve key structural elements like walls and furniture. Based on the selected style, the system dynamically

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generates a descriptive prompt that guides the generative model to apply appropriate aesthetic features while maintaining the original spatial layout of the room.

The preprocessed image and style prompt are then processed by a Stable Diffusion–based generative model, which performs controlled latent-space transformations to produce realistic interior design variations. The generated output undergoes post-processing to improve visual clarity and color balance before being stored along with user preferences in the system database. Finally, the redesigned interior image is displayed on the user interface, allowing users to compare, download, or regenerate alternative design options.

VII. TECHNICAL METHODOLOGY

The proposed AI-Powered Interior Design System begins with image acquisition and preprocessing. When a user uploads a room image, the back end validates the input format and resolution before forwarding it to the preprocessing module. Optional segmentation or edge-aware masking is performed to preserve structural elements such as walls, floors, and major furniture, ensuring that spatial integrity is maintained during generative transformation.

Once pre processing is complete, the system constructs a style- aware textual prompt based on the user's selected interior theme. This prompt encodes visual attributes such as lighting conditions, material textures, color palettes, and décor style. The processed image and generated prompt are then passed to a Stable Diffusion image-to-image pipeline. The model encodes the image into a latent representation, applies controlled noise injection, and performs conditional de-noising guided by the textual prompt. This latent diffusion process allows the system to modify aesthetic elements while retaining the original room layout and geometry.

After inference, the generated image undergoes post- processing to enhance sharpness, contrast, and color consistency. The final output, along with metadata such as selected style, timestamp, and image paths, is stored in a relational data base for history tracking and re use. The back end API then transmits the result to the frontend interface, where users can visualize, compare, and download the generated designs. This technical pipeline ensures modularity, scalability, and efficient integration of generative AI models for real-time interior design visualization.

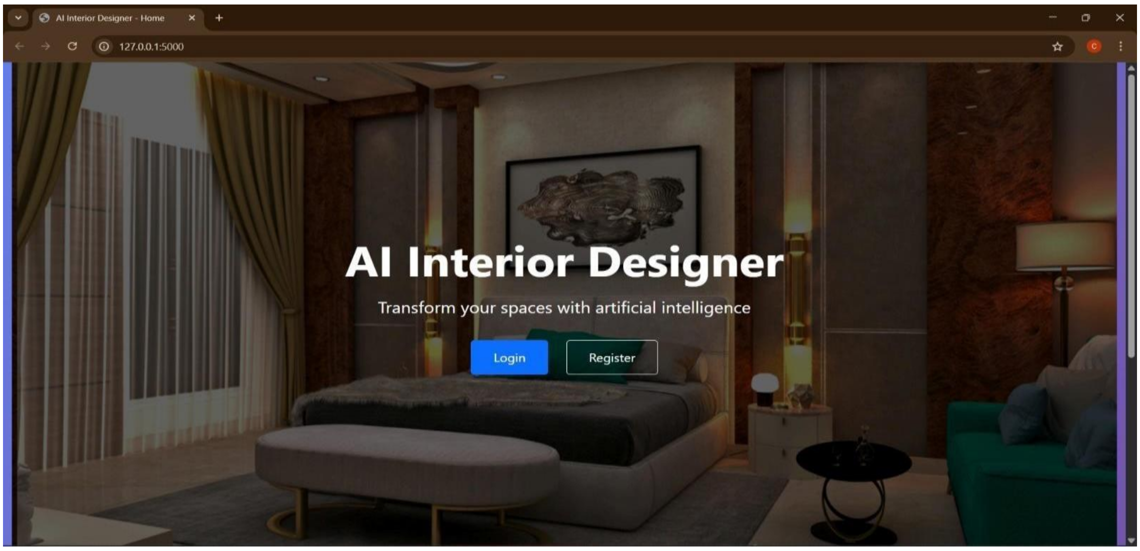

Fig.1 –Login Page

This Fig.1 shows the homepage of an AI Interior Designer web application with a modern bedroom background, highlighting AI-driven interior transformation. It features a clean user interface with Login and Register options, emphasizing ease of access and intelligent design personalization.

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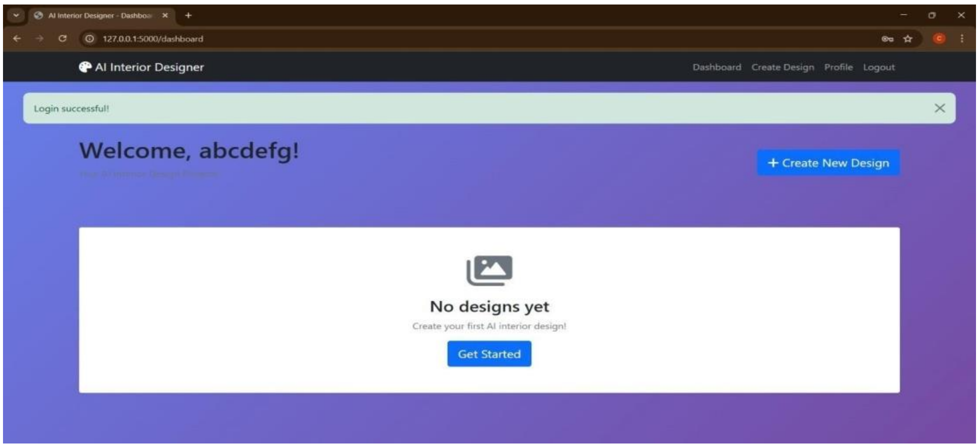

Fig.2 Home Page of AI interior

The Fig.2 displays the homepage of an AI Interior Designer web application with a modern interior design back ground. It highlights AI-based space transformation with a simple interface including Login and Register options.

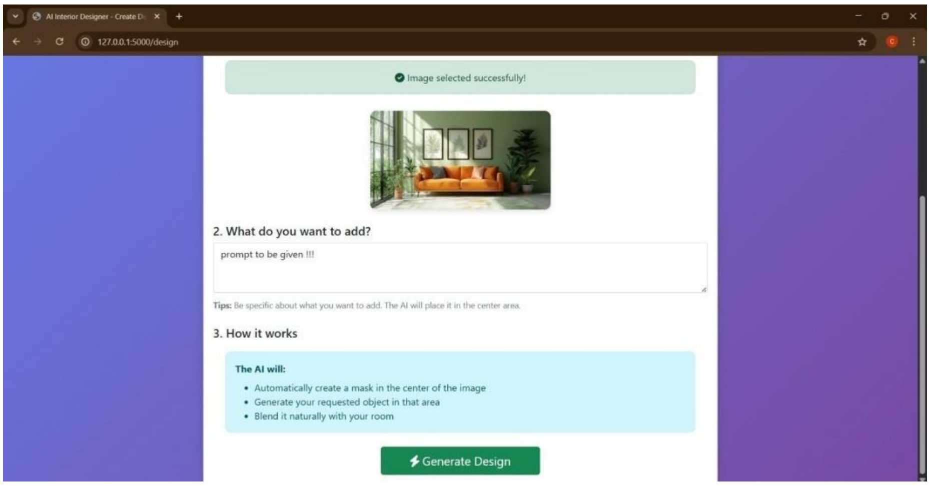

Fig.3 – User gives the prompt

This Fig.3 shows the design creation page where users upload a room image and enter a prompt to add new interior elements. The system explains how AI generates and blends the requested design automatically before producing the final output.

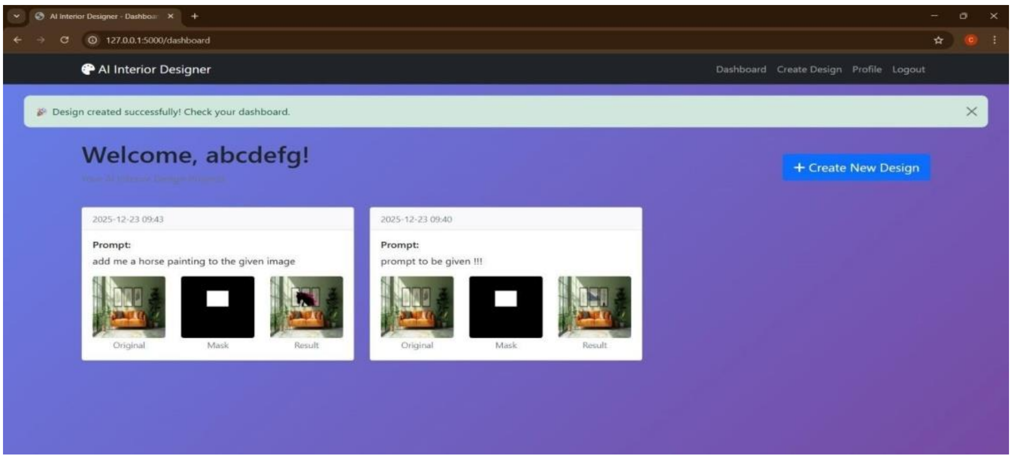

Fig.4 –User Dashboard

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The Fig.4 shows the dashboard of the AI Interior Designer application displaying previously generated design projects with original, mask, and result previews.

VIII. CONCLUSION

This work presented an AI-powered interior design visualization system that leverages generative modeling techniques to automate the transformation of real room images into visually enhanced design concepts. By integrating image preprocessing methods, a Stable Diffusion–based image-to- image generation pipeline, and a lightweight web-based interface, the system enables users to explore multiple interior styles with minimal effort while preserving the original spatial structure of the room. The proposed architecture demonstrates how generative AI can significantly reduce the time, cost, and expertise traditionally required for interior design ideation.

Experimental evaluation showed that the system produces high-quality, realistic outputs with acceptable inference time and reliable performance across different room types and design styles. The modular implementation supports scalability and future extensions, making the solution suitable for practical deployment in residential, architectural, and real- estate visualization scenarios. Overall, the proposed system validates the effectiveness of diffusion-based generative models as a powerful tool for intelligent and user-centric interior design visualization.

In conclusion, this project highlights the growing potential of AI-driven design tools to bridge the gap between technical complexity and user accessibility. By combining generative diffusion models with an intuitive interface, the system empowers users with limited design expertise to visualize professional-quality interiors efficiently. The results indicate that such intelligent systems can play a transformative role in modern design workflows, supporting faster decision-making, enhanced creativity, and more personalized interior design experiences.

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