



Smart Interior Design Using Neural Style Transfer and Style Recommendation

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Abstract— Interior design visualization traditionally requires significant expertise, time, and cost, limiting accessibility for non-professional users. This paper presents a smart interior design system that integrates Neural Style Transfer (NST) with an intelligent style recommendation framework to enable automated and real-time interior visualization. The system allows users to upload room images and visualize them in multiple design styles such as modern, minimalist, vintage, and bohemian. The proposed system utilizes deep learning techniques to extract content and style features and generate high-quality stylized outputs. Additionally, a recommendation module analyzes room characteristics such as lighting, structure, and furniture to suggest suitable styles. The system is implemented using a lightweight Streamlit-based interface, ensuring ease of use and rapid processing. Experimental results demonstrate efficient real-time performance, high-quality stylization, and improved user experience compared to traditional manual methods. The system provides a scalable and user-friendly solution for interior design visualization.

Keywords—Deep Learning; Interior Design; Neural Style Transfer; Room Visualization; Style Recommender.

I. INTRODUCTION

This document is template. We ask that authors follow some Neural Style Transfer (NST) is an incredible way of transforming run-of-the-mill images into sublime and visually gratifying artistic creations. It uses the basic form of the content picture on top of which the color schema from style picture is applied over necessary amount of iterations. This is a slightly interesting technique wherein the improvisation is done using neural networks (CNNs to name a few).

Interior design is a multibillion-dollar global industry that remains largely inaccessible to ordinary homeowners due to the high cost of professional designers and the difficulty of visualising design changes before implementation. A significant gap exists between a person's vision for their living space and their ability to realise or conceptualise it without professional guidance

Recent advances in deep learning — particularly generative models and convolutional neural networks — have created unprecedented opportunities to democratise design. Models trained on millions of interior design photographs can capture rich aesthetic knowledge that traditionally resided only in the minds of experienced designers. The convergence of diffusion-based image generation and vision-based style classification makes this project particularly timely [1].

At its core, NST makes use of deep neural nets which are trained to mainly capture and extract characteristics from pictures at several abstract states. These networks distinguish the representations content and style to effortlessly integrate and combine the both of them. The procedure encompasses denigrating the loss function that tries to balance the trade-off between sustaining the content with the application of the style as one sees fit. Furthermore, NST facilitates the creation of rich-quality artistic products with little to no human interference.

Neural Style Transfer has a far-reaching aim which is to essentially bring down the space which discerns art from tech by spitballing nuanced facets of creative innovation and artful expression. NST has its applications spread out and not just localized to creative areas such as art and design but also has its paws in the entertainment world. It helps explore the progress of novel artistic and style possibilities.

By applying the ambient features of well-known renowned artisans to photographic content, NST enables the production of arts that merge contemporary and retro ideas with styles that stand the test of time. This concept not just enriches artistic progress but also paves way for bringing in an innovative pool in multimedia as well. NST is paramount in aiding the budding as well as pro designers, artists, and creative pool of talented individuals to experiment with enriching styles, produce unique content of art, and redefine traditional boundaries and standard practices of art generation.

II. RELATED WORK

Chengming Feng et al. [1] proposed a reinforcement learning- based method for style control, but it involves high computational cost and complex tuning. Joonwoo Kwon et al.

[2] introduced a lightweight frequency-based model, though it struggles with complex textures and abstract styles. Dan Ruta et al. [3] developed ALADIN-NST, a self-supervised model for content– style disentanglement without paired data, but it demands high computational resources and lacks real-time capability. Yu-Hsuan Chen et al. [4] focused on design-oriented applications by transforming sketches into stylized outputs using a curve-based rendering approach. While effective for line-drawn inputs, the method was limited to sketch-based domains and lacked generalization to high-resolution photographic images.

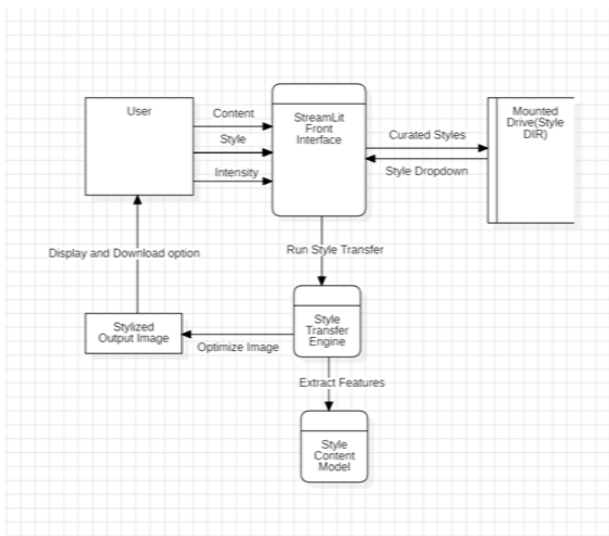
Zhanghan Ke et al. [5] proposed a color normalization-based approach with low memory usage, but it lacks structural and texture stylization. Dan Ruta et al. [6] introduced an artifact- reduction method, which depends on large datasets and has Watermarking Anonymous [8] proposed watermark-based NST which affects visual quality and lacks efficiency.

N. Deelaka [9] used a GAN-based model for flexible generation, but it requires high computation and offers limited style control. Midhun Krishnan M and Ankitha Philip [10] proposed a CNN-based disentanglement approach, but it is not optimized for real-time use.

III. PROPOSED WORK

The system is designed as an interactive application using streamlit, enabling seamless user interaction. The workflow includes:

1. **Image Upload:** The user uploads content and style



images as a part of the input fed. The content image is what the user wants to stylize. On the other hand, the style image is the one which has artistic characters like brush strokes, textures to be transferred. This step forms the basis for NST.

1. **Image preprocessing:** Both the images are decoded and then resized to accepted resolution (usually 512x512 pixels) as per standard to be complicit with VGG19 model. Then normalization which involves float conversion and scaling in the range [0-1] is done.
2. **User selects style and intensity:** The user chooses a desired style and adjusts the stylization strength to control the balance between content and style.
3. **Style transfer engine processes image:** The NST model (based on VGG19) extracts content and style features, computes losses, and generates the stylized output through optimization.
4. **Stylized output is generated and displayed:** The final transformed image is rendered on the interface, allowing users to view, download, or save the result.

Module	File	Responsibility
UI Layer	<i>app.py</i>	Streamlit web interface, user controls, before-after comparison, download
Diffusion Engine	<i>diffusion.py</i>	Stable Diffusion img2img pipeline; prompt construction; seed-controlled variation
NST Engine	<i>nst.py</i>	VGG-19 perceptual loss optimisation; Gram matrix style loss; LBFGS solver
Style Recommender	<i>recommender.py</i>	ResNet-18 classifier; heuristic fallback; fine-tuning trainer
Utilities	<i>utils.py</i>	Image resize/load, tensor conversion, colour grading, style metadata

A. System Architecture

The proposed system follows a modular architecture integrating user interaction, style selection, and deep learning- based image processing.

The workflow begins with the user, who uploads a content image (room image), selects a desired style, and adjusts the intensity level through the Streamlit frontend interface. This interface acts as the central control unit, handling user inputs and coordinating system operations.

The frontend retrieves curated style images from the mounted style directory (Style DB), which contains predefined interior design styles. These styles are presented to the user through a dropdown selection.

Once the inputs are provided, the system triggers the Style Transfer Engine, which performs the core processing. The engine forwards the input to the Style-Content Model (based on VGG19), where feature extraction is carried out. The model separates:

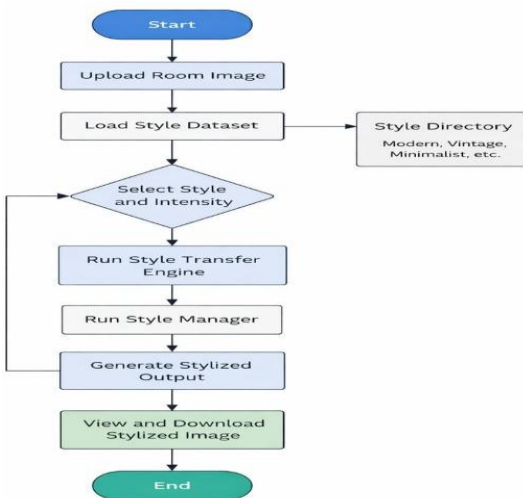
- Content features (structure of the room)
- Style features (textures, colors, patterns)

These features are combined through an optimization process that minimizes content and style loss, generating a stylized image.

The optimized stylized output is then returned to the Streamlit interface, where it is displayed to the user. The system also provides options to download or save the generated image, completing the workflow.

B. Proposed Algorithm

The proposed system performs interior image stylization using Neural Style Transfer through the following steps:



Input: The system takes a room image as input along with selected style and intensity. These parameters guide the stylization process.

User Upload Image: The user uploads a room image through the Streamlit interface. This image acts as the content image.

Load Style Dataset: The system retrieves predefined style images from the style directory. These include styles like modern, vintage, and minimalist.

Select Style and Intensity: The user selects a desired style and adjusts intensity using a slider. This controls the strength of stylization.

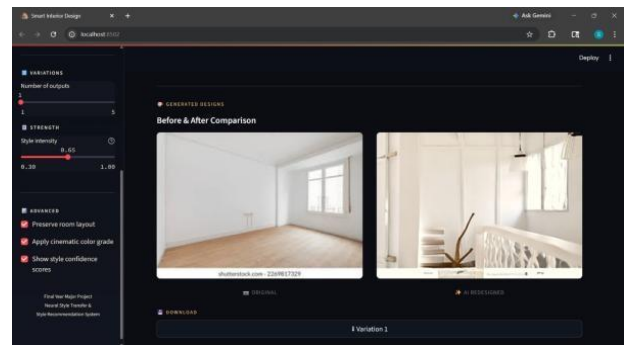
Preprocessing: Input images are resized and normalized for model compatibility. This ensures consistent feature extraction.

Load Model: A pretrained VGG19 model is loaded for feature extraction. It helps separate content and style representations.

Extract Content Features: Content features are extracted from the input image. These represent the structure and layout of the room.

Extract Style Features: Style features are extracted from the style image using Gram matrices. These capture textures, colors, and patterns.

Compute Loss: Content loss and style loss are calculated and



combined.

$$\text{Total loss} = \text{Content Loss} + (\text{Intensity} \times \text{Style Loss}).$$

Optimization: The image is iteratively updated to minimize total loss. This generates a balanced stylized output.

Generate Output: The final stylized image is produced after optimization. It blends room structure with selected style.

Display Output: The generated image is shown to the user in the interface. This allows immediate visualization.

Download Option: The user can download or save the stylized image. This completes the workflow.

IV. RESULTS AND ANALYSIS

The system was implemented using Python, Streamlit, and deep learning models. It was tested on multiple room images with different styles.

OBSERVATIONS:

- High-quality stylized outputs generated
- Real-time performance achieved
- Smooth blending of content and style
- User-friendly interaction

As shown in your diagrams (pages 12–13):

- Use-case diagram highlights system interaction
- Sequence diagram shows workflow
- Activity diagram explains processing pipeline

ADVANTAGES:

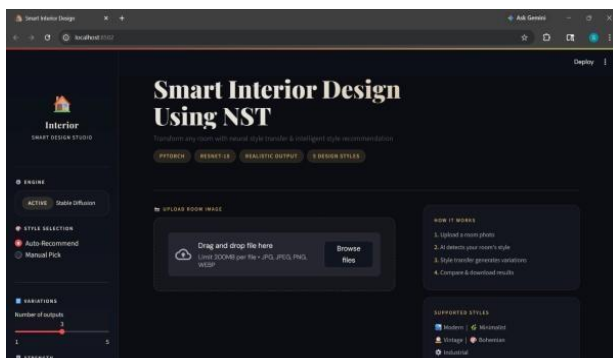
- Eliminates need for manual design tools
- Supports multiple styles dynamically
- Provides interactive visualization
- Reduces time and cost

Compared to traditional systems, the proposed model:

- Improves usability
- Enables automation
- Supports real-time experimentation

A. Output:

A streamlit interface with style selection dropdown and style intensity slider is used. Users can upload content image as desired. Image previews and stylized image are shown in the pictures.



channel RGB histogram comparison between the original cover image and the stego-image. The Original Image Histogram and Stego Image Histogram are visually identical — confirming that the embedding produced no detectable change in the pixel intensity distribution of any channel. The mean absolute difference in histogram bin counts was below 3 pixels, confirming resistance to first-order statistical steganalysis (chi-squared test). This is a direct consequence of the low embedding ratio and the uniformly distributed AES-256-GCM ciphertext bits.

V. CONCLUSION

The implementation of NST was done with focus on a domain for real world applicability of NST. Interior design was chosen as the artistic generations of NST can be used by designers in improving their design efficacy for the prowess and articulation of work. With applying transfer learning on VGG19 convolutional neural network to extract high-level content and style features from pictures and fine tuning and optimizing through a balanced style-content loss function, we enabled users to transform their original interior photos into stylized artistic renderings that align with specific interior design thematic goals like Bohemian, Minimalist, Rustic, and others.

The system has a user-friendly Streamlit-based interface, allowing users to upload images, choose from a curated set of predefined design styles, and control the degree of stylization through a style intensity slider. This not just assists amateur non-technical users to experiment with several artistic designs but also serves as a creative guide for pro individuals like interior designers, architects, and home renovator.

VI. FUTURE SCOPE

User-Defined Style Weighting: Allow users to manually adjust the style/content loss weights for overall improvement in customization strength beyond the current slider intensity. Integration with Augmented Reality (AR)

Incorporate AR for letting users to preview stylized designs in their current room environment, enhancing practical on the spot decision-making for home renovation or interior planning.

Cross-Platform Deployment

Deploy the solution to combine and integrate it with design tools like SketchUp or AutoCAD, increasing accessibility for interior designers and architectural domains.



International Journal of Recent Development in Engineering and Technology

Website: www.ijrdet.com (ISSN 2347 - 6435 (Online)) Volume 15, Issue 5, May 2026

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