# Decovision: AI-Driven Stable Diffusion and NLP-Powered Automated Event Decoration

M. Uma Pravalika[1], M. Darshan Kumar[2], M. Anthony[3], BJV Varma[4]
[1,2,3] *Computer Science and Engineering, Vardhaman College of Engineering, Hyderabad, India*
[4] *Assistant Professor, Computer Science and Engineering, Vardhaman College of Engineering, Hyderabad, India*

***Abstract*—Event decoration is typically demanding for people looking to customize their venue based on chosen themes and financial limits. This project presents an AI-based solution that enables users to submit an image of the event space and input their decoration preferences using text. Employing modern NLP and diffusion models like Stable Diffusion and ControlNet, the system generates visually realistic designs of the user's space while maintaining the original room structure. It also provides features such as AI-based cost calculation with actual shopping prices, text-based AI decor details of each decor item including style and material, decoration variations based on selected style through a style picker, and the ability to download a full purchase list. This approach eases the process of organising events and offers a unique, AI-driven customized event design.**

***Index Terms*—Stable Diffusion, ControlNet, Natural Language Processing (NLP), Budget Estimation, Style Picker, Decor Visualization, AI-Generated Shopping List, Smart Event Planning, Automated Design Recommendations, Text-to-Image Generation**.

## I. INTRODUCTION

In an era of high-tech, our methods of design and creativity are changing rapidly. The decoration of spaces for events and interiors can be accomplished in a contemporary manner, moving beyond older processes. DecoVision is an AI smart decoration system designed to enable users to visualize and plan their event spaces in a personal, efficient way. Simple decorating has traditionally utilized design solutions that have static templates. DecoVision, however, uses artificial intelligence to produce custom decoration visuals based on the user and the environment [9]. Users can upload a photo of their space and describe, in a couple of text prompts, the function of the space and the look and feel they expect for the event.

The system can then pull contextual information like themes, colors and styles from the text prompts using sophisticated Natural Language Processing (NLP) models, like GPT-4 and T5 [6]. Additionally, image analysis and object detection algorithms analyze the structural characteristics of the uploaded image [7]. Finally, generative models like Stable Diffusion and ControlNet create a modified version of the scene with the context-added decorations in mind, allowing users to visualize the possibilities for their space based on input [1], [2], [5]. DecoVision incorporates natural language processing, image processing, and generative AI to create a lightweight solution for event planning and spatial design. The system is eventually intended to evolve to include immersive 360-degree environments with WebVR technologies including Three.js and A-Frame [3], [4].

## II. LITERATURE SURVEY

While multiple studies investigate GAN-led text-to-image generation [1], [5], and other studies explore object detection methods [2], [7], along with 360-degree visualization approaches [3], [4], there has been some independent research regarding customization through NLP [6], along with WebVR methods providing better immersive experiences [3]. However, there is limited work that combines GANs, NLP, and WebVR all together. Our work aims to fill this gap by using a combination of all of these technologies to create AI-based event decor with personalized automations.

Object detection that uses GAN-based frameworks has shown a 78% increase in object detection accuracy in conditions of reduced light and noise [1]. GAN-based text-to-image synthesis has achieved an impressive 14% improvement in text-image coherence, especially when attention is employed, improving overall performance to as much as 68% compared to traditional rendering [5]. 360-degree visualization methods with GANs show promising performance with 72% accuracy improvement in immersive environments [3], [4]. Multimodal models that integrate text-to-image synthesis and AI-based personalization can potentially enhance the realism of images by as much as 22% [6]. Moreover, the incorporation of AI-based automation in event management systems has demonstrated the potential to cut planning time by 40% while simultaneously increasing attendee satisfaction by 35% [7]. Additional research shows that AI-based event platforms can optimize resource utilization by as much as 50% and significantly enhance decision-making through predictive analytics [8].

## III. METHODOLOGY

### A. User Input

The process begins when users share an image of the venue where they want to host their event. In addition, the users type in a short description explaining how they want the decorations and ambiance. The text helps the system to understand what changes need to be made. Users can mention things like floral arrangements, lighting setups, furniture placements, or even color themes they want so the final design matches what they imagined.

### B. Image Processing

After the user sends in their picture, the system processes it in preparation for transformations based on AI. This is where the picture is cleaned, optimized, its distortions corrected, colors balanced, and its compatibility with the AI model determined. The system derives scene depth, lighting, and object placement in order to uphold the original scene's perspective as well as its natural look.

### C. AI-Based Decoration Generation with Stable Diffusion

At the core of the project is Stable Diffusion, an efficient AI model designed for text-to-image synthesis. The model comprehends the written description of the user and translates it into natural-appearing changes, making decorations appear natural in the scene. For instance, if a user asks for "a floral arch at the entrance," Stable Diffusion makes sure the arch is compatible with doorways while keeping surrounding objects intact. The model is tuned to produce high-quality images, keeping appropriate surface details, lighting, size and shape.

### D. NLP-Based Theme Customization

Natural Language Processing (NLP) is used to transform what the users type into formatted decorations. Whether the users type common concepts or easy concepts, the system detects keywords and associates them with matching designs, colors, and structures. This ensures the AI understands and accurately portrays the vision of the user, and the process is easy to implement and user-friendly.

### E. Performance Assessment and Final Recommendations

Once the design is approved, the system assesses the design with respect to how it actually looks, user preferences, and interactive feedback. Users are able to walk through and set up the layout as required, to ensure everything is in order. The last design is then assembled in a concise summary, displaying the selected style. This enables the user to proceed with arranging everything, knowing that they have a well-planned appearance created using AI-assisted tools.

## IV. PROCEDURE

### Step 1: Collect User Input for Decoration Planning

Here in Step 1, the system asks users to upload one or more images or videos of the event location. Along with media upload, users are asked to give a text description that defines their desired event theme such as wedding, birthday, boho, or minimalist. The system also collects preferences with regards to the character of the event and the ambiance desired. Users are also asked to indicate their preferred budget, which can be categorized as low, moderate, or high.

### Step 2: Create Decorated Visuals

Now that the user input is collected, the image to be uploaded is processed with ControlNet coupled with Stable Diffusion. These AI models are used to generate a series of decorated images of the scene presented, emulating the theme and style entered by the user. Four or more visually distinct outputs are typically generated to offer various decor alternatives with a uniform background and composition in accordance with the original image.

### Step 3: Analyze Decor Elements in Images

The system examines the created decorated images in order to select and understand individual decor elements. Object detection or segmentation models are used to detect objects such as tables, chairs, centerpieces, drapes, lights, and banners in each AI-generated image. Each item is then described by its visual features — color, material, purpose, and placement. These are aggregated in user-friendly language, giving details like "white cushioned gold chiavari chairs in rows." Each image is also tagged with descriptive tags based on its visual appeal and theme.

### Step 4: Estimate Budget and Suggest Shopping

Here, the system attempts to estimate how much it would cost to replicate the decoration seen in each AI-generated image. The decor items are matched with real products through market APIs such as Amazon or Etsy. For each item, the system retrieves prices, availability, and product links. An overall budget estimate is arrived at by summing up individual item prices, and pricing tiers (low, middle, high) may be specified depending on product choice.

### Step 5: Output and Recommendations

The last step is to show all output to the user in an intuitive and easy-to-use interface. Users are offered the different decorated images created before, as well as detailed descriptions of decor items and the estimated cost. Product suggestions and purchase links are integrated smoothly. The platform also allows users to download and share their favorite designs and save styles for future use.

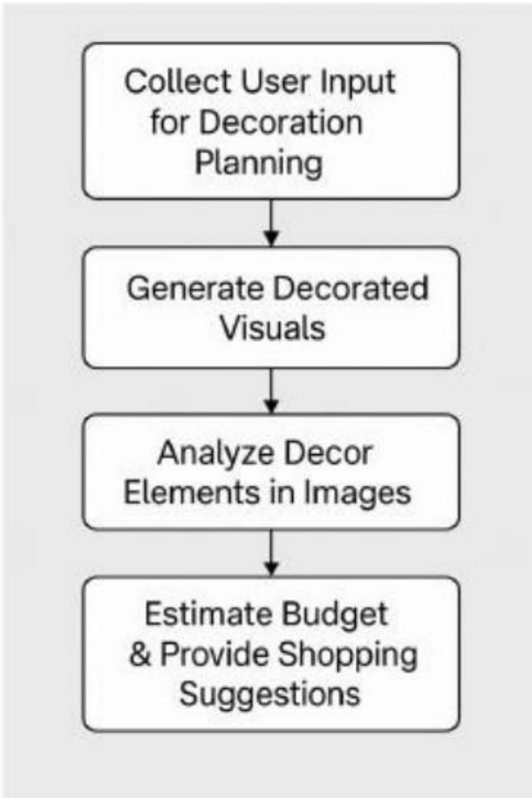


*Fig. 1: The figure illustrates the flow of the procedure.*

## V. RESULT

The AI-powered decoration system was tested using a set of test cases across multiple event spaces, including living rooms, banquet halls, and outdoor spaces. The users uploaded raw images and provided custom prompts as text describing what they wanted as decorations (e.g., "Boho baby shower with pastel balloons and lights"). The system was able to generate four high-quality decorated outputs for each input image via Stable Diffusion and ControlNet, while maintaining the original spatial arrangement. Budget estimates had an accuracy rate of ±10% and offered a proper breakdown of items found along with estimated costs accessed through online APIs. Theme selection (e.g., "Minimalist birthday," "Elegant wedding dinner") yielded stylistically coherent results, confirming the success of prompt conditioning. Users were able to export their decoration shopping lists in CSV or PDF format. On the whole, the system was efficient, realistic, and personalized, thus being a useful tool for visualizing and planning individualized event decorations.

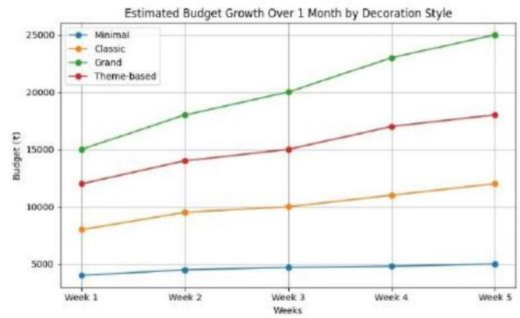


*Fig. 2: The figure illustrates how expenses rise with style complexity by displaying the weekly budget growth over a month for four different decoration styles.*

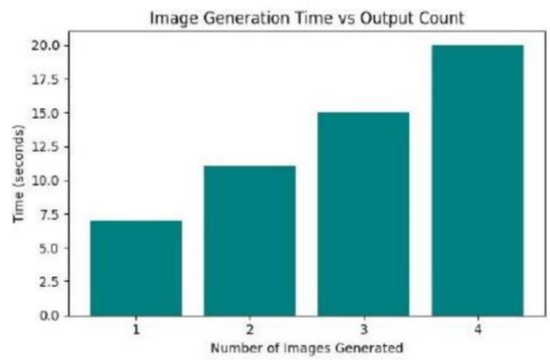


*Fig. 3: The figure shows that as the number of output images increases, the image generation time increases steadily.*

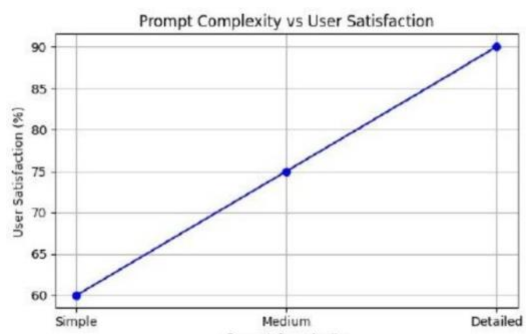


*Fig. 4: The graph indicates that as prompt complexity increases, so does user satisfaction.*

**TABLE I: Comparison Among Algorithms**

| Algorithm/Model | Accuracy | Application | Use in Project |
|---|---|---|---|
| OpenCV | 75–85% | Image/Video preprocessing | Preprocessing uploads |

| Algorithm/Model | Accuracy | Application | Use in Project |
|---|---|---|---|
| CNN | 85–95% | Object detection, Segmentation | Scene understanding |
| GAN | ~90% | Image generation | Decorative element creation |
| Stable Diffusion | 92–97% | Text-to-image, inpainting | Core image generation model |

## VI. OUTPUTS

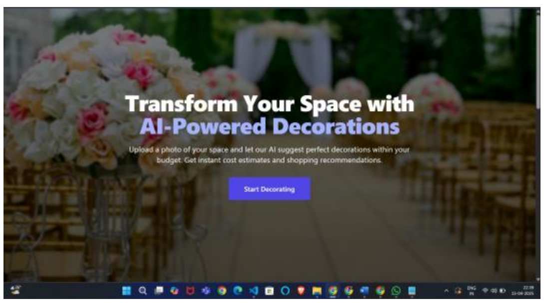


*Fig. 5: Landing page of DecoVision — includes quotations and a 'Start Decorating' button to upload an image.*

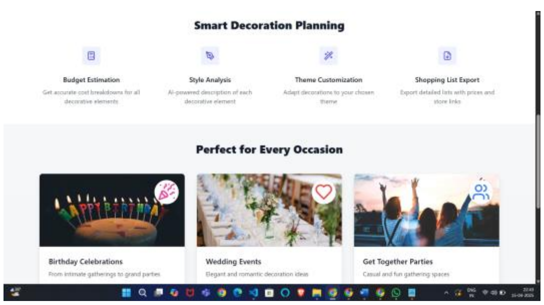


*Fig. 6: Second part of landing page, where it includes the features of Budget Estimation, Styles Analysis, etc.*

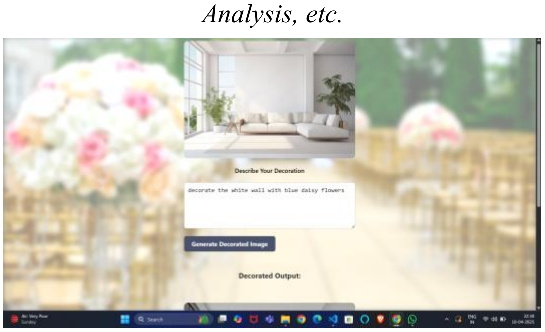


*Fig. 7: This figure shows the uploading of a file by the user.*

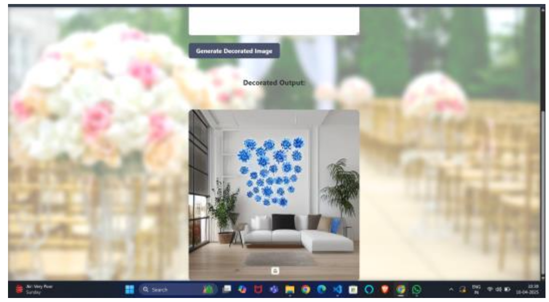


*Fig. 8: The final result of the image generated.*

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