Brand-Consistent Product Design Using AI: A LORA-Enhanced Stable Diffusion Approach

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Abstract: This paper presents an AI-driven framework for product family design using brand DNA extraction and Artificial Intelligence Generated Content (AIGC). The system employs a LORA-enhanced Stable Diffusion model to generate brand-consistent product images from textual descriptions, ensuring accurate visual representation of design attributes. An image enhancement module is integrated to improve resolution, clarity, and overall visual quality of generated outputs. Experimental analysis demonstrates improved design consistency, efficiency, and scalability compared to traditional manual and AI-assisted approaches.

Index terms - — *Artificial Intelligence Generated Content (AIGC), Brand DNA Extraction, LORA (Low-Rank Adaptation), Stable Diffusion, Product Family Design, Image Enhancement, Deep Learning, Text-to-Image Generation*

1. INTRODUCTION

In today's competitive market, maintaining a strong and consistent brand identity across product families is essential for improving recognition and customer trust. Traditional product design methods rely heavily on manual efforts, designer experience, and iterative processes, which often lead to inconsistencies and increased development time. As product categories expand, preserving brand-specific design characteristics becomes more complex and less scalable.

Recent advancements in Artificial Intelligence Generated Content (AIGC) have introduced new possibilities for automating design generation using data-driven approaches. Techniques such as deep learning and text-to-image models enable the transformation of textual descriptions into visual representations. However, existing systems often fail to accurately capture and maintain brand DNA, resulting in designs that lack coherence and distinct identity across different product categories.

To address these challenges, this paper proposes an AI-driven framework that extracts brand DNA and integrates it with a LORA-enhanced Stable Diffusion model for generating consistent product designs. Additionally, an image enhancement module is incorporated to improve the quality and clarity of generated outputs. The proposed approach aims to improve design efficiency, ensure brand consistency, and provide a scalable solution for automated product family design.

2. LITERATURE SURVEY

a) The application of artificial intelligence-assisted technology in cultural and creative product design:

In order to improve creativity and efficiency in cultural and creative product design, this study suggests a unique AI-assisted design approach that blends Variational Autoencoders (VAE) with reinforcement learning (RL). The approach greatly enhances design quality and expedites the design workflow by implementing AI-driven decision assistance. A thorough framework is established, the model is applied to four different design tasks, and its performance is validated by rigorous tests. Structured surveys and expert input are used to assess important elements, such as innovation, cultural adaptation, and practical applicability. The findings show that the VAE + RL model outperforms other methods in a number of areas. A 95% customer satisfaction rating, a 0.92 Structural Similarity Index (SSIM) score, a 93% model accuracy, and a 0.07 loss reduction are among the highlights. These results validate the model's supremacy in producing excellent designs and attaining high levels of customer satisfaction. The model also demonstrates excellent operational efficiency and generalization abilities, providing insightful information and data support for upcoming developments in cultural product design technology.

b) Big Data and AI-Driven Product Design: A Survey:

varied and customized consumer needs as living standards rise. Due to their significant subjectivity, narrow survey scope, lack of real-time data, and subpar visual display, traditional product design methodologies are inadequate. However, new developments in artificial intelligence (AI) and big data are bringing about a revolutionary approach to product design that will have a large influence on several sectors. Big data in the product lifecycle includes useful information about consumer preferences, market demands, product evaluation, and visual display. For example, product images contain shape, color, and texture information that can motivate designers to quickly create initial design schemes or even new product images, while online product reviews reflect customer evaluations and requirements. This study offers a thorough analysis of big data and AI-driven product design, emphasizing how AI algorithms may be used to handle, evaluate, and utilize large data from a variety of modalities. It highlights the shortcomings of conventional product design techniques and demonstrates how much more intelligent product design can be achieved by utilizing textual, picture, audio, and video data in product design cycles. In order to raise awareness of contemporary AI-driven product design, we conclude by outlining prospective future research topics and prospects and discussing the main shortcomings of current data-driven product design studies.

c) The Research and Design of an AIGC Empowered Fashion Design Product:

This essay addresses the opportunities and problems in fashion design while examining the revolutionary potential of Artificial Intelligence Generated Content (AIGC) in the fashion sector. The research looks at the state of fashion design today, which is characterized by an emphasis on trends, cultural diversity, and rising desire for customized goods. It highlights the shortcomings of conventional design procedures and suggests AIGC as a way to improve innovation, effectiveness, and market flexibility. The study describes how AIGC is used in the design, production, marketing, and inspiration stages of fashion design. It demonstrates how AI can streamline the design process and cut expenses by facilitating trend research, quick design iteration, virtual try-ons, and sales projection. To evaluate how AI-assisted design affects fashion designers' output quality and productivity, a comparison experiment is carried out. Notwithstanding the favorable results, the study recognizes the need of objective evaluation techniques, the necessity for sophisticated AI model training to increase the accuracy of clothing pattern development, and strategies to bridge design to production. This study essentially gives a thorough summary of AIGC's function in fashion design, emphasizing its present capabilities, constraints, and future directions for utilizing AI to transform the sector.

d) AI algorithms in visual communication design: enhancing design creativity and efficiency:

Customers' memories and decisions are impacted by the current state of product package design, which is extremely uniform and devoid of distinctive visual components and cutting-edge designs. In order to create design documents and enhance brand awareness, this article presents AIGC (Artificial Intelligence Generated Content) visual communication technology, which uses automated production and real-time feedback capabilities. In order to extract tea cultural features and modern design style characteristics, it combines neural style migration with VGG (Visual Geometry Group)-19 deep neural network technology. It then intelligently incorporates these elements into tea package design to fulfill the diverse market demands. According to the trial findings, the created green tea package has a cosine similarity range of 0.34–0.43. They significantly lessen the packaging resemblance issue when compared to the packaging items of major e-commerce platforms. The experimental design outperforms algorithms like Transformer-based Image Synthesis in terms of generation time, reaching 50 minutes, which significantly reduces the package design time. Additionally, the computation energy consumption is 240 W/h, which is better than that of other algorithms. Neural style transfer in conjunction with AIGC may boost package design originality and sustain market competitiveness, offering a practical answer for packaging design in the future.

e) Identifying Brand Consistency by Product Differentiation Using CNN:

In this study, a novel approach to machine learning employing a convolutional neural network (CNN) to detect brand consistency by product appearance fluctuation is presented. In Experiment 1, we gathered fifty mouse devices from a well-known brand over the previous 35 years in order to create a dataset of product images with predetermined design elements related to their features and look. The findings indicate that using conventional techniques like principle component analysis (PCA) and time series analysis to identify periods for the subtle development of common devices is difficult. In Experiment 2, we used deep learning to forecast how much mouse devices from different companies will differ in appearance. 6,042 pictures of mouse gadgets were gathered for the study, which separated them into Early Stage and Late Stage categories. The assessment score of brand style consistency is 0.36, indicating that the brand consistency score transformed by the CNN accuracy rate is not always flawless in the actual world. The results reveal the maximum accuracy of 81.4% using the CNN model. Future product style roadmaps and new product styles may be predicted with the use of the link between evaluation score, brand style consistency, and product appearance variance. Furthermore, the CNN heat maps provide additional hints regarding the blurred boundary by highlighting the crucial areas of design aspects of various layouts. The study sheds light on real-world issues that product designers, producers, and marketers face. In addition to advancing scientific knowledge of design creation, it gives experts in the field useful tools and techniques to enhance the design process and uphold brand consistency. These methods may be used by designers to identify characteristics that impact brand style. Then, keep your key brand principles while capturing these characteristics as creative design elements.

3. METHODOLOGY

i) Proposed Work:

The proposed work introduces an AI-driven framework for generating brand-consistent product family designs by extracting and formalizing brand DNA from product datasets. The system utilizes a Retail Product Images and Captions dataset to capture both visual and textual features, which are preprocessed and converted into structured representations. These representations are then used to fine-tune a LORA-enhanced Stable Diffusion model, enabling the system to accurately translate textual descriptions into visually coherent product designs while preserving brand-specific attributes across multiple categories.

To further improve the practicality of generated outputs, an image enhancement module is integrated into the system. This module refines the generated images by improving resolution, sharpness, and color fidelity, ensuring high-quality visual outputs suitable for evaluation and presentation. By combining brand DNA extraction, diffusion-based generation, and enhancement techniques, the proposed system delivers an efficient, scalable, and consistent solution for automated product family design.

ii) System Architecture:

The proposed system architecture is designed to generate brand-consistent product designs through a structured AI pipeline. It begins with Brand DNA Extraction using AIGC technology, where key visual and semantic attributes of products are identified from the dataset. These extracted features represent the core identity of the brand and serve as the foundation for further design generation. The processed data is then passed to the LORA (Low-Rank Adaptation) module, which fine-tunes the Stable Diffusion model to learn and replicate brand-specific design patterns efficiently.

Following this, the generated images are processed through an Image Enhancement module, which improves resolution, sharpness, and overall visual quality. This step ensures that the outputs are not only consistent with brand identity but also visually clear and suitable for real-world usage. Finally, the system produces the enhanced product design output, which accurately reflects the input description while maintaining brand coherence. As illustrated in the provided architecture diagram, the workflow follows a sequential pipeline: Brand DNA Extraction → LORA → Image Enhancement → Output, ensuring both consistency and high-quality design generation.

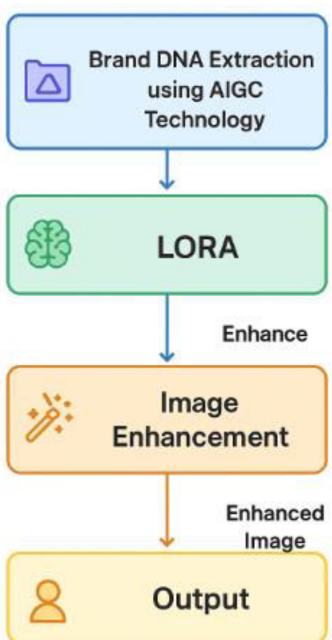

Fig1 proposed architecture

iii) Modules:

a. Importing the Packages

Initializes required Python libraries for data processing, model training, and visualization. This ensures a stable environment for executing AI-based design operations.

b. Exploring the Dataset

Analyzes product images and captions to understand data distribution and quality. This step helps in identifying useful features for brand DNA extraction.

c. Pre-processing

Transforms raw data into a clean and structured format by resizing images, removing noise, and converting text into numerical vectors for model compatibility.

d. Brand DNA Extraction

Identifies key visual and semantic features that define a brand's identity. These features ensure consistency across all generated product designs.

e. Load & Train LORA Model

Fine-tunes the Stable Diffusion model using LORA to efficiently learn brand-specific patterns and improve design generation accuracy.

f. Define Image Generation Function

Implements a function that converts textual input into product images using the trained diffusion model, enabling automated design generation.

g. Image Enhancement (Extension Module)

Improves the quality of generated images by enhancing resolution, sharpness, and color details for better visualization and usability.

h. Generate Product Designed (Output Module)

Produces the final brand-consistent, high-quality product designs by combining generation and enhancement processes.

iv) Algorithms:

a. LORA Training: By adding low-rank parameter updates that adjust the model to brand-specific product attributes, the LORA training technique facilitates the effective fine-tuning of large generative models. Its function is to improve representational precision without necessitating a complete retraining of the model, which increases flexibility and lowers computational expenses. The method enhances the model's ability to produce cohesive product designs by aligning semantic cues with stylistic features through the processing of text-based feature descriptions and associated visual examples. It maintains excellent generalization performance while enhancing accuracy, consistent convergence, and enhanced inheritance of design properties across several categories by focused parameter modulation.

b. Stable Diffusion Generative: The fundamental imaging framework that converts textual descriptions into visual outputs is the Stable Diffusion generative algorithm. It creates high-quality pictures with embedded semantic and stylistic characteristics by repeatedly denoising latent representations. Its contribution is that it makes image synthesis scalable, versatile, and controlled while maintaining brand identity and visual coherence. Robust generalization is supported by the algorithm's latent-space diffusion mechanism, which enables it to consistently generate pertinent images and comprehend abstract design cues. It manages intricate feature combinations, preserves performance stability, and offers a solid foundation for sophisticated fine-tuning methods like LORA thanks to its effective sampling strategy.

c. Caption Vectorization: This approach transforms descriptive product text into numerical embeddings so that learning and generative models may analyze them. Its main function is to maintain contextual clues, attribute connections, and semantic meaning in compact vector representations. During model training, it enables precise alignment between textual properties and visual patterns by mapping linguistic information into organized numerical space. By managing a wide range of language and different description styles while preserving constant encoding quality, the technique promotes resilience. Improved synthesis accuracy and the creation of brand-relevant designs are directly impacted by effective vectorization, which also improves the interpretability of input information.

d. Image Enhancement: By honing resolution, clarity, color balance, and structural detail, the image improvement algorithm raises the resulting images' perceived quality. Its function is to make up for shortcomings in early generative outputs that could seem low-contrast or blurry, making it possible to see minor stylistic elements. The algorithm maintains the original design purpose while strengthening sharpness and visual quality through progressive refining procedures. This improvement enables clearer visualization for end users, improves the assessment of created concepts, and increases the overall efficacy of the design workflow. It strengthens the final output quality's resilience by stabilizing appearance and minimizing artifacts.

4. EXPERIMENTAL RESULTS

The proposed system was evaluated using a product image–caption dataset to assess its ability to generate brand-consistent designs. The LORA-enhanced Stable Diffusion model successfully learned brand-specific features and generated visually coherent product images from textual inputs. Compared to traditional manual design approaches, the system significantly reduced design time while maintaining consistency across multiple product categories.

The integration of the image enhancement module further improved the quality of generated outputs by increasing resolution, sharpness, and color clarity. The enhanced images provided better visualization of fine design details, making them suitable for evaluation and presentation. Experimental observations indicate that the proposed framework achieves improved design accuracy, higher visual fidelity, and better scalability, demonstrating its effectiveness for automated product family design applications.

Accuracy: A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Classification accuracy or positive cases constitute precision. The formula for accuracy is:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: Mean Average Precision ranks quality. It considers the number and order of relevant ideas. Calculating MAP at K uses the arithmetic mean of each user or query's Average Precision (AP).

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

F1-Score: A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

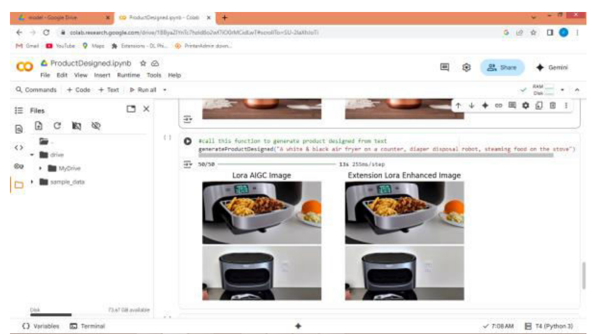

Fig2 Results

5. CONCLUSION

This paper presents an AI-driven framework for product family design using brand DNA extraction and AIGC technology. By integrating LORA-enhanced Stable Diffusion, the system effectively generates brand-consistent product designs from textual inputs. The inclusion of an image enhancement module further improves visual quality, ensuring clear and high-resolution outputs.

The proposed approach overcomes limitations of traditional design methods by improving efficiency, scalability, and consistency across product categories. Experimental results demonstrate that the system produces accurate, visually coherent, and high-quality designs, making it a reliable solution for automated and intelligent product design applications.

6. FUTURE SCOPE

The proposed system can be further enhanced by integrating real-time user feedback to enable adaptive and personalized product design generation. This would allow designers and users to iteratively refine outputs based on preferences, improving usability and satisfaction.

Future work can also focus on incorporating advanced generative models such as improved diffusion techniques or GAN-based approaches to achieve higher realism and diversity in generated designs. Extending the system to support 3D product design generation and augmented reality (AR) visualization would significantly increase its practical applications in industries like manufacturing and e-commerce.

Additionally, deploying the framework as a cloud-based platform can improve accessibility and scalability for large-scale industrial use. Developing more robust evaluation metrics for measuring brand consistency and visual quality will further strengthen the reliability and performance of AI-driven product design systems.

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