AI-driven intelligent system for bottle cap design generation*

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Abstract

The article presents the development of an intelligent system for generating bottle cap designs using the Stable Diffusion generative diffusion model, pre-trained using the LoRA method. This work is devoted to the full cycle of automated design creation, in particular, the formation of a dataset, configuration of the environment in Google Colab, training of the generative model using LoRA, and creation of a Gradio interface for interactive image generation. The proposed system allows the user to enter a text description of the design (prompt), based on which the model synthesizes new design options while preserving the key stylistic features of the original samples. The experimental analysis confirmed the effectiveness of the approach: LoRA adaptation of the Stable Diffusion model ensured high accuracy in reproducing the shape, color scheme, and graphic elements of the bottle cap designs with minimal volume. The results demonstrate the model's ability to generate generalized but recognizable new bottle cap designs that are similar in style to the training samples.

Keywords

artificial intelligence, Stable Diffusion, LoRA, Google Colab, generative models[1]

1. Introduction

The modern packaging industry places high demands on the uniqueness of product design. In particular, bottle caps are an important element of beverage branding, combining aesthetics and functionality of packaging. The traditional process of cap design requires significant time and designer involvement, while modern advances in artificial intelligence open up new opportunities for automating the design stages of bottle caps.

Stable Diffusion is a latent diffusion text-to-image model that demonstrates high-quality synthesized images at relatively low computational costs [1]. Its application in creative tasks, including automated packaging design, is being actively studied by researchers. However, without adaptation to narrow-profile tasks, the generation results may be insufficiently accurate or stylistically inconsistent. For retraining large models on specialized datasets, it is advisable to use the LoRA (Low-Rank Adaptation) method, which allows modifying the model without complete retraining. As shown in article [2], LoRA technology reduces computational costs and maintains model stability by making local changes to the weights of only selected layers. This approach has already been successfully applied to create stylized images in art, education, and industrial design [3]. The use of such models makes it possible to automatically generate a multitude of unique design options based on specified parameters (color scheme, style, brand identity), speed up the work of design departments by creating a large number of prototypes for further selection of the optimal option, take into account previous developments, corporate standards databases, consumer

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preferences and marketing research data, and create innovative stylistic solutions that are difficult to generate using traditional methods. In particular, the authors of article [4] proposed a methodological framework for the stylistic emulation of Krakow's eclectic facades using a combination of LoRA technology and diffusion models. The paper develops an approach to the typological transformation of architectural styles, which allows complex facades to be reproduced based on limited visual examples. The method combines the reduction of LoRA parameter ranks with the capabilities of generative modeling to adapt models to the architectural features of eclecticism, while preserving the detail and authenticity of the style. Additionally, the authors of article [5] proposed a new architecture for generative adversarial networks, known as StyleGAN. The main idea is to introduce a style-based block that allows controlling various aspects of the generated image, such as facial features, color, and texture at different levels of spatial detail. This approach has significantly improved control over the generation process and allowed for more realistic and varied images. The article also introduced the "perceptual path length" metric to evaluate the smoothness of the latent space and showed that the new architecture provides better interpretability and training stability compared to traditional GAN approaches. The authors of article [6] applied artificial intelligence algorithms to generate images, highlighting the promise of models such as DALL-E 3, Midjourney, ImageFX, Adobe Firefly, and Leonardo.

Artificial intelligence is widely used in various fields of human activity, demonstrating high efficiency in solving both scientific and applied problems. In particular, machine learning methods are successfully implemented in medicine for diagnosing diseases and predicting treatment effectiveness [7, 8], in industry for optimizing technological processes, product quality control, and production management [9, 10], as well as in mechanics for modeling physical processes, predicting material failure, analyzing fatigue and wear [11–13], in materials science for predicting the properties of composites [14–16], predicting the properties of shape memory alloys [17], and predicting the type of filler in basalt-reinforced epoxy composites [18, 19]. Considerable attention is also paid to the application of AI in ecology, in particular for environmental monitoring, air quality assessment, and pollution level prediction [20, 21], and in the field of information security for detecting DDoS attacks and abnormal network activity [22–24]. The role of AI in information technology should be highlighted separately [25-27]. The use of AI in education [28-30], energy [31-33], logistics and transport [34-36], agriculture [37-39], bioinformatics [40, 41], finance [42-44], and cultural heritage preservation [45-47]. Due to such broad cross-sector integration, artificial intelligence is becoming a universal tool for transforming modern production, science, education, and culture.

The aim of this work is to create an intelligent system for generating bottle cap designs using the Stable Diffusion generative model, pre-trained with LoRA on a limited dataset. The main tasks are to prepare the dataset, pre-train the model in a cloud environment, implement a user-friendly image generation interface, and analyze the results.

2. Materials and methods

Modern production of bottle caps, in particular heat-shrinkable and aluminum caps, involves the implementation of high-tech processes that ensure accuracy, repeatability, and product quality in accordance with international standards. The study analyzed the production process at JSC "Technologia," a leading Ukrainian manufacturer of packaging products.

Figure 1 shows a fragment of the production line for heat-shrinkable caps, in particular, the stage of forming blanks using heat-shrinkable film. The unit is equipped with automated modules for precise positioning, processing, and feeding of material, which ensures stable geometry and dimensional accuracy.

Figure 2 shows the decorative finishing stage. An automated installation in a sealed protective housing with impact-resistant glass is used. The equipment ensures uniform application of paint, foil, or varnish.

Poly-laminate caps with a metallized coating significantly expand the possibilities for design personalization. Thanks to glossy or matte textures, rich colors, and the possibility of applying premium design elements (embossing, holograms, foiling).

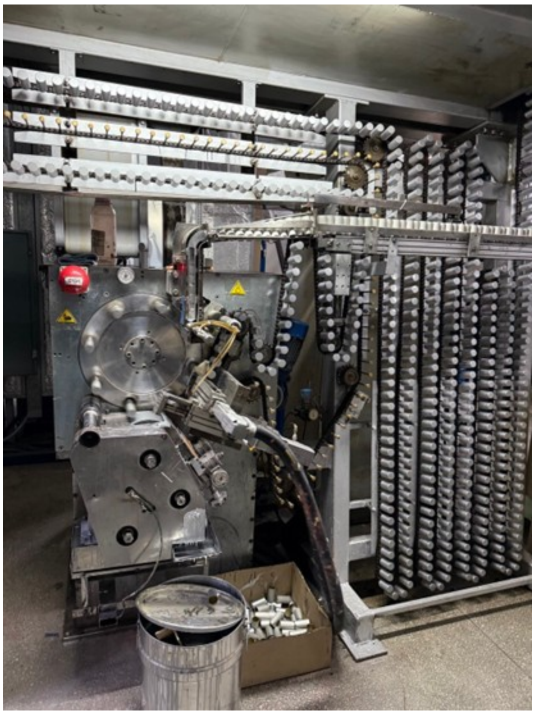

Figure 1: Production line for heat-shrinkable caps at the JSC “Technologia” enterprise.

Figure 2: Automated module of the line for applying decoration to caps at the JSC “Technologia” enterprise.

The use of poly-laminate caps significantly expands design possibilities thanks to their metallized surface, which provides deep, rich colors and creates a premium effect. Such properties require accurate visual reproduction when generating images, which increases the demands on the artificial intelligence model; in particular, it must not only reflect general features, but also preserve the texture, gloss, and structural authenticity of the material.

To model the process of creating bottle cap designs with a limited number of examples, a generative approach was used to reproduce visual complexity, multi-layered design, and style variability. Effective training of a neural network for generating bottle cap designs is based on a carefully constructed training sample. The training sample included 23 samples of bottle caps from the company “Technologia,” representing different types of caps. Each image had high resolution and a standardized background (uniform light or white), which contributed to better generalization during training. In addition, each sample was given a description summarizing its key visual characteristics, namely colors, shapes, textures, and the presence of logos or inscriptions. For example, “black and gold cap with floral band and ‘Monte Choco’ text” (for sample 4) or “shiny gold bottle cap with ‘VP’ logo on the top” (for sample 17). Such annotations were used as text prompts during the generation of new images and played a critical role in the contextual training of models that implement cross-attention mechanisms to align text and images.

To implement the intelligent bottle cap design generation system, Google Colaboratory (Colab) was chosen as the main platform for model development, training, and testing. This platform provides cloud resources (including GPU and TPU) and an integrated environment for working with Python code, which is especially convenient for artificial intelligence tasks that require high-performance computing. To prepare the Colab environment, the necessary versions of libraries such as torch, transformers, diffusers, xformers, and gradio were imported. This ensures the compatibility of all LoRA pipeline components. Additionally, Google Drive was connected to access training images, prompts, and save results.

3. Results and discussion

After completing the preparatory stages and configuring the environment, an experimental test of the image generation system's performance was carried out. The Stable Diffusion base model (stabilityai/stable-diffusion-2-1-base) is used to generate images via the Hugging Face interface, and LoRA weights are also integrated. Optimal hyperparameters were selected for retraining the model, corresponding to the capabilities of the Google Colab cloud environment and the limited amount of data. In particular, the batch size was set to 1 to avoid GPU overload, and the learning rate was set to 1e-4, which ensures stable weight updates with small samples. The total number of training steps was approximately 1,200, which is equivalent to 5 full passes (epochs) on a set of 23 samples. The LoRA rank (r) was set to 16, which allows the model to maintain sufficient expressiveness while keeping the weights compact. The image was reduced to a standard resolution of 512×512 pixels.

A Gradio interface was created for entering prompts, generating images, and previewing results (Figure 3).

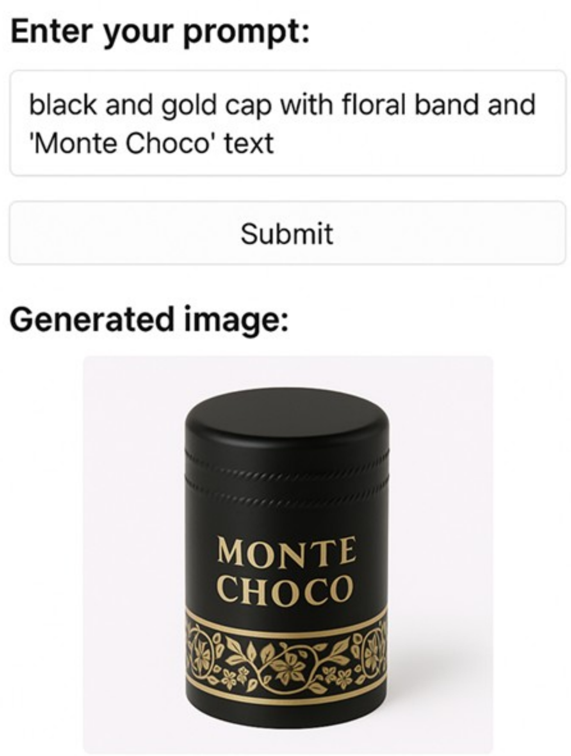

Figure 3: Example of Gradio interface design generation.

This has significantly improved the testing experience for users without in-depth programming knowledge. The developed cycle is implemented as a modular Jupyter notebook, which allows you to change model parameters, load your own prompts, and run the entire pipeline, from preparation to generation.

Figures 4-8 show examples of comparisons: on the left are fragments of the original design samples, and on the right are images generated by the model based on a similar description. Visual analysis confirms that the model has successfully learned the key features of the style. The generated images demonstrate a high level of correspondence between the text description and the result. In particular, the model accurately reproduces the shape of the cap and the main design elements. For example, sample 4 (black and gold cap with floral band and ‘Monte Choco’ text) demonstrated high accuracy in the reproduction of small decorative elements, the font was generated taking into account the brand's style, and an embossing effect was observed. In addition, sample 13 (green metallic cap with golden eagle logo) showed a good reflection of textured metal, with a clear reproduction of the logo ornament. Sample 16 (white glossy cap with butterfly prints and bee on top) demonstrated high artistic stylization with accurate reproduction of small elements (butterfly pattern, contrast on a glossy background).

The model did not simply memorize training examples, but learned to generate generalized designs in a given style. This is manifested in the ability to combine different features, creating unique variations. For example, based on the style of one of the training corks (matte dark blue with a minimalist logo), the model can generate a different color option or add a new decorative element with a new prompt, while maintaining the overall character of the design.

Figure 4: Sample 4 «Black and gold cap with floral band and 'Monte Choco' text».

Figure 5: Sample 8 «Matte black cap with 'Toro Loko' logo in white script».

Figure 6: Sample 13 «Green metallic cap with golden eagle logo and branding».

Figure 7: Sample 16 «White glossy cap with butterfly prints and top bee illustration».

Figure 8: Sample 20 «Midnight blue and gold cap with textured seal on top».

The obtained data is consistent with the results of studies on the use of diffusion models in design. The experiment with bottle caps confirms the universality of this approach: the model successfully transfers the style to new images, increasing the efficiency of the creative process while ensuring the accuracy and consistency of the design. Thus, the proposed approach has proven to be highly effective and can be recommended for automated design creation in the packaging industry. The Stable Diffusion+LoRA generative model has proven capable of quickly producing high-quality and diverse bottle cap designs based on text descriptions.

4. Conclusions

This paper presents and investigates an intelligent system for generating bottle cap designs, combining the Stable Diffusion model with LoRA fine-tuning technology. The proposed approach has demonstrated high efficiency, that is, the model successfully learns stylistic features even from a small dataset (23 images) and generates new designs with high visual accuracy. The reproduction of shapes, colors, and graphic elements in the generated caps almost completely matches the given description, confirming the quality of training. At the same time, the model avoids directly copying training examples, instead creating generalized variants, which indicates the absence of overfitting and the preservation of creative generativity. The Low-Rank Adaptation method has proven to be an effective way to fine-tune large models for a narrow task. Retraining took only a few hours on an affordable cloud server, and the resulting weight file is compact. At the same time, the base Stable Diffusion model retained its versatility, indicating the absence of "catastrophic forgetting" — after applying LoRA weights, it is still capable of generating general images outside the cork domain if adaptation is disabled. This means that a single model core can serve different tasks by connecting different LoRA modules, which is convenient for industrial applications.

The developed system has great practical potential in the field of packaging design. It allows to significantly speed up the creation of new products: instead of lengthy manual sketching, designers can instantly get several design options by changing the text description iteratively. Secondly, the system facilitates product personalization, that is, it can be used to easily create unique cork designs for specific customer requirements, which previously would have required considerable effort. Thirdly, integrating such a model into the company's workflow will automate routine design operations. The results obtained are a significant step towards the practical application of AI technologies in creative industries and confirm the promise of further research in this area.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to grammar and spell check, and improve the text readability. After using the tool, the authors reviewed and edited the content as needed to take full responsibility for the publication's content.

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