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A Lightweight Diffusion Framework for Cultural Pattern Generation Using LoRA

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Abstract

Atlas patterns, a representative element of Uyghur intangible textile heritage from Xinjiang, are renowned for their vibrant colors and intricate symbolic structures. However, existing generative AI approaches often struggle to replicate their cultural semantics or require significant computational resources. This study addresses these limitations by proposing a low-resource, high-fidelity generation method based on Low-Rank Adaptation (LoRA) applied to the Stable Diffusion (SD) model. A categorized dataset of 103 Atlas pattern images was constructed and annotated using Peirce's semiotic framework, including Iconographic, Directional, and Cultural Semiotic categories. LoRA modules were used to fine-tune the U-Net component of SD, substantially reducing training complexity and memory usage. Experimental results demonstrate that under optimal parameters (epoch = 100, batch size = 2, U-Net learning rate = 8×10^{-4}), the model achieves superior performance in MSE, PSNR, and SSIM compared to the base model. The generated patterns effectively reflect the geometric symmetry and cultural motifs of traditional Atlas textiles. This research highlights the practical potential of LoRA-adapted diffusion models in preserving and innovating cultural heritage, especially in the fields of digital fashion, pattern design, and virtual cultural applications.

Keywords: Atlas Patterns; Artificial Intelligence; Pattern Design; Low-Rank Adaptation; Cultural Heritage

1 Introduction

The Atlas pattern is a representative example of intangible cultural heritage in textile craftsmanship in Xinjiang, celebrated for its vibrant colors and intricate structures. Utilizing generative AI technology to achieve its digital reproduction and integration into fashion designing not only modernizes the preservation of this traditional art form but also facilitates its application in virtual environments. This, in turn, contributes to broader cultural dissemination and strengthens young people's recognition of traditional culture. Generative AI has shown considerable promise in the field of artistic pattern generation. Existing research, both domestic and international, primarily concentrates on the following areas: In 2016, Gatys et al. proposed neural style transfer

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as a GAN-based method for texture synthesis [1]. In 2018, Karras et al. introduced the StyleGAN series, which significantly improved the quality and detail of generated images [2]. In 2022, Rombach et al. proposed the Stable Diffusion model, which enabled high-resolution image synthesis and text-to-image semantic control. However, when applied directly to culturally specific patterns, it often struggles to capture their symbolic meaning. In 2021, Hu et al. introduced the Low-Rank Adaptation (LoRA) method, which enhances model fine-tuning efficiency by reducing the number of trainable parameters [3]. However, this technology remains largely unexplored in the domain of traditional pattern generation. Due to its advantages in high-quality image generation, diffusion models have become a popular research focus [4]. In 2020, Ho et al. proposed the Denoising Diffusion Probabilistic Model (DDPM), marking a new path for diffusion models [5]. For example, in 2024, Dai et al. applied LoRA to digitalize Chinese paper-cutting, achieving accurate reproduction of symbolic features [6]. Similarly, Alfalasi et al. integrated LoRA-tuned Stable Diffusion models into coloring therapy with Emirati patterns in 2024 [7]. Diffusion models have recently demonstrated superior performance and stability over GAN-based architectures in high-quality image generation tasks [8]. This technique has drawn increasing attention in generative tasks where domain-specific adaptation is necessary with minimal resources.

This study aims to evaluate the applicability of generative AI in handling complex traditional pattern generation through targeted experiments and to explore its potential role in cultural pattern design. While generative models have shown promise in image synthesis, their ability to learn and replicate abstract, symbolically rich textile patterns remain underexplored. To address this gap, the study applies the Low-Rank Adaptation (LoRA) technique to train an AI image generation model for Atlas patterns and assesses its output quality. LoRA is a parameter-efficient fine-tuning method for pre-trained large-scale models, such as Stable Diffusion (SD). By updating a small subset of parameters through low-rank matrix decomposition, LoRA significantly reduces memory usage and computational demands, making it well-suited for training on lower-specification hardware. In this study, the LoRA model achieved the best alignment between semantic prompts and the original dataset under the following configuration: epoch = 100, batch size = 2, and U-Net learning rate = 8×10^{-4}.

2 Method

This study utilizes a pre-trained Stable Diffusion (SD) model, enhanced with Low-Rank Adaptation (LoRA) technology, to achieve efficient parameter fine-tuning under limited GPU memory conditions. The methodology consists of three key phases. First, we collected and preprocessed 103 Atlas silk patterns to construct an image-text paired dataset, categorizing the patterns into Iconographic, Directional, and Cultural Semiotic types. Second, we experimentally optimized parameters (batch size and U-Net learning rate) and evaluated performance through loss curve analysis and quantitative metrics (MSE and SSIM). The low-rank decomposition in LoRA reduces the number of trainable parameters by 90%, enabling efficient adaptation on resource-constrained hardware. Semantic prompts (e.g., “Atlas, tassels, fence patterns”) effectively guide the model to generate images that maintain both detailed features and overall stylistic consistency with traditional Atlas images.

The computational environment for this research includes an Intel(R) Core (TM) i5-4460 CPU @ 3.20 GHz, a NVIDIA GEFORCE RTX2060 GPU, and a software environment consisting of Python 3.10.11 and PyTorch 1.12.1. The images generated through this training approach exhibit