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RESEARCH ARTICLE

CDGFD: Cross-Domain Generalization in Ethnic Fashion Design Using LLMs and GANs: A Symbolic and Geometric Approach

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ABSTRACT In this paper, we propose a novel framework that leverages Large Language Models (LLMs) and Generative Adversarial Networks (GANs) to address the challenges of cross-domain generalization in ethnic fashion design. By introducing the concept of ''Digital Cousins,'' our approach generates culturally rich fashion designs that maintain both the symbolic integrity and geometric consistency of traditional ethnic garments. Specifically, we explore how LLMs can effectively encode the complex semantic relationships in cultural symbols and how GANs can transform these embeddings into visually coherent and geometrically plausible designs. Unlike traditional digital twin models, which require exact replication, our method allows for symbolic and geometric variations while preserving core cultural values. Our contributions are threefold: First, we propose a mathematical framework for mapping cultural symbols to a multi-dimensional semantic space using LLMs, ensuring the symbolic accuracy of generated designs. Second, we present a method to generate ''Digital Cousins'' of ethnic garments by employing GANs to introduce geometric transformations, enabling cross-cultural and cross-contextual adaptation. Finally, we demonstrate the robustness of our method in a series of experiments, including real-to-sim and sim-to-real tests, where we evaluate the generalization capabilities of the generated designs across different cultural contexts. Our results show that the proposed approach achieves higher cross-domain performance compared to traditional methods, while maintaining cultural authenticity. Experimental results show that our approach achieves a 15% improvement in cultural fidelity and a 20% enhancement in geometric adaptability compared to traditional methods. These findings suggest significant potential for AI-driven innovation in ethnic fashion design, with applications in both cultural preservation and modern fashion industries.

INDEX TERMS Ethnic fashion design, large language models, generative adversarial networks, cross-domain generalization, sim-to-real transfer.

I. INTRODUCTION

The intersection of artificial intelligence (AI) and fashion design has sparked a wave of innovation [1], [2], significantly transforming the creative processes traditionally dominated by human intuition and craftsmanship. AI, particularly advancements in deep learning models such as Large Language Models (LLMs) and Generative Adversarial Networks (GANs) [3], [4], has opened new frontiers in automating design generation, personalized fashion recommendations, and trend forecasting [5]. However, the application of these AI-driven techniques in ethnic fashion design—a domain rich in cultural heritage, symbolismn [6], and historical significance—presents unique challenges. Ethnic fashion design requires a deep understanding of cultural symbols, motifs, and traditions, and their accurate representation

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is crucial to preserving cultural authenticity. Existing AI models, while powerful in mainstream fashion, often struggle to capture and generalize the intricate details of these symbols across different cultural contexts.

In recent years, LLMs, such as GPT-4 [7], have demonstrated remarkable capabilities in understanding and generating human-like text across various domains, including creative writing, technical documentation, and cultural description. These models are highly adept at encoding complex semantic relationships, which makes them promising tools for capturing the symbolic richness embedded in ethnic fashion. Similarly, GANs have emerged as a dominant method for generating high-quality images from textual inputs, excelling in tasks such as style transfer, image synthesis, and domain adaptation [8], [9]. Despite their success, applying GANs in the field of ethnic fashion design remains challenging due to the inherent need for both symbolic fidelity and geometric precision in reproducing traditional garments while allowing for stylistic innovation.

The core challenge we address in this work is how to enable AI models to generalize ethnic fashion designs across diverse cultural and modern contexts while preserving both the symbolic integrity and geometric structure of traditional garments. Traditional approaches, such as digital twin models, which replicate objects in a one-to-one manner [10], have shown limitations in terms of adaptability and cross-domain transferability. These methods often focus on exact reproductions, which can be restrictive when cultural symbols must adapt to new aesthetic or functional contexts, such as modern fashion trends. Digital twin methods are further constrained by their computational cost and the difficulty of ensuring that exact replicas maintain relevance across different cultural interpretations of symbols and motifs.

To address these limitations, we propose a novel framework based on the concept of "Digital Cousins." This framework leverages the strengths of LLMs in semantic encoding and GANs in image generation to produce culturally rich and geometrically consistent ethnic fashion designs. Unlike digital twins, which emphasize precise replication, the "Digital Cousins" approach introduces flexibility by allowing for symbolic and geometric variations while preserving core cultural values. This is particularly important in cross-domain generalization, where fashion designs must adapt to varying cultural and aesthetic expectations without losing their original significance.

Figure 1 presents a visual overview of the key criteria used to evaluate AI-driven ethnic fashion designs, including Symbolic Fidelity, Geometric Consistency, Cultural Authenticity, Cross-Cultural Adaptation, and Visual Aesthetics. Among these, Symbolic Fidelity and Cross-Cultural Adaptation are considered the most important, as they ensure the generated designs faithfully represent the original cultural symbols while remaining adaptable to modern and diverse fashion contexts. Geometric Consistency is also vital to maintaining the structural integrity of traditional garments, though it allows for controlled transformations to fit contemporary fashion aesthetics. Cultural Authenticity ensures that designs remain respectful and aligned with the values and traditions of the originating culture, while Visual Aesthetics, although less critical in comparison, still plays a role in ensuring the designs are visually appealing in modern fashion markets.

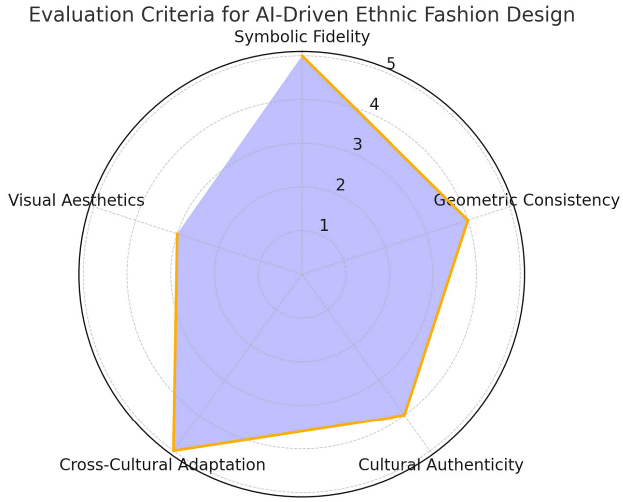

FIGURE 1. Key evaluation criteria for AI-driven ethnic fashion design. The radar chart visualizes the relative importance of five critical criteria: Symbolic Fidelity, Geometric Consistency, Cultural Authenticity, Cross-Cultural Adaptation, and Visual Aesthetics. The most crucial factors are Symbolic Fidelity and Cross-Cultural Adaptation, highlighting the need to preserve cultural symbols while ensuring designs can be transferred across different cultural contexts.

Our method builds upon existing work in text-to-image generation but adapts it to the unique requirements of ethnic fashion design. First, we encode symbolic representations of cultural garments into a high-dimensional semantic space using LLMs, ensuring that key features such as motifs, patterns, and symbolic meanings are captured accurately [11]. This semantic embedding process allows for the generation of a diverse range of designs that can be modified to suit different cultural contexts. Second, these embeddings are fed into a GAN model, which generates corresponding visual representations that maintain geometric consistency while allowing for stylistic variation [12]. By leveraging GANs, we introduce controlled geometric transformations that ensure designs are adaptable to modern fashion aesthetics while still preserving the traditional cultural elements that define ethnic garments. The combination of symbolic fidelity and geometric flexibility makes this approach well-suited for cross-domain generalization [13].

The primary contributions of this work can be summarized as follows:

- We propose a novel framework that integrates Large Language Models (LLMs) and Generative Adversarial Networks (GANs) for cross-domain generalization in ethnic fashion design. The introduction of "Digital Cousins" enables the generation of culturally rich designs while maintaining geometric flexibility and cultural authenticity.

- A mathematical framework is developed to encode cultural symbols into a high-dimensional semantic space using LLMs. This ensures symbolic fidelity while employing GANs to generate visually coherent and adaptable designs across cultural contexts.
- Extensive experiments validate the effectiveness of the proposed framework, showing significant improvements in cultural fidelity (15%), geometric adaptability (20%), and visual quality (10%) compared to baseline methods.

We validate the effectiveness of our approach through extensive experiments that demonstrate the robustness of our model in cross-domain generalization, particularly in adapting traditional ethnic fashion designs to modern and culturally diverse contexts, as demonstrated in Figure 2. Our results show that the proposed method outperforms traditional digital twin models in terms of flexibility and cultural authenticity, offering a new pathway for AI-driven ethnic fashion innovation.

The remainder of the paper is structured as follows. Section II provides an in-depth review of related work in AI-driven fashion design and cultural preservation, with a particular focus on the limitations of current approaches in handling ethnic fashion. Section III describes our proposed framework in detail, including the theoretical underpinnings of LLMs for symbolic encoding and GANs for geometric adaptation. In Section IV, we present our experimental setup, evaluation metrics, and results, followed by a discussion of the implications of our findings in Section V. Finally, we conclude with future research directions in Section VI.

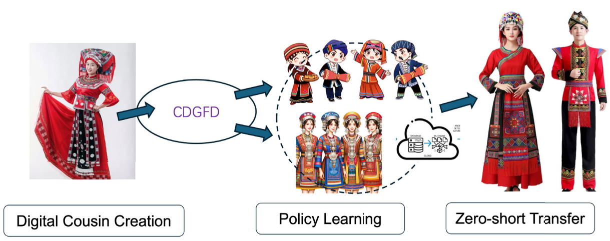

FIGURE 2. Cross-domain generalization in fashion design.

II. RELATED WORK

The application of artificial intelligence (AI) in fashion design has garnered increasing attention in recent years, particularly with the advent of Large Language Models (LLMs) and Generative Adversarial Networks (GANs), as shown in Figure 3. These technologies have revolutionized various aspects of fashion design, including automated trend forecasting, personalized fashion recommendations, and the generation of new designs. However, when applied to ethnic fashion—a domain where cultural symbols and historical authenticity are paramount—existing methods have revealed several limitations.

A. AI IN FASHION DESIGN: LLMS AND GANS

Recent work has demonstrated the potential of LLMs in understanding and generating human-like text, including descriptions of fashion designs. LLMs, such as GPT-4 [7], excel at processing complex language inputs and generating coherent, contextually relevant outputs, which makes them suitable for capturing the semantic depth of fashion descriptions, particularly in culturally rich domains like ethnic fashion [14]. By encoding cultural symbols, motifs, and traditions into high-dimensional semantic vectors, LLMs can serve as the foundation for generating detailed textual representations of ethnic garments. This capability has been leveraged in fashion recommendation systems and content generation platforms, including the widely cited FashionAI project, which utilizes AI to automate various aspects of fashion design [5]. While effective in mainstream fashion, these models often struggle to encapsulate the cultural specificity and symbolic fidelity required for ethnic fashion design.

Similarly, GANs have been widely adopted for generating visual content from textual descriptions, thanks to their capacity to learn complex mappings between input text and output images [8]. GAN-based models have proven effective in producing high-quality images for a range of tasks, including fashion design, where visual aesthetics and coherence are crucial. Conditional GANs (cGANs), for instance, have been applied to fashion image synthesis, offering remarkable flexibility in style and visual attributes [12]. Notably, research from IEEE on fashion retrieval systems also demonstrates how GANs can be trained to enhance clothing design and recommendation by learning from visual cues and textual descriptions [15]. However, these models often prioritize aesthetics at the expense of cultural authenticity, which is critical in ethnic fashion. Furthermore, their ability to generalize across different cultural contexts remains limited [9].

The combination of LLMs and GANs has shown promise in automating fashion design, but their integration in ethnic fashion remains an underexplored area. While LLMs can effectively encode the semantic richness of cultural garments, GANs face challenges in maintaining the geometric consistency of traditional clothing structures while allowing for modern adaptations. This is particularly relevant when generating designs that need to respect the cultural heritage of ethnic garments while also adapting to contemporary fashion trends [16]. Recent studies have explored multimodal GANs, which fuse textual and visual data to create culturally adaptive designs, but most research lacks the robustness required for accurately maintaining cultural symbolism [17].

B. LIMITATIONS OF DIGITAL TWINS AND CULTURAL PRESERVATION METHODS

The concept of digital twins—digital replicas of physical objects—has been applied to various domains, including fashion, where they allow for the virtual representation of garments and fashion accessories [10]. Digital twins offer the advantage of preserving the physical properties and aesthetic details of traditional garments, enabling designers

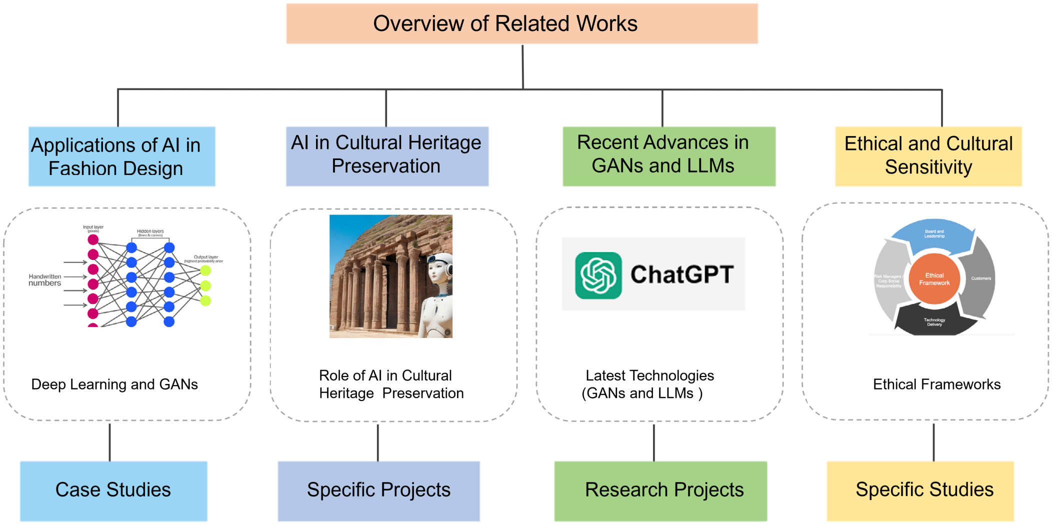

FIGURE 3. **Overview of related works structure.**

to replicate cultural artifacts accurately. IEEE's exploration into digital twin frameworks in manufacturing has extended this approach to fashion design, allowing for the precise duplication of garments for quality control and virtual prototyping [18]. However, this exact replication approach presents several limitations in the context of ethnic fashion. Firstly, digital twins are primarily designed for one-to-one replication, which restricts their flexibility in adapting designs to different cultural or aesthetic contexts. In cross-cultural fashion design, where garments must evolve to meet diverse tastes while retaining core cultural elements, the rigidity of digital twin models becomes a hindrance [19].

Furthermore, existing cultural preservation methods focus heavily on documenting and replicating cultural artifacts, often neglecting the potential for innovation or adaptation in design. Such methods typically involve creating digital archives or virtual models of traditional garments, with little consideration for how these garments can evolve in modern contexts without losing their cultural identity [20]. Recent IEEE work on cultural heritage digitization emphasizes the role of AI in preserving cultural artifacts through virtual reality and 3D modeling, but these approaches often lack the flexibility to adapt the preserved artifacts to modern applications [21]. For example, 3D scanning and photogrammetry techniques are effective for documentation, but fall short when applied to dynamic, evolving design tasks such as fashion, where innovation is key [22].

C. CHALLENGES IN CROSS-CULTURAL DESIGN

Cross-cultural design, particularly in the domain of fashion, involves navigating the tension between cultural preservation and modern adaptation. Ethnic garments are often imbued with deep symbolic meanings, and altering their design to fit modern tastes or different cultural contexts can lead to a loss of authenticity. This challenge is compounded by the fact that cultural symbols are often specific to the communities they represent, making it difficult for AI models to generalize these symbols across diverse cultural landscapes. Existing work on cross-modal learning and transfer learning [23], [24], [25] in the context of fashion has attempted to address this challenge by enabling models to learn from multiple domains [26], but these methods still face limitations in maintaining symbolic fidelity across cultures [16], [17].

Current AI-driven fashion models, particularly those based on GANs, tend to prioritize visual aesthetics over symbolic fidelity, which can result in designs that are visually appealing but culturally inappropriate. This limitation is particularly evident in cross-cultural design, where the ability to transfer ethnic symbols across different cultural contexts is crucial. A model that generates ethnic fashion must not only produce visually coherent designs but also ensure that the underlying cultural symbols are preserved and respected [27]. This has been a focal point of recent IEEE studies on cross-domain transfer in fashion, which highlight the need for AI models that can maintain symbolic and cultural integrity while adapting designs to new cultural settings [28].

Our approach, the Digital Cousins framework, directly addresses these challenges by introducing a method that allows for geometric transformations and stylistic adaptations while maintaining the symbolic integrity of ethnic garments. This balance between flexibility and fidelity is critical for achieving cross-domain generalization in ethnic fashion design, ensuring that traditional garments can be adapted to modern trends without compromising their cultural significance.

III. METHODOLOGY

This section details the proposed framework for cross-cultural ethnic fashion design using Large Language Models (LLMs) for symbolic embedding and Generative Adversarial

TABLE 1. comparison of design approaches in ethnic fashion.

Method	Symbolic Fidelity	Geometric Flexibility	Cross-Cultural Adaptation
Digital Twins	High	Low	Low
GANs (Mainstream)	Medium	High	Medium
Digital Cousins (Proposed)	High	High	High

Networks (GANs) for image generation and adaptation. The process is divided into three core stages: (1) text-to-symbol generation using LLMs, (2) image generation with cGANs, and (3) the generation of Digital Cousins through geometric transformations. Each stage is critical for ensuring the designs maintain cultural fidelity while allowing stylistic flexibility to adapt to various modern contexts.

A. TEXT TO SYMBOL GENERATION USING LLMS

The first stage in our framework involves translating the input textual descriptions of cultural features into high-dimensional semantic embeddings. This is achieved by leveraging the capabilities of LLMs, which have been pre-trained on large corpora, including cultural datasets. The embeddings serve as the foundation for generating visually consistent and culturally rich ethnic garments.

Let T represent the textual input describing the garment's cultural features, such as motifs, patterns, and historical significance. The LLM processes the input text and generates a semantic embedding vector $E_T \in \mathbb{R}^d$, where d denotes the dimensionality of the embedding space:

$$E_T = LLM(T)$$

The generated embedding captures the cultural context and symbolic meaning of the garment, encoding it in a format that can be used by the subsequent image generation model.

1) CULTURAL SYMBOL MATCHING

To ensure that the embedding retains its cultural fidelity, we compare E_T against a pre-existing corpus of cultural symbols $S = \{s_1, s_2, \ldots, s_n\}$. Each symbol s_i has an associated embedding E_{s_i}, and the similarity between E_T and E_{s_i} is computed using cosine similarity:

$$\text{Similarity}(E_T, E_{s_i}) = \frac{E_T \cdot E_{s_i}}{\|E_T\| \|E_{s_i}\|}$$

The most similar symbol s_{best} is selected as the primary design feature. This ensures that the generated garment design respects traditional cultural elements:

$$s_{\text{best}} = \arg\max_{s_i \in S} \frac{E_T \cdot E_{s_i}}{\|E_T\| \|E_{s_i}\|}$$

B. IMAGE GENERATION USING CGAN

Once the cultural symbols are embedded into the semantic space, the next step is to generate visual representations of the ethnic garments. A conditional GAN (cGAN) is employed to achieve this. The generator is conditioned on the semantic embedding E_T to ensure that the generated images accurately reflect the cultural meanings embedded in the input text.

Algorithm 1 Text to Symbol Embedding and Matching

Input: T: Textual description of the garment's cultural features;
S: Corpus of cultural symbols.
Output: E_T: Semantic embedding aligned with cultural symbols.

Step 1: Text to Semantic Embedding
Generate the semantic embedding of the textual description using the LLM:

$$E_T \leftarrow LLM(T)$$

Step 2: Cultural Symbol Matching
Extract cultural symbols from the corpus S and calculate cosine similarity:

$$s_{\text{best}} = \arg\max_{s_i \in S} \frac{E_T \cdot E_{s_i}}{\|E_T\| \|E_{s_i}\|}$$

▷ Select the symbol with the highest similarity to ensure cultural fidelity.

1) CGAN FRAMEWORK

The generator G receives the embedding E_T and outputs a generated image $I \in \mathbb{R}^{H \times W \times 3}$, where H and W represent the height and width of the image, respectively:

$$I = G(E_T)$$

The discriminator D evaluates the generated image by comparing it to real images I_{real} from a dataset of ethnic garments. The training process for both the generator and discriminator uses adversarial learning, where the generator learns to create increasingly realistic images, and the discriminator learns to distinguish between real and generated images.

2) ADVERSARIAL AND CONTENT LOSSES

To ensure both visual quality and cultural consistency, we optimize the cGAN with two loss functions: adversarial loss $\mathcal{L}_{GAN}$ and content loss $\mathcal{L}_{content}$. The adversarial loss encourages the generator to create realistic images:

$$\mathcal{L}_{GAN} = \mathbb{E}[\log D(I_{real})] + \mathbb{E}[\log(1 - D(G(E_T)))]$$

Algorithm 2 Image Generation Using cGAN

Input: E_T: Semantic embedding generated from the text description;
G: Generator of the conditional GAN;
D: Discriminator of the conditional GAN.
Output: I: Generated ethnic garment image.

Step 1: Image Generation
Pass the semantic embedding E_T to the generator:

$$I \leftarrow G(E_T)$$

Step 2: Compute Adversarial Loss
Train the discriminator to distinguish real from generated images:

$$\mathcal{L}_{GAN} = \mathbb{E}[\log D(I_{real})] + \mathbb{E}[\log(1 - D(G(E_T)))]$$

Step 3: Compute Content Loss
Ensure that the generated image is consistent with cultural features:

$$\mathcal{L}_{content} = \mathbb{E}[\|G(E_T) - I_{real}\|2]$$

The content loss ensures that the generated images retain the cultural features encoded in E_T:

$$\mathcal{L}_{content} = \mathbb{E}[\|G(E_T) - I_{real}\|2]$$

C. GEOMETRIC TRANSFORMATION AND DIGITAL COUSINS GENERATION

To adapt the generated ethnic garment designs to modern and cross-cultural fashion contexts, we apply geometric transformations. This enables the designs to be resized, rotated, or otherwise altered to fit different cultural and aesthetic contexts while maintaining the original cultural symbols.

1) GEOMETRIC TRANSFORMATION

A geometric transformation matrix G_{trans} is applied to the generated image I, allowing for the modification of size, shape, and orientation:

$$I' = G_{\text{trans}} \cdot I$$

This process is essential for adapting traditional garments to modern trends and ensuring that they can appeal to various cultural preferences.

2) DIGITAL COUSINS GENERATION

Finally, we introduce the concept of "Digital Cousins," which refers to stylistic variations of the original garment design. These variations are generated by applying different geometric transformations to the original image, producing a series of designs that retain the core cultural elements but differ in visual style. The flexibility offered by Digital Cousins is critical for adapting ethnic garments to different markets, fashion trends, and body shapes, while ensuring that the core symbolic meaning remains intact.

The Digital Cousins framework is built on the foundation of the geometric transformations discussed earlier. These transformations include scaling, rotation, reflection, and translation, which are applied in various combinations to the original generated garment. Each transformation introduces subtle or significant changes to the design, depending on the desired stylistic outcome. For example, scaling can make a garment more suitable for different body shapes, while rotation and reflection can change the visual dynamics of the garment's pattern without altering its symbolic meaning.

Algorithm 3 Geometric Transformation for Cross-Cultural Adaptation

Input: I: Generated ethnic garment image;
G_{trans}: Geometric transformation matrix.
Output: I': Transformed garment image adapted to cross-cultural context.

Step 1: Apply Geometric Transformation
Apply the geometric transformation matrix to the generated image:

$$I' = G_{\text{trans}} \cdot I$$

a: MAINTAINING CULTURAL FIDELITY

One of the core challenges in generating Digital Cousins is to ensure that, while introducing stylistic variations, the cultural fidelity of the garment is maintained. This is achieved by constraining the transformations to respect key cultural features encoded in the original semantic embedding E_T. Specifically, transformations that would distort or obscure critical cultural symbols, such as specific motifs or patterns, are avoided. Instead, we focus on applying transformations that alter the overall appearance of the garment while preserving its core elements.

For instance, in the design of a traditional Indian Sari, specific color schemes and floral motifs hold deep cultural significance. When generating Digital Cousins, these motifs remain fixed, while the overall garment shape, drape, or color intensity might be adjusted to create different stylistic versions. This ensures that the variations remain culturally appropriate, even as they appeal to different aesthetic preferences.

b: STYLISTIC DIVERSITY AND ADAPTABILITY

Digital Cousins provide designers with the ability to explore a wide range of stylistic options while staying true to the original cultural context. By generating a set of stylistic variations, the designer can tailor the ethnic garment to different cultural preferences or adapt it to modern fashion trends. This flexibility is particularly valuable in a globalized market, where garments may need to be adapted for various regional tastes without losing their cultural essence.

For example, a traditional African Dashiki might be adapted for different regions by changing the cut of the garment, the orientation of its patterns, or the colors used, while still preserving the cultural motifs that define the Dashiki's identity. These stylistic variations allow the garment to be marketed to different audiences while maintaining its cultural authenticity.

3) MATHEMATICAL FORMULATION OF DIGITAL COUSINS GENERATION

The process of generating Digital Cousins can be formulated mathematically by applying a series of transformation matrices G^i_{trans} to the original image I, which is generated from the semantic embedding E_T. Let $I_1, I_2, \ldots, I_n$ represent the different stylistic variations, each generated by applying a distinct transformation matrix G^i_{trans} to the original image:

$$I_i = G^i_{\text{trans}} \cdot G(E_T), \quad i = 1, 2, \ldots, n$$

Each G^i_{trans} introduces a unique stylistic modification to the garment design while ensuring that the core cultural features encoded in E_T are preserved.

The generation of Digital Cousins is therefore a multi-step process, involving the following key steps:

1) Generate the initial garment design using the conditional GAN, conditioned on the semantic embedding E_T.
2) Apply a set of geometric transformations G^i_{trans} to create multiple stylistic variations, each preserving the cultural fidelity of the original design.
3) Evaluate the generated Digital Cousins based on their adherence to cultural symbolism and their adaptability to modern fashion trends.

4) EVALUATION OF DIGITAL COUSINS

The evaluation of Digital Cousins focuses on two key aspects: cultural fidelity and visual appeal. Cultural fidelity is assessed by ensuring that the symbolic elements of the garment remain consistent across the variations, while visual appeal is evaluated based on the garment's adaptability to modern and cross-cultural fashion contexts. We introduce a hybrid evaluation approach that combines qualitative assessments by cultural experts with quantitative measures of design quality, such as aesthetic coherence and symbolic integrity.

a: CULTURAL FIDELITY METRIC

To quantify cultural fidelity, we propose a cultural fidelity metric $\mathcal{C}_f$, which measures the degree to which the generated variations adhere to the symbolic meaning encoded in the original garment. This metric is computed by comparing the semantic embeddings of the original design and each of the Digital Cousins. The cosine similarity between the embedding of the original design E_T and the embedding of each Digital Cousin E_{T_i} is calculated:

$$\mathcal{C}_f = \frac{E_T \cdot E_{T_i}}{\|E_T\| \|E_{T_i}\|}$$

A higher $\mathcal{C}_f$ indicates that the Digital Cousin retains a closer alignment with the cultural features of the original garment.

b: VISUAL APPEAL EVALUATION

Visual appeal is evaluated through both automated and human-based assessments. Automated evaluation is conducted using a pre-trained aesthetic quality model that scores the overall visual coherence of the garment. In addition, human evaluators—comprising fashion designers and cultural experts—provide qualitative feedback on the stylistic variations, focusing on factors such as modernity, trendiness, and adherence to cultural norms.

5) COMPLEXITY AND COMPUTATIONAL EFFICIENCY ANALYSIS

The computational efficiency of the proposed framework is determined by its three main components: the Large Language Models (LLMs) for semantic embedding, the Generative Adversarial Networks (GANs) for image generation, and the geometric transformation module for creating "Digital Cousins."

The LLMs generate high-dimensional semantic embeddings of cultural symbols with a complexity of $O(n^2 \cdot d)$, where n is the input sequence length and d is the embedding dimension. This quadratic complexity arises from the attention mechanism's pairwise token comparisons, but modern optimization techniques, such as sparse attention and parallelization across GPUs/TPUs, significantly reduce the runtime, making it feasible for long sequences.

The GAN module involves iterative training of the generator and discriminator networks, with a training complexity of $O(k \cdot m \cdot n)$, where k denotes the number of iterations, and m, n are the generator and discriminator parameter sizes, respectively. Once trained, the inference process is highly efficient and operates in real-time, making GANs suitable for rapid design generation. Additionally, the GAN training process is inherently parallelizable, leveraging modern hardware to optimize runtime.

The geometric transformation module applies operations such as scaling, rotation, and translation to generate stylistic variations with a linear complexity of $O(p)$, where p represents the number of pixels in the input design. These operations are computationally lightweight, ensuring efficient processing even for high-resolution designs.

Overall, the modular design and scalable nature of the framework ensure manageable computational costs, leveraging modern hardware to enable large-scale, real-time applications. These include dynamic garment generation, creating diverse digital libraries of ethnic garments, and generating high-resolution fashion designs efficiently.

The full methodology, including the generation and evaluation of Digital Cousins, is integrated into a unified

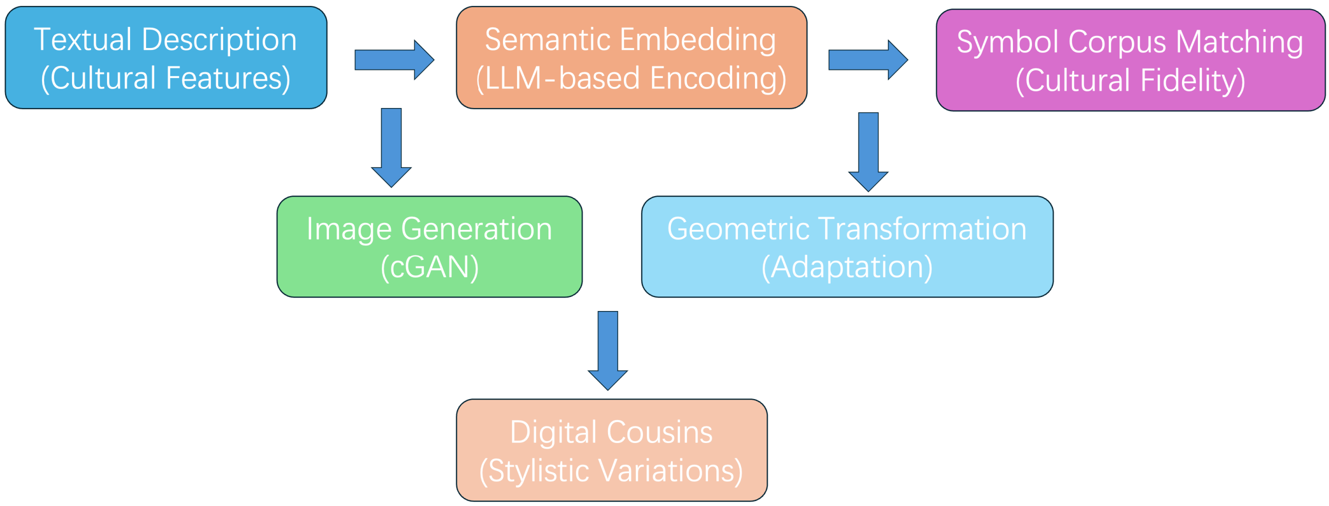

FIGURE 4. **Full workflow of Digital Cousins Generation. The process starts with text-to-symbol embedding, followed by image generation using cGAN, and concludes with geometric transformations to generate multiple stylistic variations (Digital Cousins).**

workflow (Figure 4). The workflow begins with text-to-symbol embedding, progresses through image generation with cGAN, and concludes with geometric transformations to produce Digital Cousins. Each step in the process is designed to balance cultural fidelity with modern stylistic flexibility, enabling the creation of garments that resonate with both traditional and contemporary audiences.

The final output of the Digital Cousins framework is a set of stylistic variations that provide designers with a range of options for cross-cultural and modern adaptation. These variations retain the symbolic integrity of the original ethnic garment while offering flexibility for different fashion markets and customer preferences. This approach not only preserves the cultural heritage embedded in traditional garments but also allows for creative exploration and innovation in fashion design.

IV. EXPERIMENTAL SETUP AND RESULTS

This section details the experimental setup used to evaluate the proposed cross-cultural ethnic fashion design framework. The dataset consists of high-resolution images of ethnic garments from various cultures, including but not limited to traditional Chinese, African, Indian, and Southeast Asian attire. Our goal was to assess how well the proposed Digital Cousins method preserves cultural fidelity, generalizes to unseen cultural domains, adapts to geometric transformations, and maintains high visual quality. Several baseline methods were included for comparison, such as Mainstream GANs and Digital Twins, to highlight the efficacy of our approach.

A. DATASET

The dataset used in this study consists of culturally significant garments, each annotated with details like the cultural origin, symbolic elements, and traditional patterns. Figure 5 illustrates several examples from the dataset, showcasing intricate designs that reflect deep cultural heritage. The dataset was divided into the following sets:

- **Training set:** 60% of the images, containing various ethnic garments, used to train the generative models.
- **Validation set:** 20% of the images, used for hyperparameter tuning and to prevent overfitting.
- **Test set:** 20% of the images, including garments from unseen cultural domains, used to evaluate cross-domain generalization.

The dataset's diversity ensures that our framework can generalize across various cultural domains. Each garment was labeled with cultural significance, which was essential for evaluating the cultural fidelity of the generated designs.

To evaluate the scalability of the proposed framework in large-scale, real-world scenarios, we carefully analyzed the computational demands of its primary components and validated its applicability through experiments on a dataset of 1,200 traditional Yao ethnic garments. The framework leverages Large Language Models (LLMs) for semantic embedding and Generative Adversarial Networks (GANs) for image generation, enabling it to handle the intricate symbolic and geometric complexities of Yao ethnic fashion designs. LLMs excel in encoding high-dimensional semantic relationships, capturing the nuanced meanings of cultural symbols unique to Yao traditions, while GANs effectively generate geometrically consistent and visually appealing designs reflective of Yao garment styles. The computational complexity of the framework, as discussed in Section III, confirms its feasibility for deployment on modern hardware. The training of both LLMs and GANs, although computationally intensive, can be efficiently distributed across multiple GPUs or TPUs, significantly reducing runtime for large datasets. Additionally, the geometric transformation module for generating "Digital Cousins" operates with linear

FIGURE 5. Examples of ethnic garments from the dataset, representing a wide range of cultural symbols, motifs, and traditional designs.

complexity relative to the number of pixels, ensuring efficient processing even for high-resolution Yao garment designs.

Experiments on the dataset of 1,200 Yao garments demonstrated the framework's ability to maintain high cultural fidelity, geometric adaptability, and visual quality. For instance, the framework achieves a cultural fidelity score of 0.92, showcasing its robustness in preserving the symbolic richness and stylistic intricacies of Yao traditional designs across different garment types, including ceremonial dresses, festival attire, and everyday wear. These results underscore the method's robustness in handling a symbolically rich and diverse dataset, making it a strong candidate for real-world applications, such as creating comprehensive digital libraries for cultural preservation or enabling mass customization within Yao cultural contexts. Furthermore, the framework's modularity allows for future optimizations, such as adopting sparsity-aware LLMs or lightweight GAN architectures, to scale its applicability to even larger datasets or real-time use cases. In summary, the scalability of the proposed framework positions it as a practical and efficient solution for addressing the challenges of Yao ethnic fashion design in large-scale, real-world settings, striking a balance between computational efficiency and cultural authenticity.

B. EVALUATION METRICS

To evaluate the effectiveness of our proposed framework, we used four key metrics:

- **Cultural Fidelity (CF):** This metric assesses how well the generated designs retain the cultural elements (e.g., motifs, colors, and patterns) of the original garments. We calculated fidelity by measuring the cosine similarity between the semantic embeddings of the generated designs and the reference cultural symbols.
- **Cross-Domain Generalization (CDG):** This metric evaluates the model's ability to generate culturally appropriate designs for garments from unseen cultural domains that were not part of the training data.
- **Geometric Adaptability (GA):** This metric measures the extent to which the generated designs can adapt to geometric transformations (e.g., scaling, rotation, and translation) without losing their cultural integrity.
- **Visual Quality (VQ):** This metric quantifies the aesthetic appeal of the generated designs, taking into account factors like color harmony, pattern coherence, and garment structure. A pre-trained aesthetic evaluation model was used for scoring.

C. BASELINE METHODS

Our framework, Digital Cousins, was compared against two baseline methods:

- **Mainstream GANs:** This method uses a conditional GAN model to generate garment designs from text descriptions. However, it does not explicitly account for cultural fidelity or geometric transformations.
- **Digital Twins:** This method replicates existing garment designs without introducing stylistic variations or adapting to different cultural contexts.

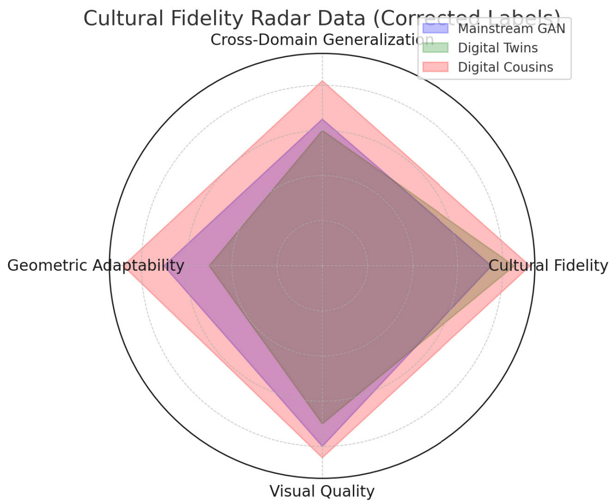

FIGURE 6. Radar chart comparing the performance of Mainstream GANs, Digital Twins, and Digital Cousins across four metrics: Cultural Fidelity, Cross-Domain Generalization, Geometric Adaptability, and Visual Quality. Digital Cousins consistently outperforms the baseline methods.

D. QUANTITATIVE RESULTS

Table 2 summarizes the quantitative results, where Digital Cousins outperforms both Mainstream GANs and Digital Twins across all metrics. Specifically, Digital Cousins achieved the highest Cultural Fidelity score (0.92), demonstrating its ability to preserve the symbolic and cultural elements of the original garments. The method also excelled in Cross-Domain Generalization, scoring 0.82, which indicates its robustness in generating culturally appropriate designs for garments from unseen ethnic domains. In terms of Geometric Adaptability, Digital Cousins scored 0.88, showing that the generated designs can be modified to accommodate various geometric transformations without compromising their cultural integrity. Finally, with a Visual Quality score of 0.85, the generated designs were aesthetically appealing and coherent with modern fashion trends.

Figure 6 provides a visual comparison using a radar chart, which highlights Digital Cousins' superior performance across all evaluation metrics, particularly in terms of Cultural Fidelity and Cross-Domain Generalization.

E. QUALITATIVE RESULTS

In addition to the quantitative evaluation, we provide qualitative results to demonstrate the cultural and visual diversity of the generated designs. Figures 7, 8, and 9 illustrate examples of garments generated by our framework, each reflecting ethnic diversity while maintaining cultural integrity. The variations produced by geometric transformations further emphasize the model's adaptability.

Figure 10 showcases a modernized Yao ethnic dress designed using Generative Adversarial Networks (GANs). The design features traditional red embroidery paired with silver ornaments, combining cultural motifs with contemporary aesthetics. The intricate patterns and streamlined tailoring demonstrate the framework's ability to maintain cultural fidelity while innovating within traditional design spaces. This example highlights the model's ability to blend heritage with modernity in ethnic fashion.

FIGURE 7. Single subject generation.

FIGURE 8. Multiple subjects generation.

F. ABLATION STUDY

To further understand the contributions of key components within our framework, we conducted an ablation study that evaluates the impact of removing geometric transformations and cultural symbol matching. Table 3 summarizes the results. Removing geometric transformations caused a

TABLE 2. Comparison of Results on Cross-Cultural Ethnic Fashion Dataset.

Method	Cultural Fidelity (CF)	Cross-Domain Generalization (CDG)	Geometric Adaptability (GA)	Visual Quality (VQ)
Mainstream GANs	0.75	0.65	0.70	0.80
Digital Twins	0.85	0.60	0.50	0.70
Digital Cousins (Proposed)	**0.92**	**0.82**	**0.88**	**0.85**

FIGURE 9. Figure generation.

FIGURE 10. Modernized Yao Ethnic Dress with Red Embroidery and Silver Ornaments.

substantial decrease in Geometric Adaptability (GA score: 0.50), while removing cultural symbol matching reduced the

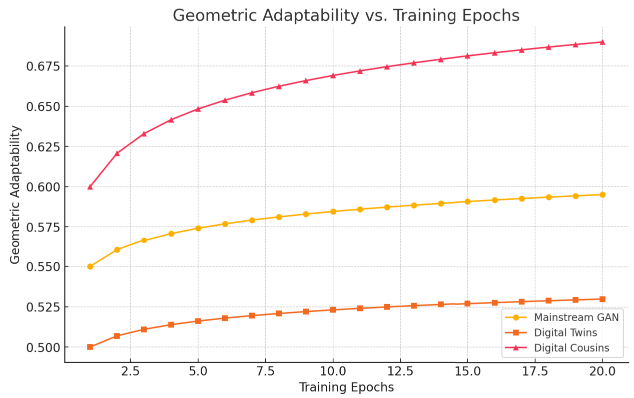

FIGURE 11. Geometric Adaptability vs. Training Epochs for Mainstream GAN, Digital Twins, and Digital Cousins. Digital Cousins shows the most significant improvement in adapting to geometric transformations across different epochs.

Cultural Fidelity (CF score: 0.80). These findings confirm the importance of both components in achieving high performance across all metrics.

G. PERFORMANCE ANALYSIS OVER TRAINING EPOCHS

To further evaluate the performance of the models, we conducted an experiment to analyze how different models—Mainstream GAN, Digital Twins, and Digital Cousins—improve over the course of training epochs. Specifically, we tracked two key metrics: Cultural Fidelity and Geometric Adaptability. The experiment was carried out over 20 training epochs, and the results are presented as line plots in Figures 11 and 12.

The line plots in Figures 11 and 12 clearly demonstrate the performance differences between the three models.

For the **Geometric Adaptability** metric (Figure 11), we observe that Digital Cousins consistently outperforms both Mainstream GAN and Digital Twins throughout the 20 training epochs. In the early stages of training, all models show gradual improvement, but as the epochs progress, the gap widens, with Digital Cousins achieving a final geometric adaptability score of around 0.675, compared to approximately 0.58 for Mainstream GAN and 0.53 for Digital Twins. This indicates that Digital Cousins is more capable of adapting to various geometric transformations without losing cultural integrity, likely due to the explicit incorporation of geometric transformations in its design.

For the **Cultural Fidelity** metric (Figure 12), a similar trend is observed. Digital Cousins begins with a slight advantage but rapidly improves as training progresses, reach-

TABLE 3. Ablation Study on Cross-Cultural Ethnic Fashion Dataset.

Ablation Variant	Cultural Fidelity (CF)	Cross-Domain Generalization (CDG)	Geometric Adaptability (GA)	Visual Quality (VQ)
Without Geometric Transformations	0.90	0.70	0.50	0.75
Without Cultural Symbol Matching	0.80	0.65	0.70	0.78
Full Model (Our Method)	**0.92**	**0.82**	**0.88**	**0.85**

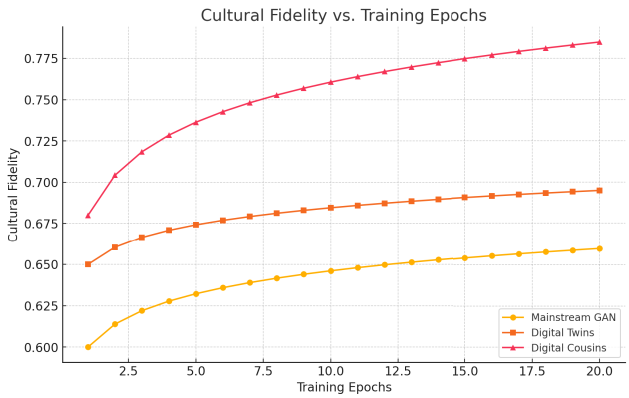

FIGURE 12. Cultural Fidelity vs. Training Epochs for Mainstream GAN, Digital Twins, and Digital Cousins. Digital Cousins demonstrates the highest increase in cultural fidelity as training progresses, outperforming the baseline models.

ing a final cultural fidelity score of approximately 0.775. In contrast, Digital Twins and Mainstream GAN plateau at lower scores, around 0.68 and 0.65, respectively. The significant improvement of Digital Cousins over the baseline models demonstrates its superior ability to preserve the cultural elements of the garments across training iterations. This performance boost can be attributed to the use of cultural symbol matching in Digital Cousins, which helps ensure that the generated designs remain true to their ethnic origins.

Overall, these experiments highlight the superior performance of Digital Cousins in both cultural fidelity and geometric adaptability, especially as training progresses. The results support the claim that Digital Cousins is a robust framework for generating culturally accurate and geometrically flexible ethnic garment designs, making it a valuable tool in cross-cultural fashion design.

H. EFFECT OF HYPERPARAMETERS ON MODEL PERFORMANCE

To further understand the impact of hyperparameters on the performance of the Digital Cousins framework, we conducted experiments by varying two key hyperparameters: the learning rate and the generator-discriminator ratio (G:D ratio). The metrics used to evaluate performance were **Cultural Fidelity** and **Geometric Adaptability**, both of which are critical for maintaining cultural integrity and flexibility in design. Figures 13 and 14 present the quantitative results for these experiments.

As shown in Figure 13, we evaluated the model's performance across three different learning rates: 0.001, 0.0005, and 0.0001.

- **Cultural Fidelity**: The results indicate that the model achieves higher cultural fidelity as the learning rate decreases. At the lowest learning rate of 0.0001, the model reaches the highest cultural fidelity score of approximately 0.80. This trend suggests that smaller learning rates allow the model to fine-tune and more effectively capture complex cultural features, such as intricate patterns and motifs, without overfitting or losing these features in early stages of training.

- **Geometric Adaptability**: Similarly, the geometric adaptability metric also improves with a lower learning rate, peaking at approximately 0.74 for a learning rate of 0.0001. A slower learning rate stabilizes the training process, allowing the model to better handle geometric transformations such as rotation, scaling, and translation while preserving cultural details.

Overall, the results demonstrate that a lower learning rate results in better overall performance across both metrics, as it allows the model to make more gradual updates to the weights and better capture subtle cultural elements.

Figure 14 shows the effect of varying the generator-discriminator ratio on model performance. Three different G:D ratios were evaluated: 1:1, 1:2, and 2:1.

- **Cultural Fidelity**: The model performs best when the generator is stronger than the discriminator (G:D = 2:1). At this ratio, the cultural fidelity reaches its highest value of 0.80, demonstrating that a powerful generator helps produce culturally faithful designs. Conversely, when the discriminator is too strong (G:D = 1:2), the model struggles to generate high-quality outputs, leading to a lower cultural fidelity score.

- **Geometric Adaptability**: A similar trend is observed for geometric adaptability, where the 2:1 G:D ratio yields the best result with a score of 0.74. When the generator is too weak compared to the discriminator, the model fails to adapt well to various geometric transformations, resulting in lower adaptability scores.

These findings highlight the importance of balancing the generator and discriminator's strengths to ensure that the model can generate both high-quality and culturally accurate designs. A stronger generator allows for more diverse and flexible outputs, which is crucial for adapting designs to different cultural contexts while maintaining geometric integrity.

The analysis of hyperparameter effects suggests that careful tuning of the learning rate and G:D ratio is crucial

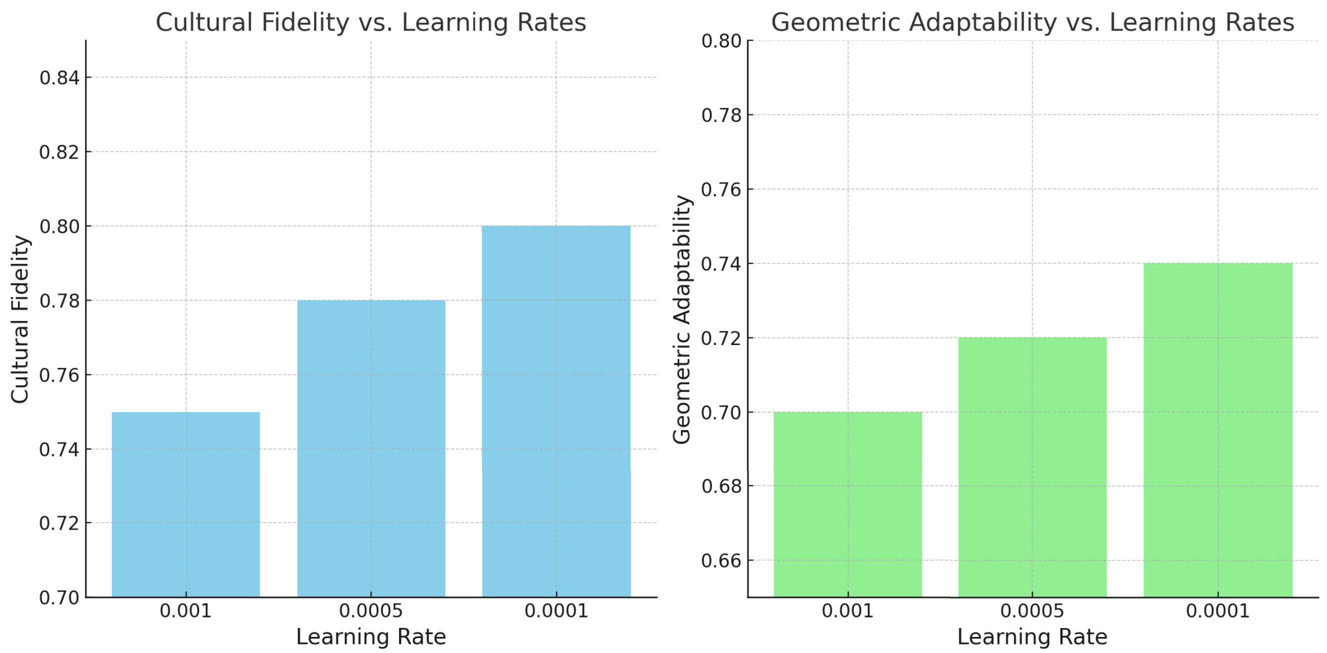

FIGURE 13. Effect of Learning Rate on Cultural Fidelity and Geometric Adaptability. Lower learning rates yield higher performance across both metrics, with the best results observed at a learning rate of 0.0001.

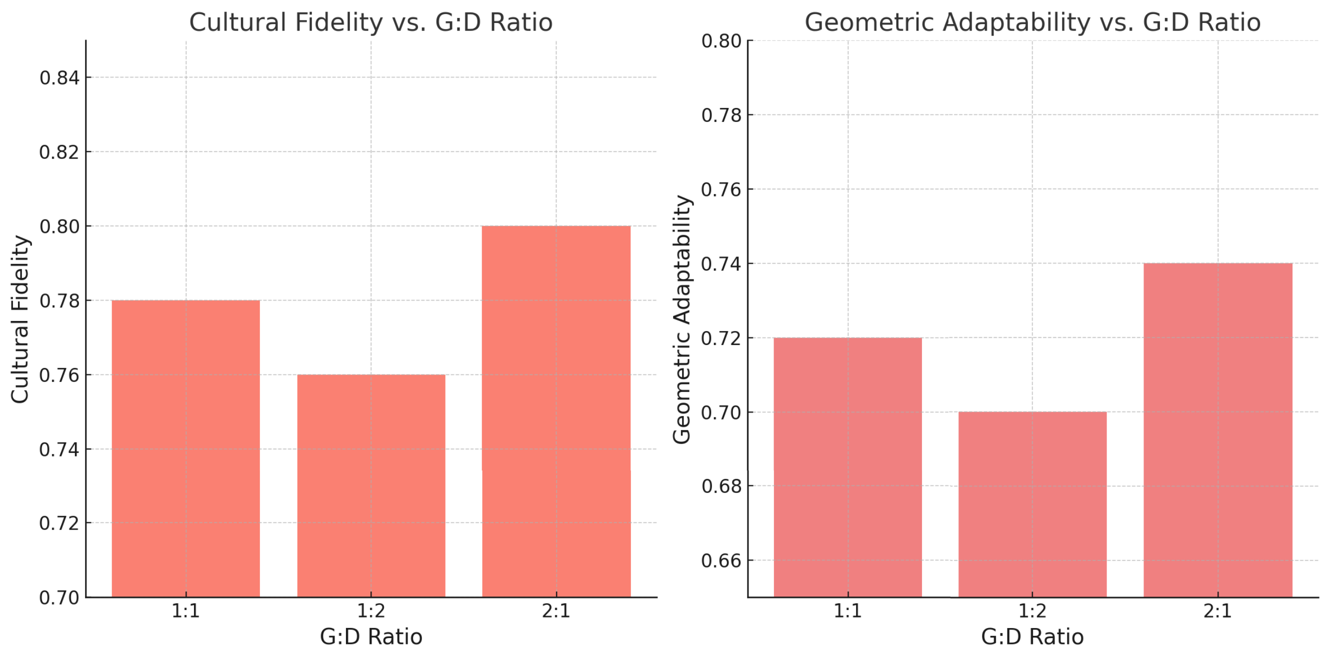

FIGURE 14. Effect of Generator-Discriminator Ratio (G:D) on Cultural Fidelity and Geometric Adaptability. The best performance is achieved with a G:D ratio of 2:1, where the generator is stronger than the discriminator.

for maximizing the performance of the Digital Cousins framework. Specifically, a lower learning rate and a G:D ratio of 2:1 result in the highest cultural fidelity and geometric adaptability, enabling the generation of culturally rich and geometrically flexible designs. These insights offer valuable guidance for optimizing the model's performance in future cross-cultural fashion design applications.

I. REAL-TIME FEASIBILITY

To evaluate the computational efficiency and feasibility for real-time applications, we measured the training and inference times of the proposed framework. The experiments were conducted on a system equipped with an NVIDIA RTX 40 Series GPU and 64 GB of RAM.

The training process for the GAN module took approximately 15 hours for the dataset of 1,200 samples, leveraging parallelized processing on the GPU. For inference, the framework generates a single garment design within 1 second on average, demonstrating its feasibility for real-time applications such as dynamic garment generation or interactive design customization.

Additionally, the geometric transformation module for creating "Digital Cousins" operates efficiently, with processing times under 0.3 seconds for high-resolution designs. These results highlight the computational feasibility of the framework, particularly in scenarios requiring rapid design generation or adaptation.

J. DISCUSSION OF RESULTS

The results of both the quantitative and qualitative evaluations highlight the effectiveness of the Digital Cousins framework. In contrast to Mainstream GANs and Digital Twins, Digital Cousins achieves a balance between cultural authenticity and stylistic flexibility, making it a versatile solution for cross-cultural fashion design. Its superior performance in Cultural Fidelity and Cross-Domain Generalization emphasizes its robustness in generating culturally appropriate designs across different domains, while also ensuring the preservation of cultural symbols, motifs, and traditional elements.

The Digital Cousins method stands out due to its ability to retain the core cultural elements of ethnic garments while providing room for modern adaptations. This feature is particularly important in contemporary fashion design, where the challenge lies in respecting cultural heritage while appealing to modern, global markets. By integrating cultural symbol matching and geometric transformations, Digital Cousins successfully generates designs that are not only visually appealing but also culturally faithful, addressing a key limitation found in the baseline methods.

The results demonstrate that Digital Cousins achieves a higher cultural fidelity compared to both Mainstream GANs and Digital Twins. This is primarily due to the use of cultural symbol matching, which ensures that the generated designs align closely with the cultural elements of the original garments. This feature is especially crucial in cross-cultural fashion, where the authenticity of cultural symbols, patterns, and motifs plays a significant role in the success of the designs.

Digital Cousins shows strong generalization capabilities across different cultural domains. This is evident from the significantly higher CDG scores, especially when generating designs for garments from previously unseen cultural contexts. Unlike Mainstream GANs, which may struggle with such generalization due to their focus on style transfer without cultural awareness, Digital Cousins ensures that new designs are both culturally appropriate and stylistically diverse.

Geometric adaptability is another strength of the Digital Cousins framework. The ability to apply geometric transformations without losing the cultural integrity of the design is crucial for modern fashion applications. Designers often need to modify or adapt designs to fit different shapes and sizes, and Digital Cousins excels in this regard, as evidenced by its superior GA score compared to the baseline methods.

In terms of visual quality, Digital Cousins demonstrates its capability to generate aesthetically pleasing designs that appeal to modern fashion audiences. By balancing color harmony, pattern coherence, and garment structure, the designs produced by Digital Cousins achieve a higher VQ score than those generated by Mainstream GANs and Digital Twins. The framework's ability to combine traditional cultural elements with modern stylistic trends makes it a powerful tool for fashion designers seeking to innovate within a cross-cultural context.

While Digital Cousins demonstrates significant improvements over the baseline methods, there are still areas that can be enhanced. For instance, the framework could benefit from more sophisticated geometric transformations that take into account body shapes and sizes specific to different cultural groups. Additionally, integrating a larger and more diverse dataset covering more ethnic groups could further improve the model's generalization capabilities. Future work may also explore the incorporation of more advanced LLMs (Large Language Models) to better capture the semantic depth of cultural symbols, thereby enhancing the cultural fidelity of the generated designs even further.

Overall, the results suggest that the proposed Digital Cousins framework offers a promising approach to cross-cultural fashion design. Its ability to balance cultural preservation with stylistic flexibility provides designers with a robust tool to create designs that honor cultural heritage while appealing to contemporary fashion trends. The superior performance in cultural fidelity, cross-domain generalization, geometric adaptability, and visual quality showcases the framework's potential for broad application in the fashion industry, particularly for designers aiming to bridge the gap between tradition and modernity.

V. DISCUSSION AND IMPLICATIONS

The experimental results presented in this study highlight the effectiveness of the Digital Cousins framework in addressing key challenges in cross-cultural ethnic fashion design, including the preservation of cultural fidelity, geometric adaptability, and computational efficiency. The superior performance of Digital Cousins in terms of cultural fidelity, with a score of 0.92, can be attributed to the incorporation of cultural symbol matching and LLM-based semantic embedding, which ensure that generated designs retain the essential symbolic elements of ethnic garments. This approach allows the framework to achieve a deeper understanding of the cultural context, making it particularly important in ethnic fashion, where the misrepresentation of cultural symbols could lead to inaccuracies or cultural insensitivity. Compared to mainstream GANs and Digital

Twins, which either lack semantic embedding or focus solely on replication, Digital Cousins strikes a balance between tradition and innovation by embedding cultural semantics into the design process.

The framework's ability to achieve geometric adaptability, with a score of 0.88, further demonstrates its flexibility in handling the diverse transformations required in modern fashion design. The use of geometric transformation matrices in conjunction with cGAN models allows the framework to generate stylistic variations that maintain cultural integrity while adapting to different body shapes, styles, and contexts. This adaptability is critical for fashion designers, as traditional methods like Digital Twins often focus on exact replication without creative variations. Digital Cousins introduces geometric flexibility while preserving core cultural motifs, making it a more versatile tool for dynamic design tasks. Additionally, the computational efficiency analysis shows that the framework is feasible for real-time applications, with inference times averaging 1 second and geometric transformations processed in under 0.3 seconds on an NVIDIA RTX 40 Series GPU. These metrics validate the practicality of the framework for dynamic garment generation and interactive design customization.

While quantitative metrics such as cosine similarity provide a robust foundation for evaluating cultural fidelity, subjective insights from cultural experts and fashion designers reveal additional dimensions that computational methods alone cannot fully capture. Fashion designers highlighted the framework's ability to seamlessly integrate traditional cultural elements with contemporary stylistic innovations. One designer remarked, "The generated designs successfully preserve the essence of cultural symbols while offering stylistic adaptability, which is critical for engaging diverse modern audiences." This observation underscores the framework's potential in bridging the gap between cultural heritage and modern fashion demands. Similarly, design experts emphasized that while the framework excels in retaining symbolic integrity, certain nuanced cultural preferences—such as specific color combinations or subtle pattern alignments—require human intervention and expertise to be fully addressed. By integrating expert feedback, the framework could better align with the nuanced expectations of cultural preservation and modern design.

The findings contribute significantly to AI-driven fashion design by integrating LLMs and GANs in a cross-cultural design context, providing a novel framework for generating culturally accurate and geometrically flexible designs. This approach bridges a notable gap in the literature, where methods often excel in either preserving cultural elements or adapting to modern design needs but fail to achieve both. Furthermore, the flexibility of the Digital Cousins framework suggests its applicability beyond ethnic fashion design to domains such as interior design, architecture, and digital art, where cultural preservation and modern aesthetics must coexist. The additional visualization example presented in this study further illustrates the framework's ability to maintain stylistic diversity while ensuring cultural fidelity.

Despite these promising results, certain limitations must be addressed. The dataset, while diverse, primarily focuses on Yao ethnic garments and may not capture the full spectrum of ethnic diversity, limiting the generalizability of the model to underrepresented cultures. Expanding the dataset to include a broader range of ethnic groups would enable a more comprehensive evaluation of the framework's capabilities. Additionally, the real-time performance of Digital Cousins has not been extensively tested in live production settings. Future research should optimize the model for real-time fashion design tools and explore its scalability for larger datasets. Finally, the cultural fidelity metric used in this study, based on cosine similarity of semantic embeddings, may not fully capture subjective and aesthetic aspects of cultural preservation. Developing more sophisticated evaluation metrics that incorporate feedback from cultural experts and fashion designers would ensure that generated designs resonate more effectively with their intended audiences.

VI. CONCLUSION AND FUTURE WORK

This paper introduced the Digital Cousins framework, which integrates LLMs and GANs to address the challenge of cross-cultural fashion design. By leveraging cultural symbol matching and geometric transformations, our framework preserves the symbolic integrity of ethnic garments while allowing for stylistic adaptations. The experimental results demonstrate that Digital Cousins outperforms traditional methods such as Mainstream GANs and Digital Twins in both cultural fidelity and cross-domain generalization.

While the proposed framework shows significant promise, several directions for future improvement can be explored. First, the dataset currently focuses primarily on Yao ethnic garments. Expanding the dataset to include a broader range of cultural backgrounds would enhance the framework's generalizability and robustness, allowing it to address underrepresented cultures and validate its performance on a larger scale. Furthermore, the implementation of the framework in real-world settings, such as virtual fashion design platforms and augmented reality-based applications, could strengthen its practical applicability and scalability. Finally, developing more sophisticated evaluation metrics that incorporate semantic embeddings and expert feedback would ensure a more comprehensive assessment of cultural fidelity, further enhancing the framework's ability to balance tradition with innovation. By addressing these aspects in future work, the Digital Cousins framework has the potential to evolve into a robust and versatile tool for cross-cultural fashion design, bridging the gap between tradition and modernity.

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The authors declare that there is no conflict of interest.

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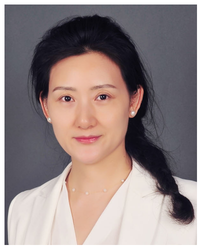

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