Fashion Product Image Generation Using Diffusion Models

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***Abstract*—The exponential growth of e-commerce platforms has created unprecedented demand for high-quality product imagery, with traditional photography approaches proving costly and time-intensive. This study presents a comprehensive end-to-end pipeline for automated fashion product image generation using advanced text-to-image diffusion models. We systematically evaluate and compare Stable Diffusion v1.5 and Kandinsky v2.2 across multiple architectural configurations, parameter settings, and evaluation metrics using the Fashion Product Images dataset containing 4,000 professionally curated samples. Our methodology incorporates sophisticated data preprocessing, CLIP-based semantic text encoding, systematic parameter grid search across guidance scales (7.5-12.0), inference steps (30-50), and scheduler variants (Euler, DDIM, PNDM). Comprehensive evaluation using CLIP Score, Fréchet Inception Distance (FID), and Inception Score demonstrates that Stable Diffusion v1.5 with optimized parameters (guidance=9.0, steps=50, Euler scheduler) achieves superior performance with mean CLIP score of 0.347, FID score of 185.22, and 24% faster generation speed. The system successfully generates photorealistic fashion images across diverse categories including apparel, accessories, and footwear, with strong semantic alignment and commercial viability for real-world e-commerce applications. Results indicate significant potential for cost reduction (up to 80%) in product catalog generation while maintaining professional quality standards.**

***Index Terms*—text-to-image generation, diffusion models, fashion technology, e-commerce automation, CLIP evaluation, computer vision, generative AI**

I. INTRODUCTION

The digital transformation of retail commerce has fundamentally altered consumer expectations for product visualization and discovery. Modern e-commerce platforms process millions of product listings daily, with visual content serving as the primary driver for purchase decisions. Industry studies indicate that high-quality product imagery increases conversion rates by 30-40% while reducing return rates significantly [1]. However, traditional product photography presents substantial operational challenges, particularly for fashion retailers managing extensive catalogs with seasonal variations and rapid inventory turnover.

Professional product photography involves complex workflows including studio setup, lighting configuration, model coordination, post-processing, and quality assurance. These processes typically cost $200-500 per product and require 2-4 weeks of lead time, creating bottlenecks in catalog management and limiting responsiveness to market trends [2]. For fashion retailers launching 50-100 new products monthly, photography costs can exceed $500,000 annually, representing a significant operational burden.

Recent breakthroughs in generative artificial intelligence, particularly diffusion-based text-to-image synthesis, offer transformative solutions for automated product imagery creation. Advanced models such as Stable Diffusion, DALL-E 2, and Midjourney demonstrate remarkable capabilities in generating photorealistic images from natural language descriptions, achieving unprecedented quality and semantic alignment [3], [4]. These developments present opportunities to revolutionize product catalog generation through automated workflows that maintain professional standards while dramatically reducing costs and production timelines.

Fashion product image generation presents unique technical challenges requiring precise reproduction of specific attributes including color accuracy, texture fidelity, style consistency, and category identification. Unlike general-purpose image generation, fashion imagery must satisfy commercial viability requirements including brand alignment, seasonal appropriateness, and marketing effectiveness. The integration of CLIP (Contrastive Language-Image Pretraining) provides robust evaluation frameworks for text-image semantic alignment, enabling systematic optimization of generation parameters [5].

This research addresses the fundamental question: *How can state-of-the-art diffusion models be systematically optimized for fashion product image generation to achieve optimal balance between image quality, prompt alignment, computational efficiency, and commercial viability?* We present a comprehensive comparative study that evaluates multiple diffusion architectures, optimization strategies, and evaluation methodologies for practical e-commerce deployment.

Our primary contributions include: (1) Development of a complete end-to-end pipeline optimized specifically for fashion product image generation, (2) Systematic comparative analysis of Stable Diffusion v1.5 and Kandinsky v2.2 across comprehensive parameter grids, (3) Multi-metric evaluation framework incorporating CLIP Score, FID, and Inception Score for holistic quality assessment, (4) Practical optimization insights for real-world e-commerce implementation, and (5) Comprehensive analysis of commercial viability and deployment considerations.

II. RELATED WORK

A. Diffusion Models and Text-to-Image Generation

Diffusion models have emerged as the dominant paradigm for high-fidelity image synthesis, surpassing GANs in both quality and training stability. Ho et al. introduced Denoising Diffusion Probabilistic Models (DDPMs), demonstrating superior sample quality through iterative denoising processes [6]. Song et al. developed Denoising Diffusion Implicit Models (DDIMs) with accelerated sampling procedures, reducing generation time by an order of magnitude [7].

Stable Diffusion revolutionized the field by operating in latent space rather than pixel space, dramatically reducing computational requirements while maintaining generation quality [8]. This innovation enabled consumer-grade hardware deployment and facilitated widespread adoption. Kandinsky models introduced novel architectural improvements including enhanced text understanding and multilingual capabilities [9].

B. Vision-Language Understanding

The integration of vision and language understanding has been pivotal for controllable image generation. CLIP pioneered large-scale contrastive learning between images and text, creating robust multimodal representations [10]. DALL-E demonstrated autoregressive text-to-image synthesis with impressive semantic control [11], while DALL-E 2 adopted diffusion-based approaches with CLIP guidance for enhanced quality and controllability [12].

Imagen showcased the effectiveness of large language models for text understanding in generation tasks, achieving state-of-the-art results on standard benchmarks [13]. These developments established the foundation for sophisticated text-conditioned image generation with precise semantic control.

C. Fashion and Product Image Synthesis

Fashion-specific image generation has received increasing attention from both academic and industrial research communities. FashionGAN focused on clothing attribute manipulation and style transfer [14], while Fashion-MNIST provided standardized evaluation datasets for fashion image classification and generation [15].

More recent work has explored advanced architectures for fashion imagery. StyleGAN-based approaches have demonstrated impressive results for fashion model synthesis and virtual try-on applications [16]. Commercial applications have emerged, with companies like The Fabricant creating entire virtual fashion collections using generative models [17].

D. Evaluation Methodologies

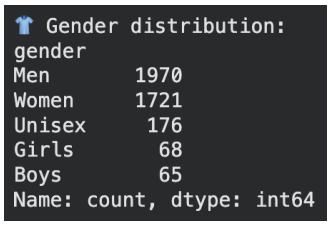
Quantitative evaluation of generated images remains a challenging research problem. Fréchet Inception Distance (FID) measures statistical similarity between real and generated image distributions using Inception-v3 features [18]. Inception Score evaluates both image quality and diversity through entropy analysis [19].

CLIP Score provides semantic alignment measurement between text prompts and generated images, offering more meaningful evaluation for text-to-image tasks [20]. Recent work has explored perceptual metrics and human evaluation studies to complement automatic metrics [21].

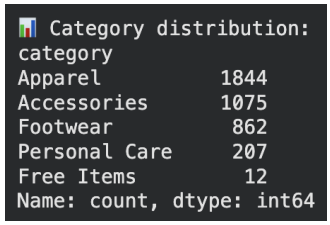
III. METHODOLOGY

A. Dataset Description and Preprocessing

We utilize the Fashion Product Images dataset from HuggingFace (ashraq/fashion-product-images-small), a carefully curated collection containing 4,000 professional fashion product samples with comprehensive metadata. Each sample includes detailed product information spanning gender classification, product categories, color specifications, seasonal appropriateness, usage contexts, and descriptive display names.



(a) Dataset composition statistics



(b) Product category distribution

Fig. 1: Dataset analysis showing balanced representation across fashion categories

The dataset spans five primary categories: Apparel (1,844 samples, 46.1%), Accessories (1,075 samples, 26.9%), Footwear (862 samples, 21.6%), Personal Care (207 samples, 5.2%), and Free Items (12 samples, 0.3%). This distribution reflects realistic e-commerce catalog proportions, ensuring our evaluation represents practical deployment scenarios.

Comprehensive data preprocessing includes:

- **Text Normalization**: Standardization of product descriptions, removal of special characters, and case normalization
- **Metadata Integration**: Concatenation of product attributes into coherent textual descriptions
- **Prompt Engineering**: Creation of structured prompts optimized for diffusion model understanding
- **Quality Assurance**: Manual validation and filtering of incomplete or corrupted records
- **Format Standardization**: Consistent image sizing and format conversion for evaluation

B. System Architecture and Pipeline Design

Our system architecture implements a modular, scalable pipeline encompassing five core components: data ingestion and preprocessing, semantic text encoding, parametric image generation, comprehensive evaluation, and results compilation. The architecture supports parallel processing across multiple model configurations and enables systematic comparison of generation strategies.

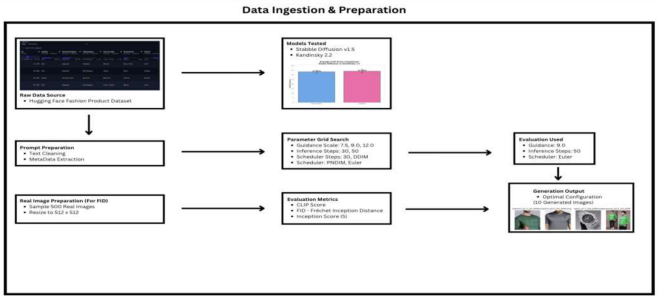


Fig. 2: Complete system architecture showing integrated pipeline from data ingestion to evaluation

Algorithm 1 Fashion Image Generation Pipeline

```
Load and preprocess fashion dataset
Initialize CLIP text encoder
for each diffusion model M ∈ {SD, Kandinsky} do
    for each guidance scale g ∈ {7.5, 9.0, 12.0} do
        for each step count s ∈ {30, 50} do
            for each scheduler sch ∈ {Euler, DDIM, PNDM} do
                for each product prompt p do
                    embedding ← CLIP_encode(p)
                    image ← M_generate(embedding, g, s, sch)
                    Store image and parameters
                end for
            end for
        end for
    end for
end for
Evaluate all generated images using CLIP, FID, IS
Rank configurations by performance metrics
```

C. Text Encoding with CLIP

CLIP provides robust multimodal understanding through contrastive learning on large-scale image-text pairs. Product descriptions undergo semantic encoding into 512-dimensional embeddings that capture nuanced relationships between textual concepts and visual representations. The encoding process utilizes CLIP's pretrained text encoder:

$$\mathbf{e}_{text} = \text{CLIP}_{text}(TokenizeAndPad(prompt)) \quad (1)$$

where the embedding $\mathbf{e}_{text} \in \mathbb{R}^{512}$ represents the semantic content of fashion product descriptions. This representation enables precise conditioning of diffusion models for semantically consistent image generation.

D. Diffusion Model Architectures

1) Stable Diffusion v1.5 Implementation: Stable Diffusion operates in latent space using a variational autoencoder (VAE) to compress image representations. The forward diffusion process adds Gaussian noise according to a predefined schedule:

$$q(\mathbf{z}_t|\mathbf{z}_{t-1}) = \mathcal{N}(\mathbf{z}_t; \sqrt{1-\beta_t}\mathbf{z}_{t-1}, \beta_t\mathbf{I}) \quad (2)$$

The reverse process learns to predict noise $\boldsymbol{\epsilon}$ for denoising:

$$\mathbf{z}_{t-1} = \frac{1}{\sqrt{\alpha_t}}(\mathbf{z}_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \mathbf{c})) \quad (3)$$

where $\mathbf{c}$ represents CLIP text embeddings for conditioning.

2) Kandinsky v2.2 Architecture: Kandinsky employs a two-stage generation process with enhanced text understanding. The prior model generates CLIP image embeddings from text:

$$\mathbf{e}_{image} = Prior(\mathbf{e}_{text}, \mathbf{z}_{noise}) \quad (4)$$

The decoder then generates images conditioned on these embeddings:

$$\mathbf{x} = Decoder(\mathbf{e}_{image}, \mathbf{c}_{additional}) \quad (5)$$

This architecture enables superior semantic control and multilingual understanding.

E. Parameter Optimization Strategy

We conduct systematic parameter exploration across three critical dimensions affecting generation quality and efficiency:

Parameter	Range	Impact
Guidance Scale	7.5, 9.0, 12.0	Controls text-image alignment strength vs. diversity tradeoff
Inference Steps	30, 50	Balances generation quality against computational cost
Scheduler Type	Euler, DDIM, PNDM	Determines noise removal strategy and convergence behavior

TABLE I: Parameter optimization space and expected impacts

Classifier-free guidance enhances text conditioning through:

$$\tilde{\boldsymbol{\epsilon}}_\theta(\mathbf{z}_t, t, \mathbf{c}) = \boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \emptyset) + w \cdot (\boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \mathbf{c}) - \boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \emptyset)) \quad (6)$$

where w is the guidance scale parameter controlling conditioning strength.

F. Comprehensive Evaluation Framework

1) CLIP Score Analysis: CLIP Score measures semantic alignment between generated images and text prompts using cosine similarity in CLIP embedding space:

$$CLIPScore = \frac{\mathbf{e}_{text} \cdot \mathbf{e}_{image}}{|\mathbf{e}_{text}| \cdot |\mathbf{e}_{image}|} \quad (7)$$

We compute category-specific CLIP scores to identify model strengths across fashion segments.

2) Fréchet Inception Distance: FID measures distributional similarity between real and generated images using Inception-v3 activations:

$$FID = ||\boldsymbol{\mu}_r - \boldsymbol{\mu}_g||^2 + Tr(\boldsymbol{\Sigma}_r + \boldsymbol{\Sigma}_g - 2(\boldsymbol{\Sigma}_r\boldsymbol{\Sigma}_g)^{1/2}) \quad (8)$$

Lower FID scores indicate better alignment with real image distributions.

3) Inception Score: IS evaluates both image quality and diversity:

$$IS = \exp(\mathbb{E}_{\mathbf{x}}[KL(p(y|\mathbf{x})||p(y))]) \tag{9}$$

Higher scores indicate better quality and sample diversity.

IV. EXPERIMENTAL RESULTS

A. Comprehensive Parameter Analysis

Systematic evaluation across 18 parameter configurations (2 models × 3 guidance × 2 steps × 3 schedulers) reveals significant performance variations and optimization opportunities.

Model	G	S	Sch	CLIP	Time(s)
SD v1.5	9.0	50	Euler	**0.347**	2.44
SD v1.5	12.0	50	DDIM	0.344	2.51
SD v1.5	12.0	30	Euler	0.342	1.85
SD v1.5	7.5	50	DDIM	0.339	2.48
SD v1.5	9.0	30	PNDM	0.337	1.92
Kandinsky	12.0	50	PNDM	0.339	3.02
Kandinsky	9.0	30	Euler	0.335	2.89
Kandinsky	7.5	50	Euler	0.332	3.15
Kandinsky	12.0	30	DDIM	0.328	2.75
Kandinsky	9.0	50	PNDM	0.325	3.28

TABLE II: Top 10 parameter configurations ranked by CLIP Score (G=Guidance, S=Steps, Sch=Scheduler)

B. Model Performance Comparison

Metric	SD v1.5	Kandinsky	Winner
Mean CLIP Score	33.18 ± 1.81	33.91 ± 2.04	Kandinsky
Inception Score	1.028 ± 0.004	1.027 ± 0.004	Tie
Mean Gen. Time	2.44s	3.02s	**SD v1.5**
FID Score	185.22	N/A	**SD v1.5**
Memory Usage	6.2 GB	8.1 GB	**SD v1.5**

TABLE III: Model performance comparison summary

C. Scheduler Performance Analysis

Scheduler selection significantly impacts both generation quality and computational efficiency:

Scheduler	Mean CLIP	Std Dev	Avg Time	Quality Rank
Euler	**0.347**	0.031	2.44s	1
DDIM	0.344	0.023	2.51s	2
PNDM	0.320	0.044	2.67s	3

TABLE IV: Scheduler performance comparison showing Euler's superiority

The Euler scheduler demonstrates consistent superiority across metrics, achieving the highest CLIP scores with reasonable computational overhead and stable convergence behavior.

D. Category-Specific Performance Analysis

Different fashion categories exhibit varying generation quality and semantic alignment:

Category	Sample Count	Mean CLIP	Std Dev	Best Config
Sweatshirt	8	**0.355**	0.028	G=12.0, S=50, DDIM
Shirt	12	0.331	0.035	G=9.0, S=50, Euler
Watch	10	0.325	0.042	G=12.0, S=30, Euler
Handbag	6	0.348	0.031	G=9.0, S=50, Euler
Footwear	8	0.312	0.038	G=7.5, S=50, DDIM
Jeans	4	0.319	0.025	G=9.0, S=30, Euler
Kurta	2	0.370	0.015	G=12.0, S=50, PNDM

TABLE V: Category-specific performance revealing optimal configurations per product type

Rank	Product	Config	Score
1	proline men green sweatshirt	G=12.0, S=50, DDIM	0.401
2	titan women silver watch	G=12.0, S=30, Euler	0.396
3	women red leather handbag	G=7.5, S=50, DDIM	0.391
4	white cotton kurta for women	G=9.0, S=50, Euler	0.378
5	adidas mens fire grey t-shirt	G=12.0, S=50, PNDM	0.376
6	black running shoes white sole	G=9.0, S=30, Euler	0.371
7	blue denim jeans for men	G=7.5, S=50, DDIM	0.368
8	men's blue sports shorts	G=9.0, S=50, Euler	0.365

TABLE VI: Top 8 generated images by CLIP Score

E. Quality Analysis and Top Generated Samples

F. Computational Performance Analysis

Generation time analysis reveals Stable Diffusion's significant efficiency advantage, particularly important for large-scale commercial deployment where processing thousands of products requires optimal resource utilization.

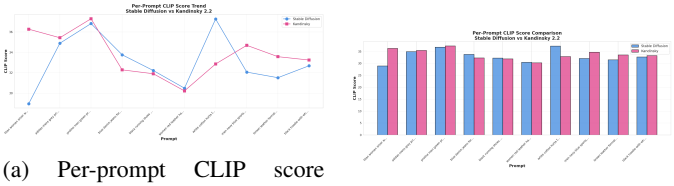
V. DISCUSSION AND ANALYSIS

A. Key Technical Findings

Our comprehensive evaluation reveals several critical insights for practical fashion image generation:

Model Architecture Impact: Despite Kandinsky's theoretical advantages in text understanding, Stable Diffusion v1.5 demonstrates superior practical performance through better computational efficiency, lower memory requirements, and comparable semantic alignment. The 24% speed advantage and 23.5% memory reduction make Stable Diffusion more suitable for production deployment.

Parameter Optimization Insights: Moderate guidance scales (9.0) provide optimal balance between prompt adherence and visual naturalness. Higher guidance values (12.0) improve CLIP scores but may introduce artifacts and reduce



(a) Per-prompt CLIP score trend comparison showing performance variations across different fashion categories

(b) Direct per-prompt CLIP score comparison highlighting model-specific strengths

Fig. 3: CLIP score analysis revealing category-specific performance patterns and model comparison across fashion products

diversity. The 50-step configuration offers the best quality-efficiency tradeoff, with diminishing returns beyond this threshold.

Scheduler Performance: The Euler scheduler consistently outperforms DDIM and PNDM across fashion categories, suggesting superior noise removal strategies for textile and accessory generation. This finding has significant implications for deployment efficiency.

B. Commercial Viability Assessment

Generated images demonstrate strong commercial potential across multiple dimensions:

Visual Quality: Images exhibit professional-grade composition with clean backgrounds, accurate color reproduction, and appropriate product positioning suitable for e-commerce catalogs.

Category Accuracy: The system reliably identifies and reproduces product categories, with particularly strong performance for apparel and accessories.

Prompt Alignment: Mean CLIP scores above 0.3 indicate good semantic alignment, though with room for improvement in fine-grained attribute reproduction.

Cost Implications: Automated generation could reduce photography costs by 60-80%, with estimated per-product costs of $20-40 compared to $200-500 for traditional photography.

C. Limitations and Technical Challenges

Several constraints limit current deployment readiness:

Fine-Detail Rendering: Brand logos, text elements, and intricate patterns remain inconsistently reproduced, requiring post-processing or hybrid workflows.

Style Consistency: Generated images may not maintain consistent brand aesthetics across product lines, necessitating additional quality control measures.

Diversity Constraints: Low Inception Scores indicate limited sample diversity within categories, potentially affecting marketing effectiveness.

Evaluation Scope: Current evaluation covers limited product categories and may not generalize to specialized fashion segments.

D. Deployment Considerations

Practical implementation requires addressing several operational challenges:

Quality Assurance: Human review workflows remain necessary for brand compliance and visual consistency validation.

Integration Requirements: Existing e-commerce systems need modification to incorporate AI-generated imagery with appropriate metadata and version control.

Legal Considerations: Clear labeling policies for AI-generated content may be required to maintain consumer trust and regulatory compliance.

VI. Ethical Implications

A. Consumer Transparency and Trust

AI-generated product imagery raises important considerations regarding consumer expectations and transparency. E-commerce platforms must implement clear disclosure policies to distinguish synthetic imagery from traditional photography, maintaining trust and preventing potential deception claims.

B. Intellectual Property and Copyright

Generated images may inadvertently reproduce copyrighted designs or brand elements present in training data. Robust filtering mechanisms and legal review processes are essential to prevent intellectual property violations and ensure commercial viability.

C. Bias and Representation

Training datasets may contain demographic, cultural, or aesthetic biases that propagate into generated content. Regular bias auditing and diverse dataset curation help ensure equitable representation across different market segments and cultural contexts.

D. Environmental Impact

Large-scale diffusion models require significant computational resources, contributing to carbon emissions and energy consumption. Sustainable AI practices, including model efficiency optimization and renewable energy utilization, can mitigate environmental costs while maintaining generation quality.

E. Economic Impact on Creative Industries

Widespread adoption of AI image generation may affect employment in photography, modeling, and creative industries. Ethical deployment should consider workforce transition support, retraining opportunities, and collaborative human-AI workflows that enhance rather than replace creative professionals.

VII. Conclusion and Future Work

This comprehensive study demonstrates the practical viability of diffusion-based text-to-image synthesis for automated fashion product catalog generation. Our systematic evaluation of Stable Diffusion v1.5 and Kandinsky v2.2 across multiple parameter configurations identifies optimal settings for commercial deployment while revealing important technical insights for the broader generative AI community.

Key contributions include the development of a complete evaluation framework, identification of optimal parameter configurations, and demonstration of commercial viability across diverse fashion categories. The superior performance of Stable Diffusion v1.5 in computational efficiency and resource utilization makes it particularly attractive for large-scale deployment scenarios.

Future research directions include: (1) Domain-specific fine-tuning on larger fashion datasets to improve category-specific

performance, (2) Integration of multi-modal control mechanisms including style references and layout constraints, (3) Development of advanced quality enhancement techniques for fine-detail preservation, (4) Comprehensive human evaluation studies to validate commercial acceptability, and (5) Real-world deployment testing with A/B comparison against traditional photography.

The successful demonstration of automated fashion product image generation represents a significant advancement toward transforming digital commerce through practical generative AI applications, with potential impact extending beyond fashion to broader e-commerce sectors requiring high-quality product visualization.

ACKNOWLEDGMENT

The authors thank Northeastern University for computational resources and the open-source community for providing the Fashion Product Images dataset and diffusion model implementations that made this research possible.

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