Application of Cycle Generative Adversarial Networks for Unpaired Image Style Transfer in Product Packaging Design

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The rapid advancement and extensive application of AI technology in the past few years have also spurred rapid evolution in deep learning. Image recoloring, detection, recognition, and creative style transfer are some of the most common applications of deep learning technology. Visual art styles are also frequently transferred using methods based on deep learning. The goal of this paper is to develop an algorithm for rapid visual art style migration based on building confrontation networks. The CelebA-HQ celebrity faces dataset, collected from multiple sources of artistic and product design images, was used to assess the effectiveness of style transfer. The preprocessing stage involves resizing all images to a fixed resolution and Min-max normalizing, ensuring consistent input and stable GAN training for effective visual style migration. A feature extraction technique, such as Histogram of Oriented Gradients (HOG), is employed to evaluate structural consistency before and after style migration. This paper introduces a novel method for automatically generating image-quality art using the Cycle Generative Adversarial Network (CycleGAN) and a migration algorithm. The CycleGAN produced high reconstruction quality with a PSNR of 23.84 and strong structural consistency with an SSIM of 0.81, confirming its effectiveness in artistic style migration for packaging design. To enhance the effect of image creative style migrations, the image is identified using a multiscale discriminator. The results of the trial show that this strategy is very valuable and applicable for advertising and use.

Povzetek: Obravnav je problem neparnega prenosa umetniških slogov v embalažno oblikovanje. Predlagana je metoda CycleGAN z večlestvenim diskriminatorjem in HOG-analizo za ohranjanje strukture. Model doseže visoko kakovost prenosa ter učinkovito in koherentno ustvarja nove slogovne vizualizacije za industrijsko in komunikacijsko oblikovanje.

1 Introduction

Images are the first form of creative endeavor and an integral part of humanity's culture since they reflect their authors' complex and unusual ideas and feelings. A great piece of drawing reflects the individual imaginative flair of the creator. Creators significantly enhance their creative abilities by studying the distinctiveness of the artistic style. In this context, when computer technology develops and is used more quickly, more and more people are becoming interested in machine vision and image processing in addition to conventional instruction in art theory [1]. By carefully employing computer vision technology, artists may learn how to express their distinctive, imaginative formation style by studying real-world settings or images and applying the correct painting methods. In recent years, specialists and academics in artificial intelligence have begun to pay more attention to the generative adversarial network (GAN), a crucial subfield of deep learning. The produced information and the actual example are separated using the discriminator, and the generator settings are changed to make the generated data seem more accurate [2]. The generator creates information using noise that is near the original sample. The network completes the objective of the position by producing data that is as close to the actual sample as possible through the generator's and discriminator's adversarial training, which simultaneously improves the accuracy of the discriminator's categorization and the generator's forecast. Additionally, as research has advanced, many GAN variations have been used, and the GAN's image applications have grown significantly [3]. Many academics now use GAN-based style migration algorithms for works of art. Painting techniques were transferred to photos utilizing a synthesis of the underlying image's texture characteristics, while the pictures' lexical importance was ignored. Using a convolutional neural network (CNN), it is feasible to extract significant information from images and modify the style to produce more realistic images [4].

A generalized style migration technique that migrates any number of image styles to a single model by directly matching the feature covariance of content and style images through whitening and coloring modifications. A CycleGAN was used to perform unpaired visual transformation between images of product packaging and artistic style domains. GAN-based image style migration techniques are being employed more and more frequently in creating different forms of paintings as art, and successful product packaging design direction outcomes have been attained [5]. The majority of the artworks created utilizing style migration techniques may keep the majority of the Outline and general shade data of sincere photographs, provided the training data are sufficient. However, according to a recent study, they still need to be artwork-level flawless. For instance, it can be challenging to match the content structure of particular photographs with important subject aspects and more complicated semantic information through style migration [6]. Consequently, some produced photos exhibit local features that must be added or blurred, local color distortion, and emphasized image topics. The researchers provide a method for migration of the image-to-artwork style based on Cycle-GAN to more effectively accomplish style migration from the artworks from the viewpoint of visual study. To create artwork pictures in a three-dimensional creative class, the artistic color, shape, texture, and dimension are combined with artistic qualities [7].

1.1 Problem statement

In many traditional visual design processes, the process of integrating artistic styles into industrial applications tends to lack efficiency and flexibility. Existing style transfer methods encounter challenges in the conservation of structural coherency and crucial content across domains. Thus, the need for an automated method allowing efficient and predictable relocation of artistic styles exists. The present methods cannot produce visually acceptable results for packaging and communication design. Therefore, for our approach, we have proposed a CycleGAN method with multiscale discrimination and HOG feature analysis to overcome these limitations.

The research aims to develop a CycleGAN-based algorithm that allows quick and coherent visual art style transfer within an industrial, packaging, and communication design context. Structural consistency is maintained through the use of Histogram of Oriented Gradients (HOG) as an evaluation of the features, and a multiscale discriminator is introduced to allow for the transfer of style in an accurate and detailed manner. This methodology provides a streamlined creative process, which enables the combination of artistic elements into product design to enhance productivity and engagement in visual communication.

1.2 Contributions of the research

- The research aims to advance a CycleGAN-based framework for rapid visual art style migration, enhancing creative design processes across industrial and communication domains.
- CelebA-HQ celebrity faces data was collected from diverse visual artworks and product design samples, permitting training and evaluation across multiple artistic styles.
- The preprocessing stage involved resizing all images to a fixed resolution and applying Min-Max normalization to ensure consistent input dimensions and stable CycleGAN training.
- Features were extracted using Histogram of Oriented Gradients (HOG) to assess and maintain structural consistency before and after style migration.
- The adopted method employed a CycleGAN architecture enhanced with a multiscale discriminator to preserve fine-grained style details during unpaired image-to-image translation.
- The model effectively enabled seamless style transfer, generating visually coherent designs suitable for product development, packaging, and visual storytelling applications.
- The results confirmed that the CycleGAN-based strategy facilitated stylistic adaptability in design outputs, with strong applicability in creative industries, particularly in advertising and visual communication design.

The rest of the paper is structured as follows: A summary of related works is provided in Part 2, a more detailed description of the methodologies is given in Part 3, the results and the discussion are covered in Part 4, and the conclusion is provided with future scope in Part 5.

2 Related works

The research creates a colour images as colored pencil sketches using cluster-based segmentation, two-tone mapping, line integral convection is used collectively for texture generation the contours formerly from a neon transform [8]. Blending the textured layers with the contours produces a stylized sketch effect. The results showed that the method allows for an extremely fast and efficient option to transform images with attractive results mimicking pencil drawings. However, implementations of the method exhibited challenges for accurately capturing the deep subtle tonal transitions and erratic stroke motion inherent in handmade/hand drawn artwork. The research shows improved visual quality and structure through object-specific style transfer by utilizing Wavelet Transform (WT) and Visual Geometry Group Network (VGGNet19) [9]. The result of our research exceeds the current ways of creating images in realism, and the correlation of intrinsic features in images. But the method is computationally intensive and, in making them perform well requires constant tuning of wavelet parameters and a comprehensive understanding of the content class being converted. The research developed Deep Reinforcement Learning (DRL) to enhance autonomous driving control in dynamic traffic scenarios [10]. The implementation leverages AirSim as a simulation environment, via Deep Deterministic Policy Gradient (DDPG) and Recurrent DDPG (RDPG), and a Convolutional Neural Network (CNN) to process images of each timestep in real-time. Additionally, developed an original reward system to help to improve convergence times and control accuracy. These results confirm the potential of DRL-based methods for enhancing autonomous vehicle control performance. The limitation included to how can manage rare edge cases and derive generalization of conclusions across myriad driving scenarios. To improve artistic image style transfer, a modified CycleGAN model incorporated into the generator architecture the use of an attention mechanism was created [11]. The investigation was to maintain image detail, blur the boundaries of the target, and improve stylization. The usability findings for our experiments show better visual quality and user satisfaction compared to the standard CycleGAN. The model performs with increased clarity and application value in artistic image processing. Research introduced Edge feature and Self-Attention (ESA-CycleGAN), a style transfer model which uses edge features and self-attention [12]. The architecture used a generator, discriminator, and an edge feature extraction network. Self-attention is used to catch global features in an image and edge features used to preserve fine details. Experimental results showed ESA-CycleGAN has a higher Inception Score (IS) and Fréchet Inception Distance (FID) which showed the model has better image quality and fine detail preservation. The limitation of the model is its difficulty dealing with very complex textures along with the amount of computational resource it requires for training. A related works analysis, a literature review, or a systematic review is discussed regarding image migration based on CycleGAN. It requires a comprehensive examination and evaluation of the research body, shown in Table 1.

Table 1: Related works

Ref	Objective	Findings	Limitation
Wang [13]	Digital art classification and aesthetics evaluation using hierarchical deep learning	The model employs Dense Convolutional Network (DenseNet), Convolutional Next (ConvNeXt), and Vision Transformer (ViT) models to more accurately acquire and classify complex artistic features.	limited to classification tasks, does not accommodate for real-time artistic style migration or throughout other modes of image generation transformation
Jin [14]	Design a cross-modal attention-based generative adversarial network (CMAGAN) for converting text into high-quality artistic design images.	Proposed a three stage Generative Adversarial Network (GAN) with Recurrent Neural Network (RNN) encoding and Attention-on-Attention (AoA) to generate semantically aligned high-fidelity artistic images using the low-dimensional text embedding.	Concentrated on text-to-image generation; does not address image-to-image style transfer or multi-domain image migration.
Li and Guo [15]	Develop a brain visual cognition-based image classification model integrating deep convolutional neural networks (DCNN).	Integrated DCNN with Long Short-Term Memory (LSTM) and attention mechanisms to simulate brain visual processing; achieved high accuracy across visual regions and reduced loss	The model is focused on EEG-based image classification. This model is not able to do any real-time image generation, artistic style transfer.
Liu and Zhou [16]	Investigated automated layout generation in graphic design with the generative adversarial network for layouts (LayoutGAN)	Showed that the wireframe rendering discriminator provides better layout quality than a relation-based discriminator, allowing for fully automated room floor plan generation.	The model reliant on real-time designer input because intelligent layout continues to be semi-automated as a result of black-box constraints that occur in statistical learning.
Lee et al. [17]	Create a soft computing neural network model to	Focused on altered facial landmarks using only RGB image data, while	It only applies to facial forgery detection; it cannot account for

	detect fake facial images generated by Handcrafted Facial Manipulation (HFM)	deliberately avoiding use of any metadata; achieved improved detection performance compared to state-of-the-art classifiers.	any other form of image manipulation
Wang et al. [18]	Enhance ink painting style transfer by addressing domain asymmetry	Asymmetric CycleGAN with Salient Edge and Feature-wise Cycle Loss	Improved brushstroke detail, ink diffusion, and efficiency over existing methods.
Jiangsha et al. [19]	NDT image simulation via extra-supervised CycleGAN	Used x-ray welds with label-guided CycleGAN	Technical; not focused on artistic transfer or real-time adaptability
Suwannik [20]	Use CycleGAN with randomly generated data to transfer traditional art style to silhouette images	Achieved better style transfer results on black-and-white silhouettes compared to previous methods.	Issues remain with artifacts and spikes in the output images.

2.1 Research gap

Earlier research exposed several limitations in AI-driven style transfer applications. Fine art generation using CycleGAN lacked contextual style depth and remained confined to sketch-based rendering [8]. Chinese painting synthesis relied on domain-specific deep learning, with limited adaptability beyond classical styles or low-resource environments [9]. Style transfer for animated costumes using FCN and CycleGAN achieved task-specific coherence, but produced low style fidelity and faced inconsistencies due to dataset limitations [10]. The present technique overcomes these limitations by integrating multiscale discriminators and HOG-based structural consistency checks to preserve detail and context across diverse visual domains. CycleGAN is adapted for generalized, high-fidelity style migration, enabling broader applicability beyond domain-specific constraints.

3 Methodology

The research aims to use a CycleGAN-based approach for visual art style migration. Preprocessing involves resizing and min-max normalizing images to guarantee consistent input. Histogram of Oriented Gradients (HOG) is applied as a feature extraction method to assess structural consistency both before and after a style translation. A multiscale discriminator improves style fidelity and detail preservation. The technique is effective in generating visually coherent outputs for industrial, communication, and packaging design, as shown in Figure 1.

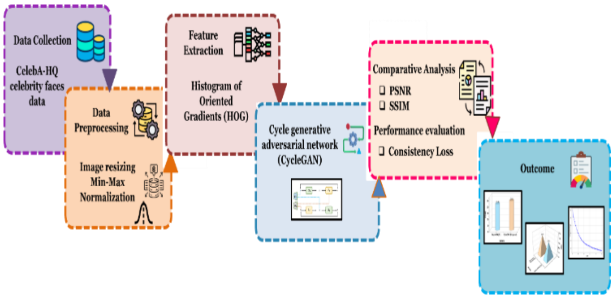

Figure 1: Semantic diagram of the CycleGAN approach

3.1 Data collection

The CelebA-HQ celebrity faces data was collected from the source Kaggle. A dataset consisting of 30,000 high-quality celebrity faces resampled to 256px. NVIDIA used this dataset in the research paper Progressive Growing of GANs for Improved Quality, Stability, and Variation. This dataset is meant for generative models: only images with no attributes/labels.
Source:
https://www.kaggle.com/datasets/badasstechie/celebahq-resized-256x256/data

3.2 Preprocessing

Preprocessing is the first step in deep learning (DL). It consists of preparing the raw inputs for model training. This typically consists of bringing the raw images into a consistent format and quality. Preprocessing typically resizes images to the same resolution and normalizes pixel values to lessen input discrepancies and isolate variability to help in obtaining stable training results. These steps help the model embed meaningful pattern information and increase residual variability in the input.

❖ **Resizing**

It allows to ensure all input images are the same size before they are passed into the CycleGAN model. This consistent size enhances training stability and quality of the style transfer. Using fixed-size inputs better manages computational complexity and memory usage. During the resize process, the input images keep their potential salient visual items while ultimately transforming non-salient visual feature variation. This means the model is able to learn style patterns in a more effective manner across the two domains.

❖ **Min-max Normalization**

The pre-processing phase begins with min-max normalization so that the pixel values are on the same scale for all input images. This linear transformation of pixel values (min-max normalization) produces a consistent value distribution, which allows CycleGAN to use consistent values during training. The normalization method is defined in equation (1):

$$W_{new} = \frac{W - \min(w)}{\max(w) - \min(w)} \quad (1)$$

Where W_{new} is the normalized pixel value, W is the original pixel value, max(w) and min(w) represent the minimum and maximum values in the image dataset. The Min-max normalization ensures that pixel values are standardized across images for uniform input. This results in a more stable training environment for the CycleGAN model and allows for more accurate style transfer. This allows the model to create aesthetically stable and structurally consistent results in art style migration.

3.3 Feature extraction using histogram of oriented gradients (HOG)

HOG advance a rapid visual art style migration algorithm using CycleGAN, enhancing image translation for industrial and visual communication design. To support rapid and coherent visual art style migration, feature extraction using HOG is combined to evaluate structural consistency across original and transformed images. HOG captures essential shape, edge, and orientation information, guaranteeing that key visual features, especially those critical to product design and visual communication, remain intact after style translation using CycleGAN. This strengthens the fidelity of creative style migration by quantifying preservation of structural details during the generative process. Block-wise gradient vectors are normalized to reduce lighting sensitivity, using the equation (2)

$$e = \frac{u}{\sqrt{||u||_2^2 + f^2}} \quad (2)$$

where u is the unnormalized gradient vector and f is a small constant. This ensures robustness in the detection of stylistic preservation. This allows for accurate measurement of creative transitions across visual domains. HOG ensures that essential structural elements are preserved during style migration. This enhances the reliability of CycleGAN-generated outputs by maintaining edge clarity and design integrity across visual transformations.

3.4 CycleGAN

CycleGAN was invented to overcome the unpaired image-to-image translation problem in computer vision. The essence of CycleGAN is to enforce cycle consistency to overcome mode collapse, which is common in other GANs. In particular, CycleGAN contains two generators $S_\Theta: x \to y$ and $L_\Upsilon: y \to x$, two discriminators φ_Φ and ψ_Ξ , which are implemented using weight-parameterized neural networks $\Theta, \Upsilon, \Phi, \Xi$, for the picture conversion issue between two domains y and x, as illustrated in Figure 2.

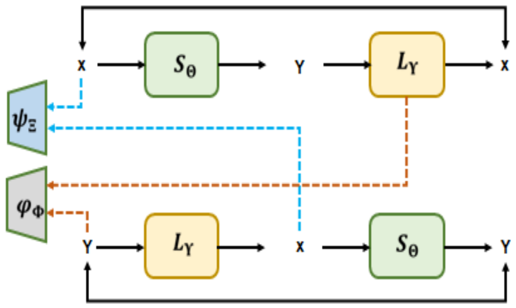

Figure 2: Standard CycleGAN architecture

Figure 2 shows the standard architecture of CycleGAN, adapted for unpaired style transfer between original product images (domain x) and an artistic style (domain y). This structure enables visual art style migration by allowing for consistent translation between artistic styles and existing design projects while maintaining core visual characteristics. The following min-max problem is then solved to estimate the unknown generator parameters Θ and ϒ as presented in equation (3)

$$\min_{\Theta,\Upsilon} \max_{\Phi,\Xi} f_{CycleGAN}(\Theta, \Upsilon\Phi, \Xi) \quad (3)$$

Where Θ, Υ are the generator parameters optimized to minimize the CycleGAN loss by translating images between two visual domains. Φ, Ξ are the discriminator parameters optimized to maximize the same loss by distinguishing real from generated images in each domain. This optimization enables successful visual art style migration through learned bidirectional mappings that retain structured features while transferring artistic styles of interest from source designs and target visual domains. When loss is indicated by equation (4)

$$f_{CycleGAN}(\Theta, \Upsilon\Phi, \Xi) = f_{Cycle}(\Theta, \Upsilon) + f_{Disc}(\Theta, \Upsilon\Phi, \Xi) \quad (4)$$

Where $f_{CycleGAN}(\Theta, \Upsilon)$ is the cycle consistency loss, ensuring that an image translated from one domain to another and then back remains close to the original, preserving core content. Θ, Υ, and discriminators Φ, Ξ perform in creating realistic images and detecting fakes. It enables effective visual art style migration by maintaining key design features while transferring stylistic attributes. The cycle-consistency term offered in this context is$f_{Cycle}(\Theta, \Upsilon)$, which is denoted by equation (5)

$$f_{Cycle}(\Theta, \Upsilon) \coloneqq \int_y \left\| y - S_\Theta\left(L_\Upsilon(y)\right)\right\| t\mu(y) + \int_x \left\| x - L_\Theta\left(S_\Theta(x)\right)\right\| tc(x), \quad (5)$$

Here, S_Θ represents the Generator that maps from the domain x. L_Υ is the generator that maps from domain y back to domain x, $y - S_\Theta\left(L_\Upsilon(y)\right)$ measures how much the image in domain y, after being mapped to domain x and back, deviates from its original form, enforcing backward consistency. $\mu(y), c(x)$ are the probability distributions over images in domains y and x, respectively. t typically represents the norm type (often L_1or L_2) used for measuring reconstruction error. The discriminator loss is$f_{Disc}(\Theta, \mathcal{H}; \Phi, \Xi)$ is described as equation (6)

$$f_{Disc}(\Theta, \mathcal{H}; \Phi, \Xi) = \int_y log(\varphi_\Phi(\mathrm{y}))t\mu(y) + \int_x log(1 - \varphi_\Phi(S_\Theta(\mathrm{y})))tc(x) + \int_x log(\psi\Xi(x))tc(x) + \int_x log(1 - \psi_\Xi(L_\Upsilon(\mathrm{y})))t\mu(x), \quad (6)$$

Where μ and c are, y and x probabilities, respectively. CycleGAN $\varphi_\Phi$attempts to differentiate between the real $y \in Y$ and the false created by$S_\Theta(x)$, and ψ_Ξ is the discriminator that determines the dissimilarity among the real $x \in X$ and the one generated by $L_\Upsilon(y)$.

The algorithm 1 employs artificial intelligence as a method to seamlessly embed creative visual styles into industrial ideas, opening up previously unimaginable opportunities for creativity. The CycleGAN also enables the generation of visually coherent depictions of style-based designs—based on the pre-established structure of meaning. Thus, aiding practical applications for packaging, product aesthetics, and visual narratives within the industry.

Algorithm 1: CycleGAN

Step 1: BEGIN

Step 2: FOR training iterations, ACTIVATE:

Step 3: Take n data samples from the W field$\{W^{(1)}, .. W^{(m)}\}$

Step 4: Take m data samples from the Y field $\{Z^{(1)}, . Z^{(n)}\}$

$$K_{real}^{(D)} = \left(\frac{1}{m}\right)\sum_{j=1}^{M}(C_w\left(W^{(j)}\right) - 1)^2 + \left(\frac{1}{m}\right)\sum_{j=1}^{M}(C_Z\left(Z^{(j)}\right) - 1)^2$$

Step 5: Calculate the produced data's discriminator loss

$$K_{real}^{(D)} = \left(\frac{1}{m}\right)\sum_{j=1}^{M}(C_w\left(H(W^{(j)})\right) - 1)^2 + \left(\frac{1}{m}\right)\sum_{j=1}^{M}(C_Z\left(E(Z^{(j)})\right) - 1)^2$$

Step 6: Adjust the discriminator network's settings.

Step 7: Determine the generator's loss by Z ⟶ W

$$K^{(E)} = \left(\frac{1}{M}\right)\sum_{j=1}^{n}\left(C_w\left(E_y{}^{(j)}\right) - 1\right))^2 + K_{Cycle}^{Z\to W\to Z}$$

Step 8: Calculate the generator loss of Z ⟶ W

$$K^{(H)} = \left(\frac{1}{M}\right)\sum_{j=1}^{n}\left(C_w\left(E_y{}^{(j)}\right) - 1\right))^2 + K_{Cycle}^{Z\to W\to Z}$$

Step 8: Optimize generator network parameters.

Step 9: END FOR.

Step 10: END

4 Result and discussion

This section describes the results of the model implementation, which include performance assessment and comparison analysis. The CycleGAN-based method for unpaired image style transfer in product packaging design can be applied to capture various art forms while preserving the necessary structure. The results show the effectiveness of the model at preserving visual consistency, allowing for artistic adaptation, and improving against baseline models.

4.1 Experimental setup

The implementation of the CycleGAN-based visual style transfer model was developed using Python 3.11.4. The experiments were run on a high-performance desktop equipped with 64 GB RAM and an AMD Ryzen 5900X processor under Windows 11. This configuration ensured efficient training and evaluation of the model across multiple unpaired image domains, enabling consistent testing of visual style adaptation for both artistic and product design applications.

4.2 Parameters setup

The hypermeters for the CycleGAN method are described in Table 2.

Table 2: Parameter's setup

Hyperparameter	**Selected Values**
Hidden units per dense layer	256, 512
Epochs	100
Dropout rate	0.5
Optimizer	CycleGAN
Batch size	64
Learning rate	0.0002
Number of filters	64
Activation function	ReLU, Leaky ReLU
Number of convolutional layers	3
Pooling size	2×2

4.3 Performance evaluation

In the performance assessment, Consistency Loss is used to evaluate how well the model retains structural information as it undergoes style transfer. A downward trend in the observed loss in training epochs indicates a more effective representation of possible image reconstructions, along with stable translations and a consistent model, which means that the model retained important elements from the original packaging design during several transfers using artistic style.

❖ **Consistency loss**

It calculates the difference between the original image and the image reconstituted after performing one forward and one backward translation. It guarantees that critical structural characteristics of product packaging do not change as a result of style transfer. The lower the amount of consistency loss components, the greater the content that remains unchanged during artistic migration. Figure 3 displays the diminishing consistency loss trend during CycleGAN training for package style adaptation.

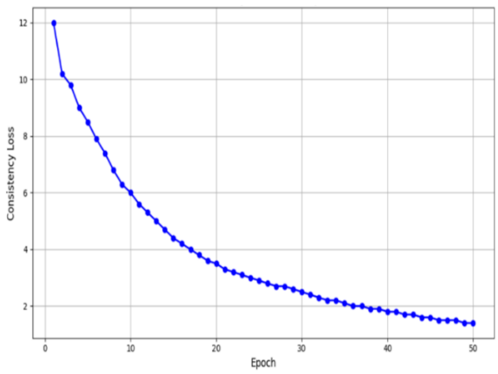

Figure 3: Consistency loss trend in the style transfer process

The graph shows a drastic decline in Cycle Consistency Loss from 12.0 at epoch 1 down to approximately 1.4 at epoch 50, which indicates an improving quality of reconstruction. This decreasing trend substantiates the model's ability to maintain key packaging forms while transferring the artistic style from Picasso to Warhol. The consistently falling loss indicates stable training of the CycleGAN and strong structural retention.

4.4 Comparison phase

In the comparison phase, the research explores the visual translation performance of CycleGAN in comparison with Exposition-Generative Adversarial (Expo-GAN) [21], with Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) as evaluation metrics. Expo-GAN emphasizes expressive style control, while CycleGAN enforces cycle consistency and multiscale discrimination. The evaluation stresses reconstruction accuracy and structural similarity between generated and target images. Table 3 shows the comparative evaluation results.

Table 3: Performance comparison of CycleGAN and Expo-GAN

Models	**PSNR**	**SSIM**
Expo-GAN [21]	21.39	0.76
CycleGAN [Proposed]	**23.84**	**0.81**

Table 3 presents the comparison of the image translation quality between Expo-GAN and the proposed CycleGAN. The CycleGAN has a higher PSNR of 23.84; its image reconstruction fidelity is better than that of Expo-GAN, which scored 21.39. For SSIM, CycleGAN acquired a somewhat higher value of 0.81, indicating better structural similarity as compared to 0.76 for Expo-GAN. This further shows that CycleGAN is improved at maintaining visual detail and style consistency.

❖ **Peak Signal-to-Noise Ratio (PSNR)**

PSNR measures the quality of image reconstruction by comparing the maximum power allowable of a signal to the power of the noise that could corrupt the signal. A larger PSNR value means that the translated image retains more of the original image detail and has lower noise distortion, indicating better visual quality in style-transferred images. Figure 4 indicates the PSNR improvement of CycleGAN compared to Expo-GAN for style-transferred package images.

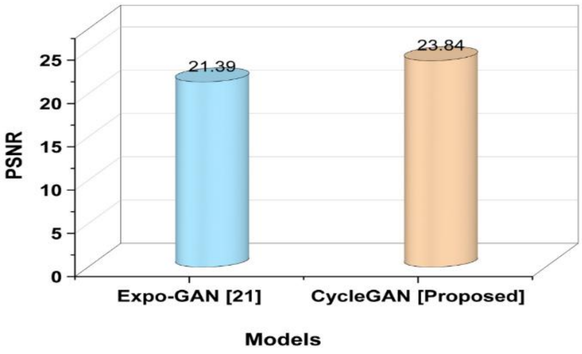

Figure 4: PSNR comparison between Expo-GAN and CycleGAN models

The CycleGAN achieved a PSNR of 23.84, indicating higher fidelity in preserving image quality compared to Expo-GAN, which recorded a PSNR of 21.39. This improvement reflects reduced distortion and better structural consistency in the translated outputs. The comparison highlights CycleGAN's advantage in maintaining visual clarity during style transfer.

- **Structural similarity index measure (SSIM)**

SSIM analyzes image quality as a function of its luminance, contrast, and structural components. It provides a measure of the similarity between the transformed image and the reference, with a focus on preserving perceptual consistency. High SSIM values indicate accurate preservation of visual qualities in the successively transferred style to facilitate extended transfer of artistic features. Figure 5 demonstrates the SSIM value of CycleGAN compared to Expo-GAN, demonstrating better structural preservation.

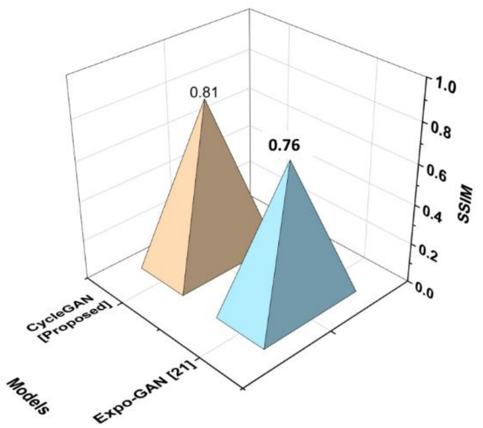

Figure 5: Structural similarity comparison between proposed models

The SSIM value of 0.81 for CycleGAN suggests, compared to 0.76 for Expo-GAN, superior structural similarity with the target image. This indicates CycleGAN's superior ability to maintain texture, edges, and perceptual detail during style transfer. The higher score indicates that CycleGAN has superior visual coherence.

4.5 Data comparison

The comparison illustrates the differences in focus between the datasets. CelebA-HQ is focused on explicit, structured facial features and is better for examining identity preservation and realism in style transfer tasks. Meanwhile, the Art Style Migration Performance dataset [22] focuses on artistic abstraction to examine adaptability in creative space. The Art Style Migration Performance data was collected from the source Kaggle. This dataset comes from actual-time visual transformations of different design and art images. It preserves significant image features, transformation patterns, and stylistic changes during migration. The data is flattened to a structured format that is ready for assessment, comparison, and investigation in creative design, digital art, and visual media use cases. It covers various content and style domains as they apply to contemporary visual communication and design processes. A comparison of CycleGAN's performance on two datasets is displayed in Table 4.

Table 4: Comparison of CycleGAN performance across datasets

Metrics	**CelebA-HQ**	**Art Style Migration [22]**
PSNR	23.84	21.97
SSIM	0.81	0.67

The PSNR score for CelebA-HQ reached 23.84, which means that the image quality after style migration was comparatively better than 21.97 for the Art Style Migration dataset. The SSIM values also indicate greater structural similarity in CelebA-HQ (0.81) compared to the Art Style Migration set (0.67), which signifies a greater preservation of features. These results show that CycleGAN was much more efficient on structured facial data compared to the Art dataset because the lower metric scores in the Art dataset indicate more variety and complexity that are more difficult to process as diverse artistic textures.

4.6 Discussion

The research aims to create a CycleGAN-based model for unpaired image style transfer in product packaging design, maintaining product identity while emphasizing various artistic styles. Expo-GAN [21] cannot imitate the structural intricacy of the layout or contain distinctive visual details, often resulting in incorrect or visually distorted outputs. Therefore, there was a lack of brand identity that maintained the brand after producing package layouts, in addition to never receiving fidelity styles with complex layouts. The recommended CycleGAN model addresses these limits by employing structural feature alignment and multiscale discrimination, producing visually consistent, brand-aligned packaging designs that preserve essential content while adapting creative visual characteristics.

5 Conclusion

The research aims to develop effective approaches for artistic style migration using CycleGAN for packaging design. Data were gathered from the CelebA-HQ dataset and from several artistic and product design sources to create visual diversity. Image data was pre-processed, including resizing and min-max normalization, to develop common inputs for stable GAN training. To extract structural features, HOG (Histogram of Oriented Gradients) was used to evaluate content preservation across style translations. The method described here uses CycleGAN, having a multiscale discriminator to extract detail and to generalize the varying visual styles to packaging, while retaining important product features. Results demonstrated strong reconstruction quality, resulting in a PSNR of 23.84 and SSIM of 0.81, showcasing the high-level visual fidelity and structural consistency of outputs. A limiting component is that performance is weaker when subjected to highly abstract or non-uniform artistic styles. Future work may consider adaptive attention methods or domain-aware training strategies for generalization across wider artistic domains and better creative flexibility in the potential packaging transformations.

Declaration

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.

Competing interests: here are no have no conflicts of interest to declare.

Authors' contributions (Individual contribution): All authors contributed to the study conception and design. All authors read and approved the final manuscript

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