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ORIGINAL RESEARCH ARTICLE

Enhancing image style transfer for real-time indoor geometric data using GAN

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ABSTRACT

The need for two-dimensional (2D) simulated environments, such as those seen in VR/AR and the multiverse, has grown substantially in the rapidly emerging modern era. To reduce the need for human interaction, the present studies have focused on the automated transfer of image processing styles inside a 2D virtual world through the application of computer vision. However, there are several limits to the current research on 2D environment-style transfers that rely on modelling. One thing to keep in mind is that there is a significant amount of style image data required for training a style transfer network specifically for 2D simulations. All this information must be combined with perspectives that are fairly accurate representations of the internet. The second issue was that the 2D structures were inconsistent. Most of the research relies on 2D input image attributes and ignores 2D scene geometric data. Lastly, changing the way something looks does not change the fact that every object has its own distinct qualities. To address these issues, we propose an enhanced Generative Adversarial Networks (GAN) approach for image style transfer in which oversampling and fine tuning is used to improve the data loss. Image Style transfer is an approach to image-to-image translation that supports the transfer of the style of an image to a real-time image and is mainly used to enhance the resolution and quality of an image. The performance of the proposed approach is analyzed using the MIT dataset, which is retrieved from Kaggle. It is an open-source dataset that contains 67 indoor categories and has more than 15,000 images. The proposed approach is implemented using MATLAB simulation tool. The results of proposed approach show that, content loss and style loss are lower than other deep learning models such as VGG16 and Alex Net.

Keywords: generative adversarial networks; deep learning; convolutional neural network; image processing; image style transfer

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1. Introduction

Style transfer frequently used in image- to-image translation that contains two images; one is used as content images and another as reference style. These two images are blended to generate an image having similar contents as of content image and styled with reference style. Style transfer mainly used for feature visualization, feature conversion and feature representation[1]. Deep learning provides effective contribution in image style transfer with modifications in the appearance of an image, without changing the contents of image[2]. Deep learning models, such as VGG16, VGG19 and Alex Net learn to represent images across number of layers, for both high-level and low-level feature characteristics, through the feature representation process[3–5]. These features make it easier to separate the content and style information from an image. Moreover, convolutional neural networks (CNNs) extract classified features from images and allow the network to understand both the content and features of the images[6]. Using pre-trained CNNs, it is possible to separate content and style representation of an image. Content representation include objects organization and their features in the image, while style representation focuses on visual patterns, colours and texture of the objects in the image. Deep learning models blend content and style representations of more than one images to reconstruct the image during reconstruction process. They create the images by optimizing, the aesthetic of one image with contents of another image. Various loss functions are defined to provide the right direction for reconstruction process, by evaluating the difference between reconstructed image and content and style representation in original image. These losses are helpful to change the parameters during training period of the networks, so that images can be generated with higher precision and different styles[7].

Generative Adversarial Networks (GANs) are combination of neural networks and deep learning architectures that are commonly used for unsupervised learning for generation of new images, image-to image translation and for style transfer. These networks consist two networks; generator network and discriminator network. The generator network generates new images by combining existing images or datasets with random noise samples; while discriminator network distinguishes between newly generated image with original image[8]. The discriminator network evaluates the output/newly generated image on a scale of 0 to 1. If the value is greater that 0.5, then the generated image is considered as real image; otherwise, it is considered as false image and sent back to the generator network through back propagation mechanism to reduce the value of error by varying network parameters. GAN models may learn internal representation and distribution of data and generate new images with different styles[9]. GAN networks are used in character generation, face generation, object detection, image classification and augmentation, image synthesis, image blending and inpainting, style transfer, image-to-image translation, image classification and segmentation, 3D image generation, text-to-speech generation, and other applications. GAN models can produce high-quality data in parallel at a rapid rate[10]. When working with GAN, the problem of mode collapse must be considered because it limits the applicability of GAN for text-to-image-generating jobs by producing images with limited output diversity. The content image is a single image, and a patch of this image is used as the style image, reducing calculation time and the need for massive image datasets[11].

The contribution of paper is:

- To examine the role of deep learning models in image style transfer for indoor image data.
- To proposed enhanced GAN-based approach that uses oversampling fine tuning for image style transfer improvements.
- To analyze the performance of the proposed approach with existing Cycle GAN and IPCGAN-Alex Net models with performance metrics called content loss style loss and adversarial loss.

The paper is divided into five sections; Section 1 provides the role of deep learning in the image style transfer scenario. Section 2 covers related work; in Section 3, proposed methodology has been presented; Section 4 provides results and discussion; and at last, in Section 5, conclusion and future research directions have been discussed.

2. Related work

Using Generative Adversarial Networks, the quality of images either in the case of feature extraction, enhancement, augmentation, image blending, style transfer or image processing etc. can be improved. The approaches of Image-to-image translation using GAN is used to improve the quality of image by applying some selected features of one image to another image or mapping among two images or more than two images. Style transfer has major concern in the field of image processing and computer vision. It improves the quality and resolution of images as well as transfer new styles on existing images. According to the previous research in style transfer, one image can be modified according to the style of second image. In style transfer two images are required, one is content image whose contents are preserved during the transfer/mapping and another is style image, whose style is mapped on the content image. Earlier, neural style transfer methods were used to transfer the style of images and Boltzmann machines, variational autoencoders and hidden Markov models were used to generate new images/data[8]. After the advancement of Generative Adversarial Networks, neural networks in combination with GAN networks performed well in style transfer. Some existing GAN approaches used for image style transfer are as under:

Zhu et al. proposed mapping between two domains, from first domain to second domain and back from second domain to first domain. For the mapping between two domains, this model named Cycle GAN, used two separate generators and two discriminators, which work in parallel for both domains. In addition to adversarial loss, calculated for every GAN model, cycle consistency loss was also calculated in cycle GAN and added in the objective function of the network. Training speed of the network was decreased due to the use of two generators and two discriminators and make the network unstable. For image style transfer, cycle GAN uses gram matrix method with pre-trained deep model and the emphasis of this GAN model was to acquire mapping between different images collections instead of only two images by capturing high level features[12].

Martin Arjovsky et al. proposed Wasserstein distance minimization between different data distributions and generate high quality images, as discriminator network provide better learning signal to generator network. Wasserstein GAN used Wasserstein distance instead of addition of random noise at the input stage and minimize the problem of mode collapse, which improved debugging and estimation of hyperparameters. The loss function of WGAN model represented the properties of convergence and evaluate the model in quantitative manner with improved optimization. Training of generative network was more stable than standard networks and easier to implement the architecture with minor changes in standard deep convolutional GAN. Modified GAN provided more stability in training of network with least variation in hyperparameter tunning[13].

Tero Karras et al. proposed feed forward generator network, which consist two separate networks called mapping network and synthesis network. Mapping network contains 8 layers and synthesis network has 18 layers, in which 2 used for each resolution. This network omitted input layer and use adaptive instance normalization. This Style GAN model has complex architecture but improved performance with separate high-level attributes due to the use of 26.2 million trainable parameters, while traditional network has 23.1 million. Perform faster due to weight demodulation and lazy regularization and code optimization. This model includes perceptual path length and calculate FID and precision and recall on two datasets to generate high quality images with different style[14].

Han et al. proposed another approach of artwork style transfer of images, based upon depth extraction generative adversarial network. They used a multi-feature extractor network to extract color, shape, depth of content feature, with the help of depth feature extractor and fast Fourier transform. The Depth Extractor GAN model improved the aesthetics and quality of texture and image clarity. This model represented self-encoder structure to extract the features from image and further processed by depth extraction network and represent the image in three-dimensional creative style[15].

Ulyanov et al. proposed texture network style transfer using instance normalization instead of batch normalization to enhance the resolution of texture in an image and to make the training of stylizing network easier and permit the training process to attain lower loss levels by normalizing each content image individually. The texture network maximized the minimum difference of each pixel value of output images to visualize the diversity, by using noise as another input. If the minimum value of each pixel was zero, then no gradients were required for optimization of parameters. To avoid zero gradient problem and visible diversity, average function was maximized instead of minimum[16].

Liu et al. presented an approach to improve training efficiency and quality of image, by considering new perceptual loss formulations. In this GAN, size of model was reduced and processing speed of training of model was increased by using chroma-sub sampling. Noise samples were added to three RGB channels separately, and feed to convolutional neural networks for further processing. Another difference of this models was the use of standard down sampler at initial stage and up-sampler at output stage instead of down-sampling layer after first convolutional layer and up-sampling layer before the last convolutional layer. Different object function was used to improve the diversity of images[17].

Xu et al. proposed a GAN model for artistic style transfer, which contains two separate networks; style encoding network and style transfer network. Style class-aware mechanism was used by style encoding network to generate style images. In style transfer network various residual blocks were used to extract the features more precisely and further processed by applying adaptive instance normalization and by calculating style classification loss along with adversarial loss and perceptual loss. This model efficiently performed artistic style transfer, while having lack multiple style images. Due to separate residual blocks, the network architecture became complex and consume more processing time as Cycle GAN[18].

Zheng presented an approach to learn the style from a single image by converting this image into multiple patches. These multiple patches of style image further used to train the network, which improved the computational efficiency as compared to other models. This model used Vgg16 pretrained deep learning model for processing the images and calculated only content loss in addition to adversarial loss. The conversion of style image into multiple patches and then train the network with these multiple patches increased the processing time of the network. This model named P2 GAN, preferred separate texture descriptor to evaluate the style transfer quantitatively and produced better-quality style transfer with single style image, which also improved the computation efficiency[19].

Although there have been major advances in the state of the art for deep learning for picture style transfer on 2D data images, there are still issues and research gaps that need to be resolved:

Research gap derived from literature:

- Enhanced content preservation: Even though current methods concentrate on successfully transferring artistic styles, more work needs to be done to better retain the original image's content features during the style transfer process. It's still difficult to change styles without losing the integrity of the material.
- Stability and consistency: Some techniques have trouble yielding outputs that are stable and consistent across a range of input images or stylistic elements. It is a constant struggle to provide consistency in the style transfer process, independent of the input data.
- Real-time processing: A lot of the current techniques need a lot of computation, which reduces them unsuitable for real-time applications. The development of more effective algorithms that can carry out style transfer in real-time or almost real-time is lacking.

3. Proposed methodology

Indoor image recognition is a thought-provoking problem in high-resolution visualization. Most of the image recognition models, that work outstanding for outdoor scenic images, perform worst for the indoor environment. The main challenge is that, while some indoor scene images like corridors images, can be well characterized by spatial properties; others like bookstores are better characterized by the objects they hold. To address this indoor scene recognition problem, we need a model that can exploit complete information from different images having different environments.

In this section, we provide a proposed approach that uses GAN with VGG19 model for image style transfer. The proposed framework has been depicted in **Figure 1**. Initially, we collected the MIT real dataset of indoor images from Kaggle. The MIT dataset is a collection of indoor images of rooms, kitchens, corridors, buildings, airports, offices, living rooms, etc.[20]. The required images for research on style transfer in indoor scenes are available in high quality in this dataset and are publicly available for researchers. The labelled images are available in JPG or JPEG format. After collecting the dataset, the images are pre-processed to avoid any anomalies and resized to 224 × 224 pixels. After data organization, various loss functions are calculated to finalize the optimization function. After that, the collected data is preprocessed to fetch out the required data for analysis. Furthermore, oversampling of data is performed before training models. In deep learning, oversampling is used to address class imbalance issues in datasets. In a classification problem, class imbalance occurs when one class (or category) of data substantially outnumbers another. This disparity can result in biassed models that perform inadequately for minority groups. Oversampling is one method for mitigating this problem. In oversampling, the aim is to increase the representation of the minority class by generating synthetic examples or duplicating existing ones[21]. This assists the deep learning algorithm in acquiring knowledge from a more balanced dataset, thereby reducing its bias towards the majority class. After oversampling, masking is performed to isolate specific areas of input image from the rest, for more precise editing and blending[22]. In the next step, models are trained, and the GAN model is fine-tuned to retrieve the optimal result. Tuning hyperparameters is essential for optimizing the performance of a GAN model and enhancing the reduction in loss. The style can be transferred from any image to a selected content image by keeping the same contents.

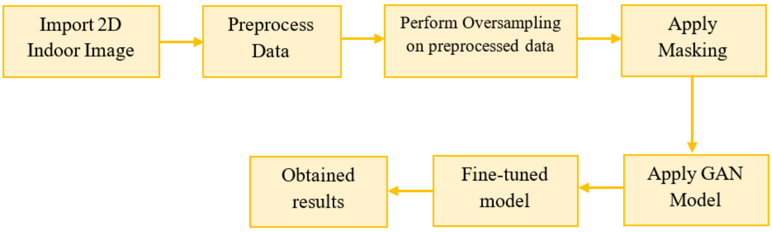


Figure 1. Proposed Framework.

Network losses and functions

Adversarial loss: In proposed model, the adversarial loss of least square of GAN is applied to the mapping function and its discriminator D.

$$G: \{x, z\} \rightarrow y$$

Here, *z* represents random noise, *x* is real/observed image and *y* is generated image.

$$L_{Adversarial} = L_{Generator} + L_{Discriminator}$$

Objective function of Generator is:

$$L_{Generator} = E_x \sim P_{data}(x)\left[\left(D\big(G(x,z)\big) - L_{real}\right)^2\right] \quad (1)$$

Here, L_{real} represents real data and $G(x, z)$ represents generated images that looks like images from domain y.

$$E_x \sim P_{data}(x) = \text{data distribution in domain } x$$

Objective function of Discriminator is:

$$L_{Discriminator} = E_y \sim P_{data}(y)\left[\left(D\big(G(x,z)\big) - L_{real}\right)^2\right] + E_x \sim P_{data}(x)\left[\left(D\big(G(x,z)\big) - L_{fake}\right)^2\right] \quad (2)$$

Here, L_{fake} represent fake data, and D shows the difference between translated image $G(x, z)$ and real image y.

Combined objective function is:

$$L_{Discriminator} = E_y \sim P_{data}(y)\left[\left(D\big(G(x,z)\big) - L_{real}\right)^2\right] + E_x \sim P_{data}(x)\left[\left(D\big(G(x,z)\big) - L_{fake}\right)^2\right] \quad (3)$$

Perceptual loss/content loss: To controls the system constrained and preserve the contents in the image, perceptual/content loss is calculated and the perceptual loss function for the proposed model is:

$$L_{perceptual} \text{ or } L_{content} = \left[\frac{1}{2}\ mean\ [(transfered\ content\ feature) - (content\ feature)]^2\right] * W_c$$

Here, W_c represents weights of content image.

Style loss: Difference between low level features of original image and generated image is calculated by style loss function, which is

$$L_{style} = mean\,[(transfer\ style\ feature) - (style\ feature)]^2 * W_s * 1/(h * w * c)^2 \tag{4}$$

Here, h, w, c represents the feature map of style image and W_s represents weights of style image

Objective function: This function represents overall loss of the model as the sum of all losses of proposed model is given as:

$$\begin{gathered} L_{FULL} = L_{Adversarial} + aL_{content} + bL_{style} \\ L_{Adversarial} = L_{Generator} + L_{Discriminator} \\ L_{FULL} = (L_{Generator} + L_{Discriminator}) + aL_{content} + bL_{style} \end{gathered} \tag{5}$$

Here, a and b are constants to control the value of content loss/perceptual loss and style loss.

Diversity: Diversity of the output image depends upon the sum of content loss and style loss.

$$\begin{aligned} Diversity &= L_{content} + L_{style} \\ Diversity &= \left[\frac{1}{2}\ mean\,[(transfered\ content\ feature) - (content\ feature)]^2\right] * W_c \\ &\quad + mean\,[(transfer\ style\ feature) - (style\ feature)]^2 * W_s * 1/(h * w * c)^2 \end{aligned} \tag{6}$$

4. Results and discussion

The proposed approach has been analyzed using MATLAB. To analyze the performance of the network, a real dataset MIT of indoor images, collected from Kaggle, that contains 67 indoor image categories and a total of 15,620 images. The MIT dataset is a collection of indoor images of rooms, kitchens, buildings, corridors, book stores, airports, offices, living rooms, class rooms etc. The required images for research on style transfer in indoor scenes are available in high quality in this dataset and are publicly available for researchers. The labelled images are available in JPG or JPEG format. The number of images varies across categories, but there are at least 100 images per category. This dataset contains different types of indoor scene images, including circular, rectangular, square, triangular, and free-hand-selected objects. To obtain the results, one image is used as content image, and one patch of this content image is used as the style image. Firstly, both images are resized from their original size and represented in [224 × 224] image size, and a random noise ratio of 0.7 is considered for all experiments and added to the input content image for further processing. For optimization of parameters of a neural network and to enhance the accuracy and speed of the network, Adam optimizer is used. To evaluate the results more precisely and to analyze the impression of style and losses on the output-generated images, the style transferred images are checked after 100 and 200 iterations separately. **Figure 2** depicts the obtained results of style transfer for different content images with their respective patches used as style images. A patch of content image, whose style is to be transferred, is used as a style image, and applied to the selected shape of the content image. The styles are applied to different shapes, like rectangular, circle, square, triangular, free-hand shape designs, etc.

The results signify the output image with applied styles. The output images show that the style can be transferred to any object, having a geometric shape, of an image either big, small. The losses can be minimized by varying the noise levels at input stage. **Figure 3** shows separate content loss, style loss and adversarial loss calculated and represented for each style transferred image. These losses are also used to train the network again to minimize the overall loss function of generate and discriminator network.

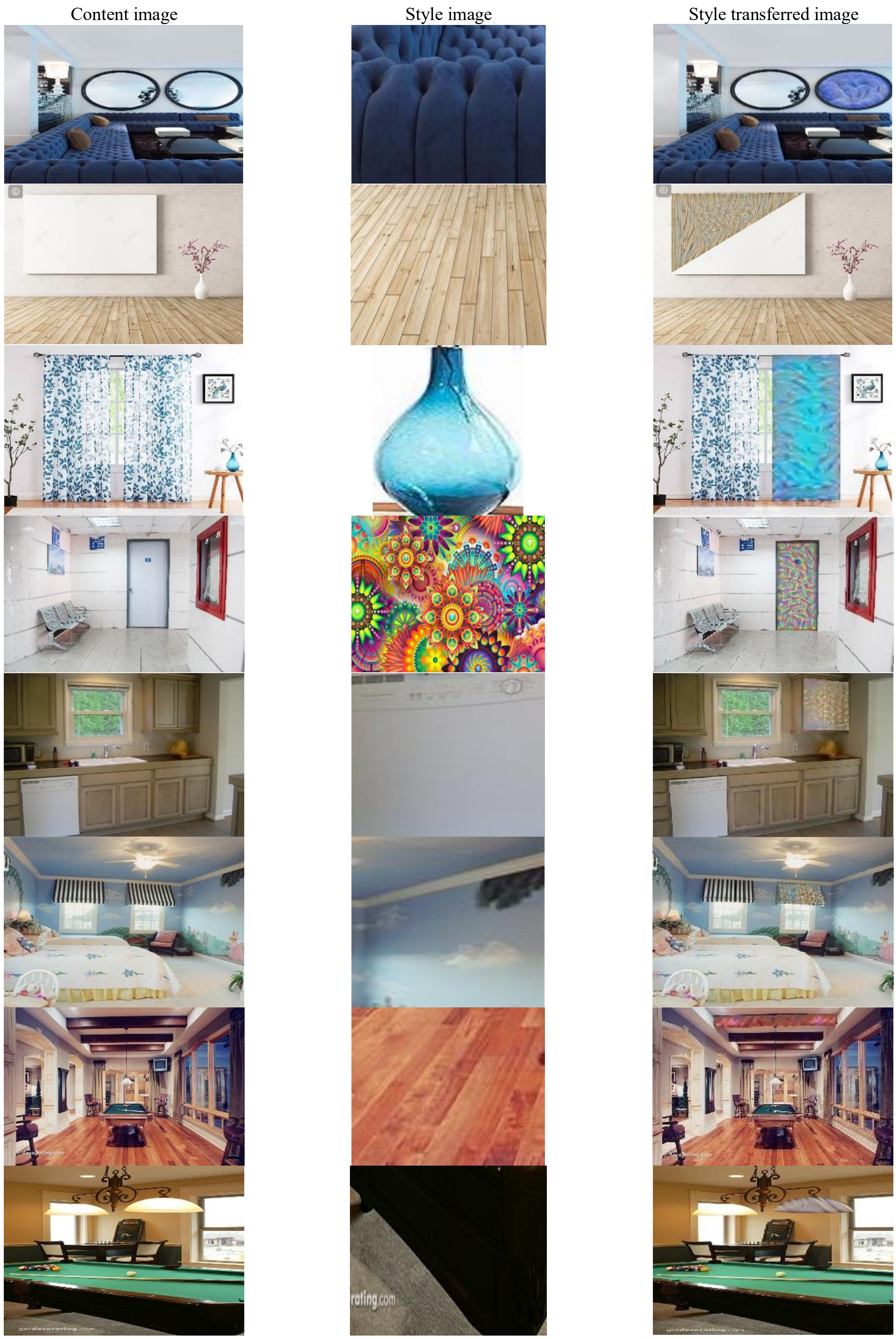


Figure 2. Results of style transfer on different content images using proposed model.

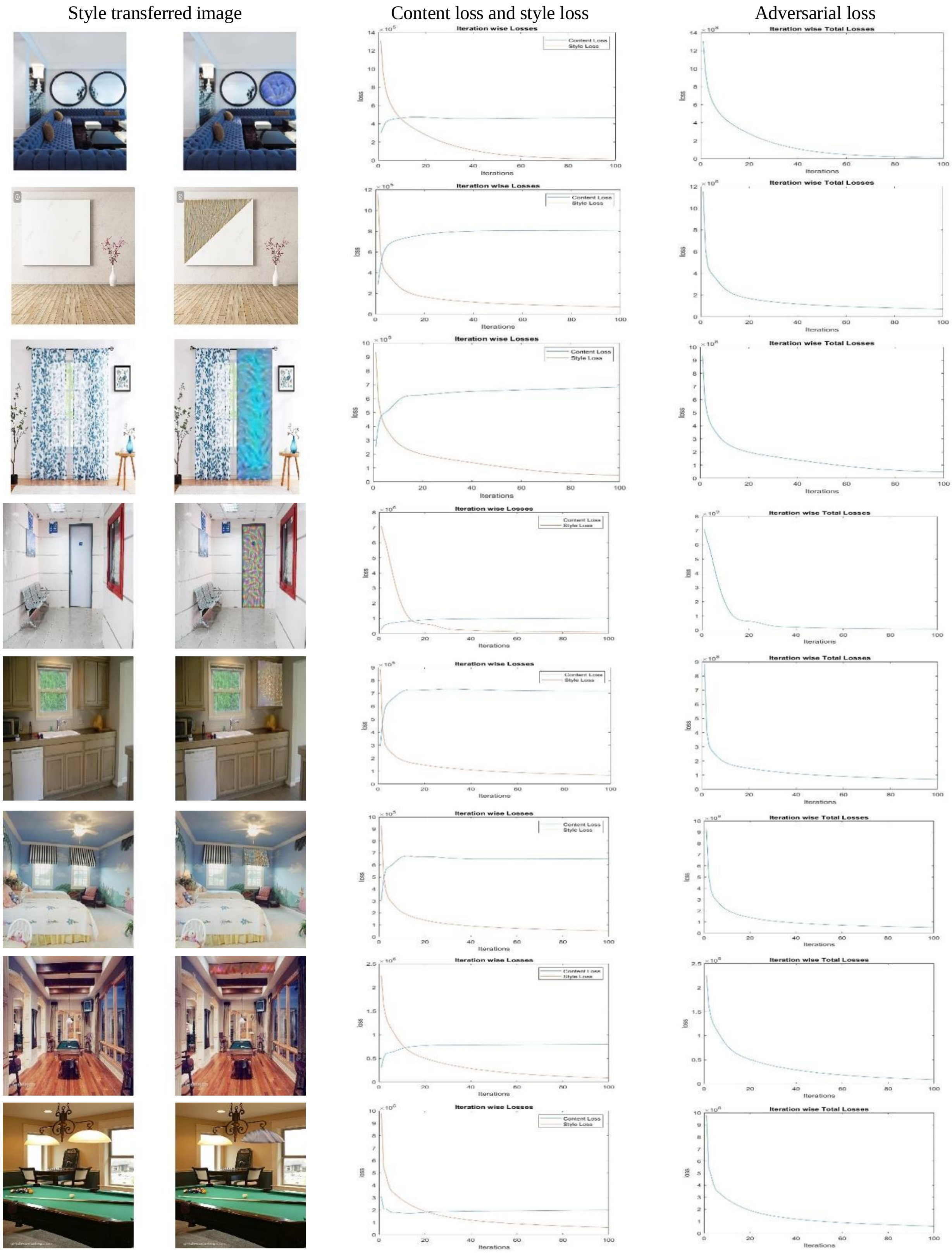


Figure 3. Representation of content loss, style loss and adversarial loss of proposed model.

The results shown in **Figure 4** after style transfer, represents the variation in diversity for all networks. It represents the style transferred images for each model separately, which shows improved diversity of proposed model than Cycle GAN and IPCGAN-Alex Net model. The loss values for the images are calculated as content loss, style loss and adversarial loss and represented in graphical form, occurred after 100 iterations and 200 iterations for each model one by one on similar images; to analyze the impact of losses, due to increased number of iterations on style transferred images. Furthermore, **Figure 5a, b** depicts content loss for each image for every model. According to the results, it is clearly indicated that due to the increase in number of iterations, content loss is slightly increases. In proposed approach content loss is low in perspective of Cycle GAN and IPCGAN-Alex Net models.

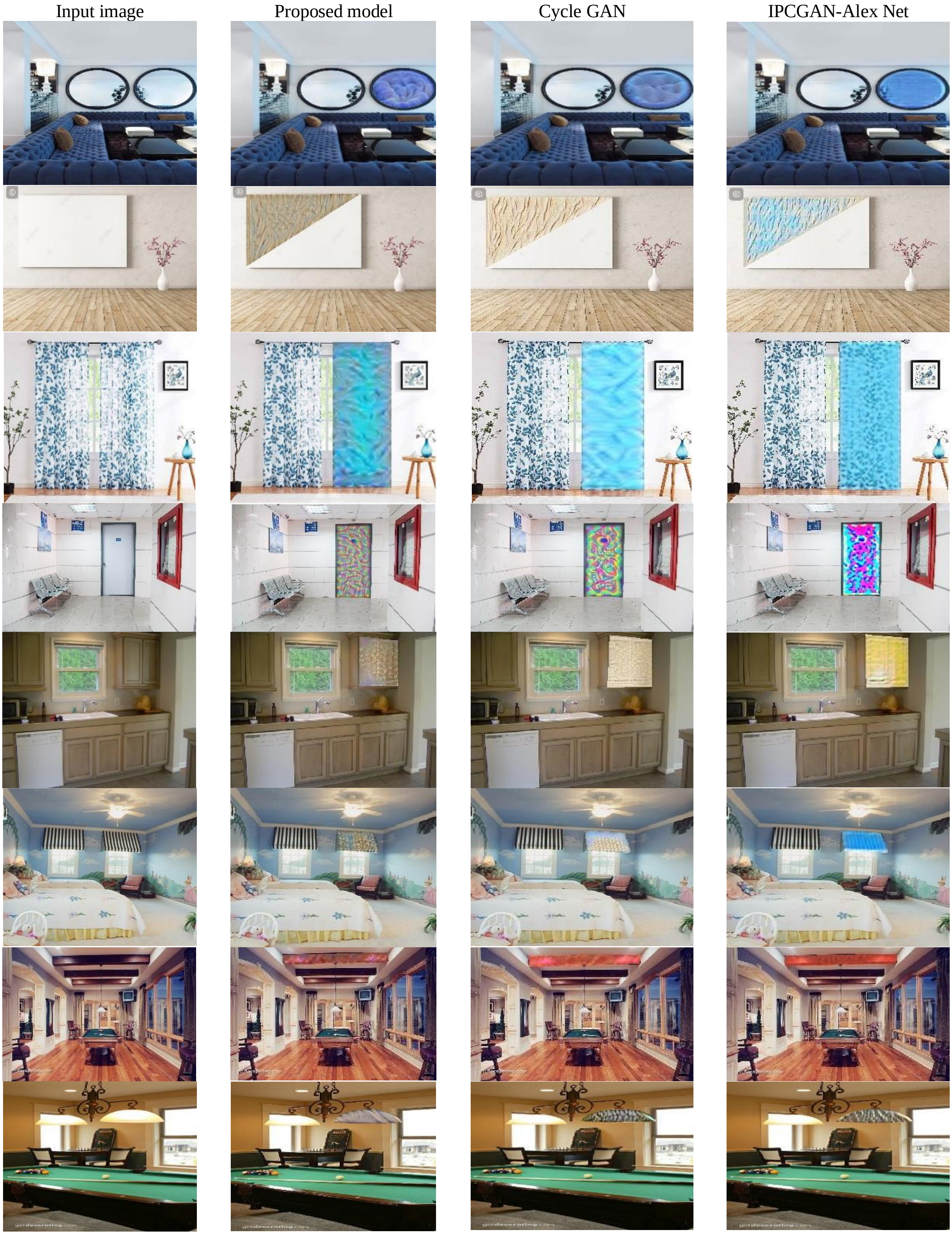
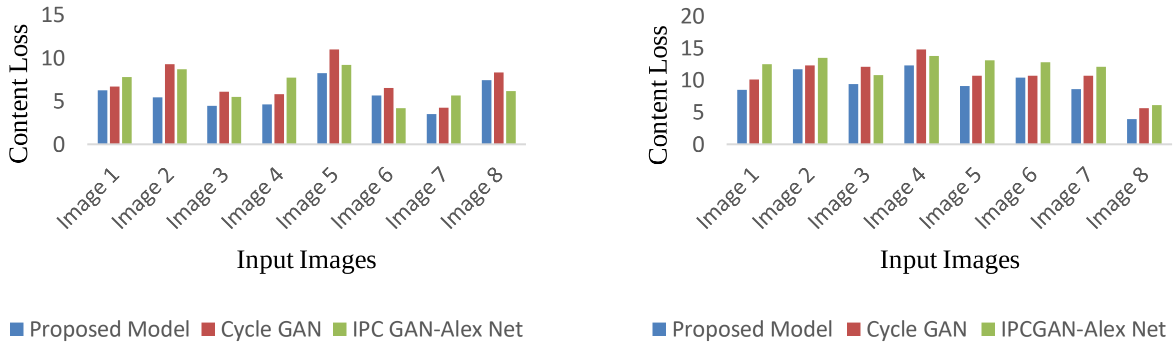


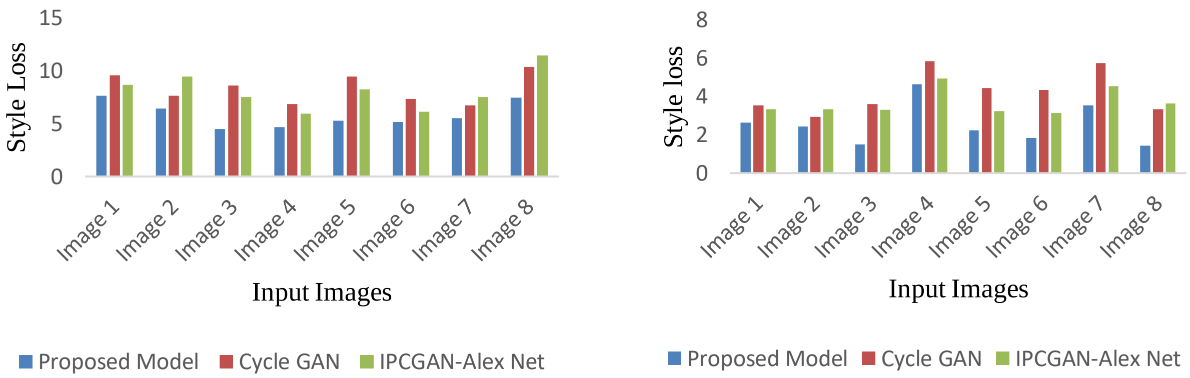
Figure 4. Results of style transfer with proposed model, Cycle GAN model and IPCGAN-Alex Net model.



(a) **(b)**

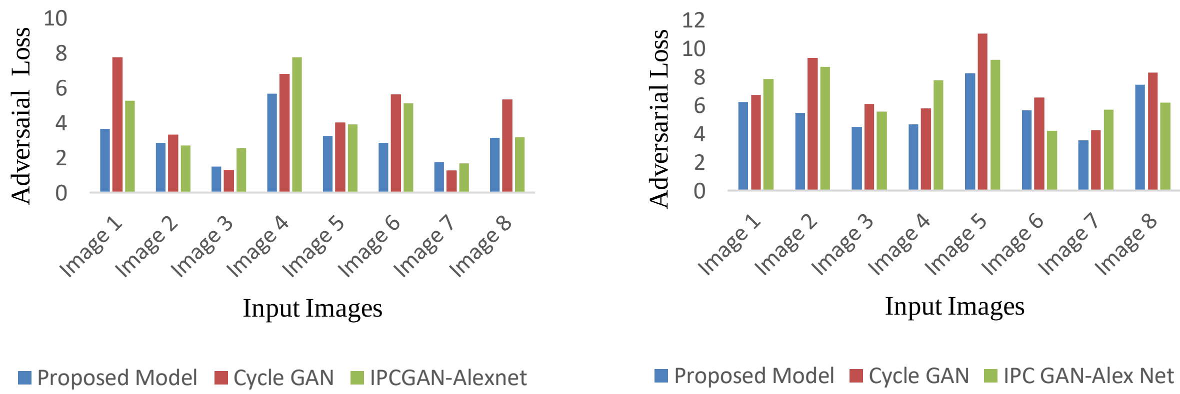
Figure 5. (a) content loss for three models after 100 iterations; **(b)** content loss for three models after 200 iterations.

Whereas. **Figure 6a, b** shows style loss, respectively for above all images by using all three models. The value of style loss is decreasing with increase in number of iterations for all models. In proposed framework value of style loss is low in comparison with other two models. Furthermore, **Figure 7a, b** represents the values of adversarial loss computed by all three models for each respective image, separately. In terms of diversity, the proposed model provides improved diversity with better style transfer among all models.



(a) **(b)**

Figure 6. (a) style loss for three models after 100 iterations; **(b)** style loss for three models after 200 iterations.



(a) **(b)**

Figure 7. (a) adversarial loss for three models after 100 iterations; **(b)** adversarial loss for three models after 200 iterations.

5. Conclusion

The process of image style transmission via generative adversarial networks (GANs) includes the modification of an image's visual appearance without altering its fundamental content. It is critical to maintain a consistent style throughout various elements of the image to prevent the introduction of artifacts or elements that are not realistic. Maintaining realism during stylistic transitions (such as from contemporary to vintage) continues to be a formidable task. In this paper, an attempt has been made to propose an enhanced GAN-based approach that uses a single image as the content image and a patch of this content image as the style image, which minimizes the requirement of large image data collection to perform the style transfer. The proposed approach has been implemented using MATLAB, and the performance has been analyzed using real indoor images from the MIT dataset. The performance is compared with existing GAN models Cycle GAN and IPCGAN-Alex Net in terms of diversity, content loss, style loss, and adversarial loss. In proposed approach, the content loss and style loss are less as compared to the other two models. In future, the quality of image style transfer for indoor scenes could be improved by creating better loss algorithms that are specifically designed to maintain geometric structure while changing style. Moreover, user experience and utility can be improved by creating techniques that let users participate in and manage the style transfer process, such as by defining style elements or modifying the degree of style transfer. Furthermore, real-time style transfer for indoor scenes can be facilitated by refining GAN designs or investigating novel models that minimize computational complexity without sacrificing quality.

Author contributions

Conceptualization, SK and KK; methodology, SK; software, SK; validation, SK, KK; formal analysis, SK; investigation, SK; resources, SK; data curation, SK; writing—original draft preparation, SK; writing—review and editing, SK; visualization, SK; supervision, KK; project administration, SK; funding acquisition, SK. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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