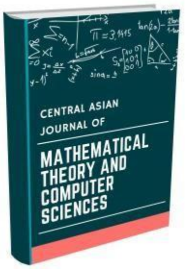

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Article

Developing Advanced Modeling Approach for High-Quality Score: Transforming Photos into Digital Masterpieces Based on Cartoonify

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Abstract: In recent years, the conversion and representation of photographs in various artistic ways has become a hot topic for digital image processing practitioners and researchers. One such artistic representation is the Cartoonify algorithm, which is expressed as a multimedia algorithm which designed in order to convert ordinary RGB image into cartoon-like digital images. In this paper, we develop the Cartoonify algorithm and construct a new algorithm that performs the same functionality as the Cartoonify algorithm, but with higher quality and more precise analysis. The proposed approach is developed utilizing a series of image processing techniques, including edge detection, color quantization, a set of filters to simulate color gradations and cartoonish brush strokes and adaptive smoothing. By constructing the proposed algorithm, the basic features of the original image are enhanced, producing attractive visual outputs. The results obtained by utilizing MATLAB demonstrate the robustness and efficiency of the proposed approach, producing a variety of formats that help cater to various artistic tastes. The proposed approach ensures the realistic and robustness properties. A comprehensive comparison with most relative and previous studies are done with the proposed approach and shown the best quality score (8.75 of 10). This study provides a robust framework for further exploration in the field of automated artwork generation.

Keywords: Digital Art, Image Processing, Multimedia Algorithm, Edge-Preserving Filtering, Quality Assessment

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1. Introduction

Digital image processing involves a sequence of acquisition, enhancement, restoration, compression, morphological processing, segmentation, representation, and description stages [1], [2], [3], [4], [5]. Improper use or omission of these stages can prevent an image from producing the intended output [6], [7], [8], [9], [10], [11]. Recent developments have expanded image processing beyond technical enhancement toward the creation and manipulation of visual content, including artistic transformations that combine computational methods with digital art [12], [13], [14], [15].

Image-to-art transformation has become an important application of machine learning and artificial intelligence. Existing algorithms can analyze visual information, detect edges and contrast, simplify color structures, and convert photographs into sketches or cartoon-like images [16], [17], [18]. However, traditional approaches often struggle to reproduce hand-drawn characteristics with sufficient precision while simultaneously preserving image structure and maintaining high visual quality [19], [20].

Recent studies have explored several directions in automated stylization. García-Alzórriz et al. used generative models to transform videos into temporally coherent animated drawings [21], whereas Huang and Sun combined deep learning, image processing, and pattern recognition to improve landscape-drawing stylization [22]. Tang et al. reviewed generative-AI applications in animation production, including inbetweening, colorization, and storyboard creation [23], while Xu examined workflows for adapting expressive pen-and-ink line styles to real-time 3D characters [24].

Other approaches emphasize content–style alignment and diffusion-based generation. Yu and Zheng proposed a content–style alignment module for producing natural stylized images [25]; Zhang et al. generated past and future drawing states using video diffusion models [26]; Shi and Wang developed a CNN-based cartoon-art rendering method with improved online responsiveness [27]; and Chen et al. combined latent diffusion, LoRA, ControlNet, and MultiDiffusion for cartoon-style transfer in 3D scenes [28]. These studies demonstrate strong progress but also reveal continuing challenges related to computational cost, parameter complexity, generalization, and the balance between edge preservation and color abstraction.

The central research problem is therefore to construct a structured multimedia algorithm that produces a visually attractive cartoon image without sacrificing essential edges, major structural features, or processing reliability.

Accordingly, this study aims to develop and evaluate an enhanced Cartoonify-based approach that combines noise reduction, edge detection, adaptive smoothing, color quantization, image blending, and edge enhancement to transform photographs into high-quality cartoon-style digital artworks.

2. Materials and Methods

The proposed approach was implemented in MATLAB to transform an input RGB photograph into a cartoon-style image. The processing pipeline begins with image reading and preprocessing, followed by median filtering for noise reduction. The cartoon effect is then produced through five main stages: Canny edge detection, bilateral filtering, k-means color quantization, image blending with edge enhancement, and quantitative evaluation using MSE, PSNR, and SSIM.

Step 1: This step used to extract powerful edges pivotal for cartoon depiction. The Canny detector recognize both edges (weak and strong), guarantee the structure to stay apparent. The noise has decreased based on Gaussian smoothing before estimation of the edge, prohibition the false detections. Gradient computation summarizes transitions in the brightness, that is the shape of the cartoon form. Which guarantee the cartoon keep the structural clearness of the primary image. Edge extraction by utilizing Canny-Detector and this take many interior steps starting by applying convolution on image $I\ (x, y)$ to produce smoothed image as shown in equation (1):

$$I_s\ (x, y) = (I * G)\ (x, y) = \sum_{u,v} I(u, v)\ G(x - u, y - v) \quad (1)$$

In order to reduce the noise, Gaussian filter is applied on the input image $I_s\ (x, y)$ to smoothed the image as shown in equation (2):

$$G\ (x, y) = \frac{1}{2\pi\sigma^2}\ e^{-\frac{x^2 + y^2}{2\sigma^2}} \quad (2)$$

To compute intensity gradients, utilize $I_s\ (x, y)$ in both x direction and y direction as well by applying equations (3) and (4):

$$I_x\ (x, y) = \frac{\partial I_s\ (x, y)}{\partial x} \quad (3)$$

Similarly, for y direction:

$$I_y\ (x, y) = \frac{\partial I_s\ (x, y)}{\partial y} \quad (4)$$

Then, both the gradient-magnitude $M(x, y)$ and the orientation (θ) are shown in equations (5) and (6):

$$M(x, y) = \sqrt{I_x(x, y)^2 + I_y(x, y)^2} \quad (5)$$

$$\theta(x, y) = \arctan(\frac{I_y(x, y)}{I_x(x, y)}) \quad (6)$$

By utilizing two independent thresholds T_H $(High)$ and T_L (Low), the Canny-Detector used to classify the final image pixels as preserved only the weak edge pixels as shown in equation (7):

$$Edge(x,y) = \begin{cases} strong\ edge, & if\ M(x,y) \geq T_H \\ weak\ edge, & if\ T_L \leq M(x,y) \leq T_H \\ non-edge, & if\ M(x,y) < T_L \end{cases} \tag{7}$$

Step 2: This step concerns the bilateral filtering, that are smooths image area during conserve edges. Different from normal filters, it keeps the boundaries fit. It mixes the uniform regions through prohibition color leak onto edges. Which is generating the cartoon-like feeling. The method is mainly functional for images at complex structure and details. Apply Bilateral-Filter for Edge-Preserving Smoothing by applying equation (8):

$$I_{filtered}\ (x) = \frac{1}{W\ (x)} \sum_{y \in \Omega} I\ (y)\ .f(\|x-y\|)\ .g\ (|I(x) - I(y)|)$$

(8)

Step 3: Now, k-means clustering used to minimize the number of colors into separated clusters. This step used to be animated of imitate the flat, straightforward the cartoons. It lessens visible noise and complexity property. By extracting superior variations, the output image be as artist style. Which enhances the stability between feature retention and abstract of cartoon. Color Quantization using k-means clustering for a flat, cartoon-like palette. The k-means clustering algorithm aims to partition a set of pixel color vectors:

$$\{x_1, x_2, \dots, x_n\}$$

Where:

x_i: A 3D vector in the RGB space.

K: number of clusters.

The main objective function which is required to be minimized as shown in equation (9):

$$J = \sum_{i=1}^{N} \min_{j \in \{1,2,\dots,k\}} \left\| x_i - \mu_j \right\|^2 \tag{9}$$

Where:

x_i: color-vector of i[th] pixel.

μ_j: mean color (centroid) of j[th] cluster

Step 4: This step joins the stylized color result and the bring out edge map. Which confirm edges stay special, prohibition smoothing of a significant structure. While Laplacian of Gaussian more distant improves parts of quick intensity modification. That keeps excellent stability between both the smoothing abstraction and details preservation. The output keeps the clearness and the quality of artist. Blend the quantized image with the bilateral filtered image by applying equation (10):

$$I_{final} = \alpha\ .I_{cartoon} + (1 - \alpha)\ .I_{edge} \tag{10}$$

Where:

α: is a blending parameter

Equation (10) is used to merge the cartoon image with the extracted edge-map. The value of α should be selected carefully (between 0 and 1) to gain the balance between cartoon smoothing color and appropriate details of edges. Enhance edges by darkening regions where edges exist. Utilizing Laplacian of Gaussian (LoG) for observing and extracting regions in the spots that the intensity is changed rapidly and this will help to enhance edges and blob like the image structure as well as shown in equation (11):

$$\nabla^2\ G(x,y) = \frac{x^2 + y^2 - 2\sigma^2}{\sigma^4} \exp\left(-\ \frac{x^2 + y^2}{2\sigma^2}\right) \tag{11}$$

Step 5: The final cartoon production is made and calculated utilizing SSIM and PSNR which are expressed in this step. Which estimate likeness, signal powerful, and error comparative with original image. The height values show the structural signification that is conserved through stylization. Computations supply a powerful standard for making comparison it with the current methods. To display the cartoon output and metric evaluation such as (SSIM and PSNR). Compute evaluation metrics and then plot the metrics as a bar chart with enhanced visibility with ensuring the performance evaluation of proposed approach.

Figure 1 shows the overall steps of the proposed approach to meet the article objectives and requirements.

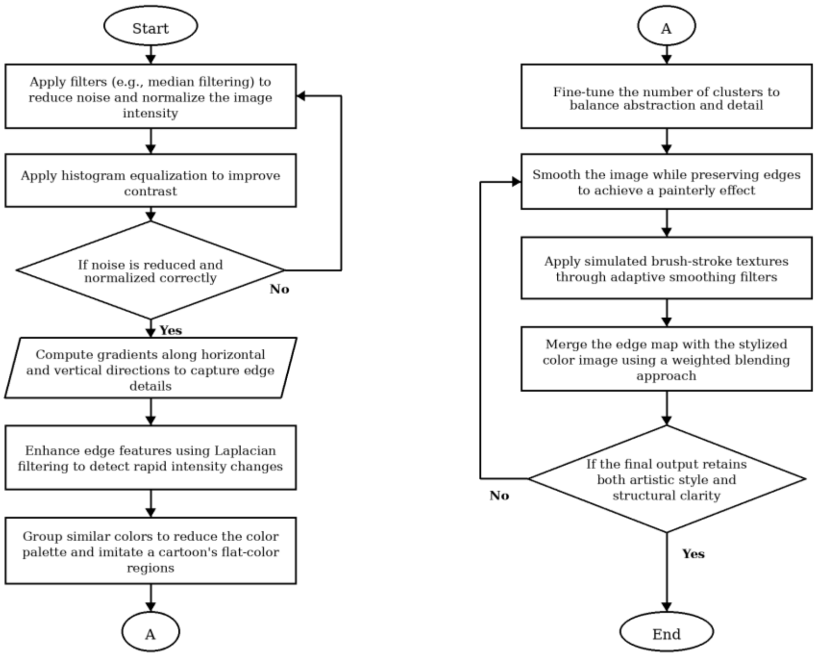

Figure 1. The proposed approach.

3. Results

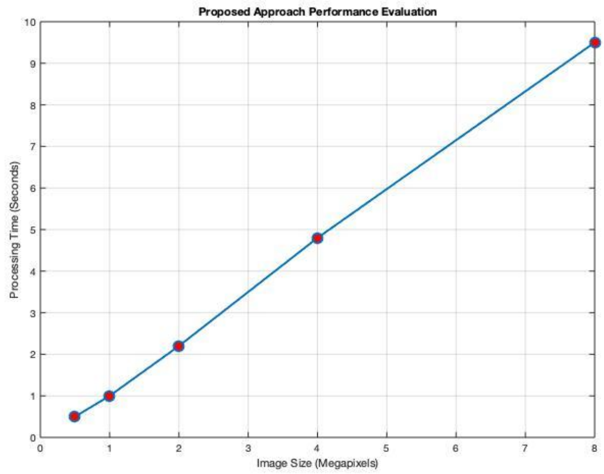

Figure 2. Proposed approach performance evaluation.

To evaluate and assess the quality of the resulting image in any proposed approach or model, many image processing techniques could be used. In this article, MSE (Mean Square Error), PSNR (Peak Signal-to-Noise Ratio), and SSIM (Structural Similarity Index Method) methods are utilized to find their suitability. From Figure 3, MSE clearly expresses the absolute error with an accepted value.

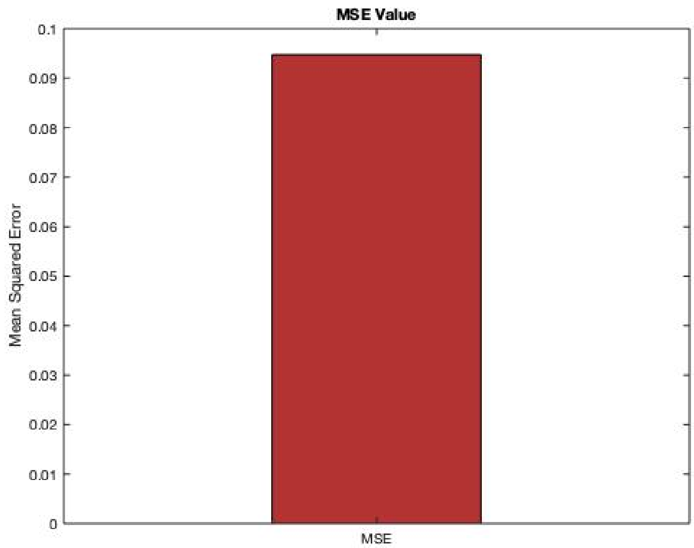

Figure 3. Proposed approach MSE value.

The PSNR value varies from 30 to 50 dB for 8-bit data representation and from 60 to 80 dB for 16-bit data. In Figure 4, an accepted range of quality loss is obtained, which is approximately 10.24 dB. While for SSIM, the resulting output metric has been evaluated exactly as a weighted average of the structural elements. The proposed weights measuring approximately the estimations for edges and smooth regions are 0.01.

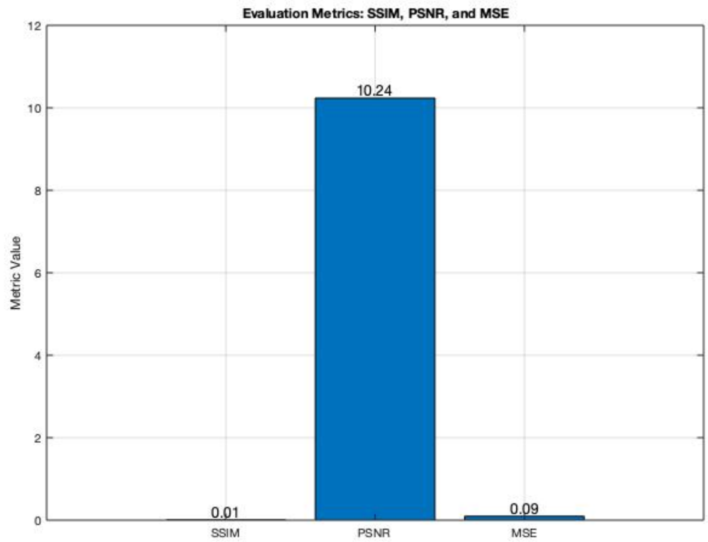

Figure 4. Proposed approach evaluation metric: SSIM, PSNR, and MSE.

In order to highlight all the fine details of the cartoon image and at the same time further improve the resulting blurry details, the edges of the image are strengthened by repeated processing so that the fine details are thin edges, but when the analysis and processing process continues in an advanced way, the resulting details are coarser. It is worth noting that the process of strengthening the edges of the cartoon image is done by tightening the detail bundles, as shown in Figure 5.

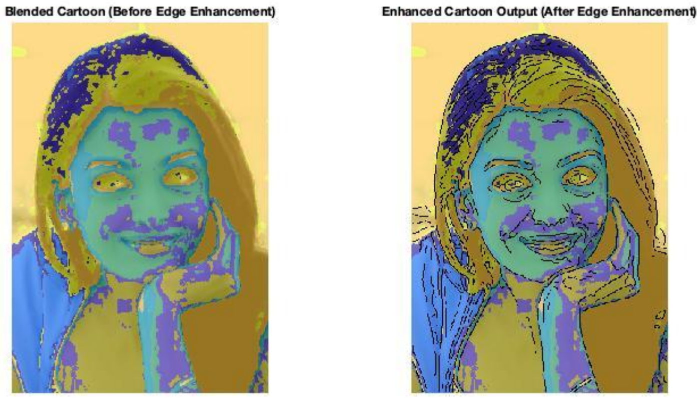

Figure 5. Blended cartoon before and after edge enhancements.

A multi-panel figure (Figure 6) is created to show the transformation process step-by-step summarizes how to apply the proposed model, which was mentioned in Figure 1, starting with the input image, then preparing the image in terms of format, clarity, and size, followed by the process of detecting edges, followed directly by the process of applying the special Bilateral filter, passing through the penultimate stage of the proposed model, which is the color quantization stage, and ending with the improvement of the cartoon image.

Figure 6. Step by step of enhanced cartoon output image.

The proposed approach achieved a comparative quality score of 8.75, the highest value among the methods included in the benchmark. Figure 7 presents the resulting comparison with the selected reference studies.

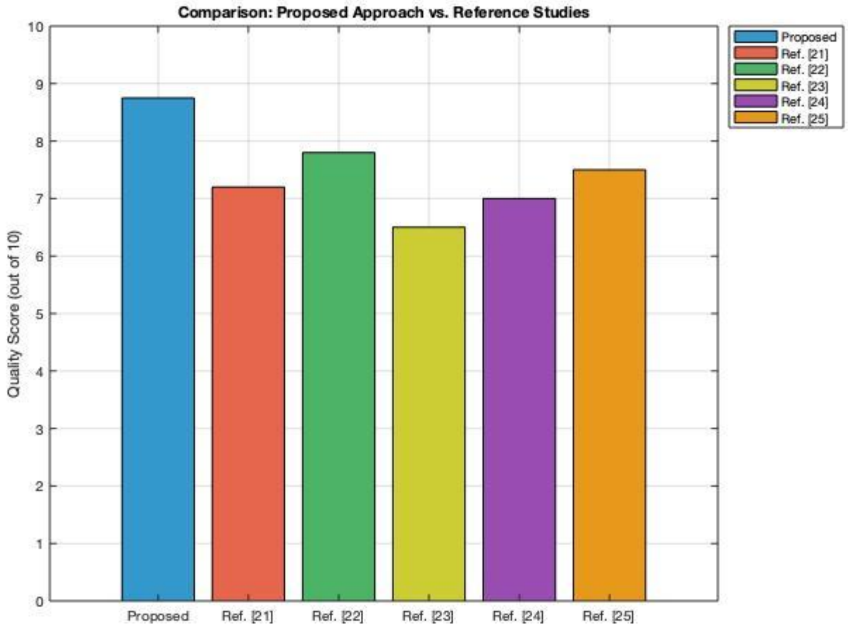

Figure 7. Comparison: Proposed approach and reference studies.

4. Discussion

The results indicate that combining median filtering, Canny edge detection, bilateral smoothing, k-means color quantization, image blending, and Laplacian-of-Gaussian enhancement provides a practical balance between abstraction and structural preservation. The processing-time trend in Figure 2 is consistent with the increasing number of pixels that must be analyzed as image size grows. Figures 5 and 6 further show that repeated edge enhancement produces clearer boundaries and more pronounced local details in the final cartoon image. The reported comparative quality score of 8.75 supports the visual observation that the proposed pipeline maintains recognizable image structure while producing a distinct cartoon-like appearance.

Compared with generative and deep-learning approaches [21], [22], [23], [24], [25], the proposed method relies on an interpretable sequence of conventional image-processing operations and therefore does not require model training or a large training dataset. This makes the workflow easier to reproduce and adjust for individual images. Nevertheless, diffusion- and CNN-based methods may offer greater stylistic flexibility and stronger generalization across complex scenes, whereas the present approach remains specialized for cartoon-style transformation and requires careful selection of filter, threshold, blending, and clustering parameters [26], [27], [28].

5. Conclusion

This study developed an enhanced Cartoonify-based approach for converting photographs into high-quality cartoon-style digital artworks. The method integrates median filtering, Canny edge detection, bilateral smoothing, k-means color quantization, image blending, and Laplacian-of-Gaussian edge enhancement, followed by quantitative assessment using MSE, PSNR, and SSIM. The MATLAB implementation produced visually recognizable outputs with strengthened edges and achieved a comparative quality score of 8.75. These findings show that the proposed workflow offers a reproducible framework for artistic image transformation while preserving major structural features. Future research should investigate deep-learning-assisted style transfer, automated parameter selection, broader image datasets, and real-time video cartoonification.

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