Image Transformation in The Field of Design Using Computer Vision

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Abstract

This paper delves into the realm of image processing within the context of design, harnessing the power of the OpenCV library to enact a trilogy of distinctive transformations on images. Firstly, the 'White to Colored Transformation' leverages the `cv2.applyColorMap` function, which transmutes grayscale images into pseudo-colored representations, imbuing formerly achromatic visuals with a vivid palette. This process, exemplified through the use of the 'COLORMAP_JET' color map, yields visually arresting and dynamically expressive images. The 'Colored to White Transformation' pursues a contrasting objective, simplifying complex scenes into minimalist compositions. Through grayscale conversion and subsequent application of binary thresholding, high-intensity regions are isolated, yielding bold white contours against a black backdrop. This innovative reductionist approach endows images with an aura of clarity and simplicity. Lastly, the 'Sketch Transformation' employs a multi-step process, commencing with grayscale conversion, followed by inversion to produce a negative. The introduction of a Gaussian blur emulates the characteristic softening seen in pencil sketches. The blurred negative is once again inverted, acting as a divisor for the original grayscale image. The resultant output mirrors the aesthetics of a hand-drawn pencil sketch, with intricate details set against a textured background, evoking a palpable sense of artistry by hand. These transformations collectively demonstrate the malleability and expressive potential that image processing, facilitated by OpenCV, offers within the realm of artistic interpretation.

Keywords *– Image transformation, Computer Vision, Image Processing, Digital Design, Innovation.*

1. Introduction

Image transformation in the field of design using computer vision has gained significant attention in recent years. With advancements in technology and computer vision techniques, researchers have been able to develop innovative methods to transform photos of real-world scenes into cartoon-style images. This transformation process is valuable and challenging, as it combines elements from both computer vision and computer graphics. By leveraging generative adversarial networks (GANs), researchers have been able to achieve impressive results in photo cartoonization (Yang *et al.*, 2018).

The application of computer vision technology in digital painting has also been explored. In a study by Levin (2006), the author proposes the use of computer vision technology to address existing problems in modern art painting, such as poor composition, limited tools and materials, and improper colour matching. The author defined Computer Vision as abroad class of algorithms that computers use to make intelligent assertions about digitally generated images, film and animated images. By applying computer vision techniques, designers can enhance their creative process and overcome these challenges (Cui, 2023).

Transformers, originally proposed for natural language processing tasks, have also found applications in computer vision. While transformers have become the standard architecture for tasks in natural language processing, their applications in computer vision are still limited. However, recent research has shown promising results in using transformers for image recognition at scale. This opens up new possibilities for image transformation in the field of design using computer vision (Dosovitskiy, 2020).

Ethical considerations are also important in the context of computer vision and design. Rostamzadeh *et al.* (2021) discuss the ethical implications of using computer vision in creative applications, including art and design. As computer vision technology becomes more prevalent in the design world, it is crucial to consider the ethical implications and ensure that the technology is used responsibly and ethically.

A comprehensive survey by Khan (2021) provides an overview of transformer models in the computer vision discipline. This survey serves as a valuable resource for understanding the different transformer models and their applications in computer vision tasks, including image transformation.

Image transformation in the field of design using computer vision has seen significant advancements in recent years. Techniques such as photo cartoonization and the application of computer vision in art painting have shown promising results. The use of transformers in computer vision tasks, including image recognition, has also opened up new possibilities for image transformation. However, it is important to consider the ethical implications of using computer vision in art and ensure responsible and ethical use of the technology.

2. Review of Related Literature

Image transformation using deep learning has gained significant attention in recent years. Deep convolutional neural networks (CNNs) have been widely used for various image processing tasks, including image registration, reconstruction, and super-resolution (Krizhevsky et al., 2017; Vos et al., 2019; Li & Fan, 2022; Xu et al., 2022; Lee et al., 2018). These deep learning methods have shown promising results in improving the accuracy and efficiency of image transformation algorithms.

One area where deep learning has been successfully applied is image registration. Traditional image registration algorithms often require manual feature extraction and matching, which can be time-consuming and prone to errors. However, deep learning techniques, such as CNNs, have been used to learn image features and predict spatial transformations for image registration (Vos et al., 2019; Li & Fan, 2018; Mok & Chung, 2020). These deep learning-based methods have demonstrated faster and more accurate registration compared to traditional approaches.

Another application of deep learning in image transformation is image reconstruction. In the field of medical imaging, low-dose computed tomography (LDCT) reconstruction is a challenging task due to the limited amount of available data. Deep learning methods, combined with adaptive sparse modeling, have been proposed to improve the reconstruction quality of LDCT images (Chen et al., 2022). These approaches leverage supervised deep learning and unsupervised transform learning to achieve robust reconstruction.

Deep learning has also been utilized for super-resolution image reconstruction. Conventional microscopy techniques often produce low-resolution images, limiting the ability to observe fine details. However, deep learning algorithms have shown the potential to transform low-resolved images into super-resolved images, enhancing the resolution and quality of microscopy images (Xu et al., 2022).

Overall, deep learning techniques, particularly CNNs, have revolutionized image transformation tasks by enabling the processing of raw image data and learning image features directly from the data (Soetje et al., 2020). These methods have demonstrated superior performance in various image processing fields, including medical imaging, microscopy, and computer vision (Krizhevsky et al., 2017; Li & Fan, 2022; Lee et al., 2018). The combination of deep learning with traditional image transformation algorithms has the potential to further improve the accuracy, efficiency, and quality of image transformation tasks.

Wang *et al.* (2018) suggested the use of the perceptual adversarial loss, which involves an adversarial training procedure between the image transformation network T and the concealed layers of the discriminative network D. The hidden layers and output of the discriminative network D are continuously and automatically improved to identify the differences between the transformed image and the corresponding ground-truth. Meanwhile, the image transformation network T is trained to minimise the differences identified by the discriminative network D. By combining the generative adversarial loss and the perceptual adversarial loss, D and T can be trained sequentially to address image-to-image transformation challenges. The usefulness of the suggested PAN and its advantages over many previous works are demonstrated by experiments conducted on various image-to-image transformation tasks, such as image deraining and image inpainting.

Maiel et al. (2019) provided a comprehensive introduction to deep learning in the field of medical image processing, starting from the fundamental theoretical principles and progressing towards practical applications. Initially, they examine the overarching factors contributing to the widespread use of deep learning, encompassing significant advancements in the field of computer science. Next, they commence the examination of the fundamental principles of the perceptron and neural networks, as well as some essential theory that is sometimes overlooked. By doing so, they comprehend the factors behind the surge of deep learning in various fields of application. Undoubtedly, the field of medical image processing has been significantly impacted by this quick advancement, namely in the areas of image detection and recognition, image segmentation, image registration, and computer-aided diagnosis.

Karanam *et al*. (2020) delves into the distinctions between natural images and medical images within the realm of Deep Learning. Natural images exhibit a diverse array of objects with varying structures, enabling the network to acquire complex filters, particularly in deeper layers. Conversely, medical images, particularly fundus retinal images, present a lower degree of diversity in patterns, where subtle variations in a few details significantly impact classification outcomes. This phenomenon is evident in the pronounced dissimilarity observed in the filters of deeper convolutional layers. Filters from a network trained with retinal fundus images are notably simpler compared to those derived from the ImageNet dataset. The paper briefly outlines diverse applications of deep learning across various fields, emphasizing its distinct advantages in medical image processing. It underscores the potential areas where deep learning algorithms can be effectively applied, particularly in the context of medical image processing.

Petrellis (2021) emphasises the need of noninvasive monitoring of morphological characteristics in fish farming, a procedure often performed manually resulting in substantial expenses. To tackle this difficulty, the article combines image processing and machine learning methods, utilising innovative approaches like edge and corner recognition, as well as pattern stretching, to evaluate the proportional length, height, and picture coverage of a fish. The suggested technique, suitable for many fish species, can be extended to calculate precise measurements when employing a pair of cameras for fish that are hidden or at an angle. In addition, the approach detects essential fish components, such as the caudal, spiny and soft dorsal, pelvic, and anal fins. The study specifically examines four widely recognised fish species, namely Dicentrarchus labrax, Diplodus puntazzo, Merluccius merluccius, and Sparus aurata, as there is a lack of extensive publicly available data for these particular species. The training and testing process involved using 25 images for each species. This resulted in a fish length prediction error ranging from 1.9% to 13.2%. This error is similar to the errors observed in other approaches that were trained using larger datasets. However, these other approaches do not have all the capabilities provided by the proposed method.

Kong *et al.* (2019) utilise preprocessing techniques like wavelet denoising to precisely define the boundaries of different tissues, such as the skull, cerebrospinal fluid (CSF), grey matter (GM), and white matter (WM), in five MRI head imaging datasets. Automatic picture segmentation is accomplished by employing convolutional neural networks in deep learning, which incorporates parallel computing to substantially decrease processing time in comparison to human and semiautomatic methods. This development is crucial for improving both the speed and accuracy, particularly as the number of acquired samples continues to increase. The calculated volumes of segmented grey and white matter show potential for quantitative diagnosis of brain atrophy. In summary, our research highlights the possibility of combining image processing and deep learning to automatically segment tissue, demonstrating its major ramifications in the field of neurology medicine.

3. Materials and Methods

This section describes the processes involves the processes involved in the use of computer vision in transforming images from black and white to coloured, from coloured to sketch, and white. Figure 1. describes the architecture of the proposed system.

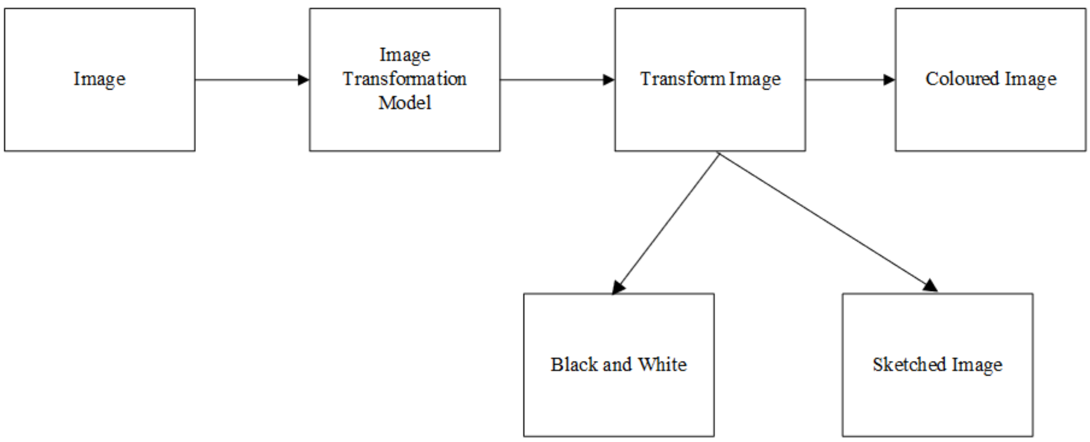

Figure 1: Architectural Design of the Proposed System

Image Transformation Model: This is the core component responsible for altering the appearance of an input image. It could be a deep learning-based model, possibly a convolutional neural network (CNN), trained to perform various image transformations.

OpenCV: OpenCV (Open-Source Computer Vision Library) is a powerful open-source computer vision and machine learning software library. It provides a wide range of tools and functionalities for working with images and videos.

Image Input: This is the starting point of the process. It could be any image in a supported format (e.g., JPEG, PNG). The image may be in colour or grayscale.

Image Output: After the image passes through the transformation model and any further processing using OpenCV, the resulting image is generated. This output image will reflect the desired transformation (e.g., black and white, sketch, etc.).

1. **Transformations**: The Image Transformation Model, in conjunction with OpenCV, performs a range of image alterations. In this case, the specified transformations include:
2. **Coloured Image**: The original image in full colour with multiple channels (typically Red, Green, and Blue).
3. **Black and White**: A grayscale version of the image, where each pixel is represented by a single intensity value.
4. **Sketches**: A representation of the image with lines and edges emphasized, similar to a pencil sketch.

1. Scaling:

- Nearest Neighbor Interpolation:
  NewPixelValue = OriginalPixelValue * ScaleFactor
- Bilinear Interpolation:
  NewPixelValue = (1 - FractionalPart_X) * (1 - FractionalPart_Y) * OriginalTopLeftPixelValue
  + FractionalPart_X * (1 - FractionalPart_Y) * OriginalTopRightPixelValue
  + (1 - FractionalPart_X) * FractionalPart_Y * OriginalBottomLeftPixelValue
  + FractionalPart_X * FractionalPart_Y * OriginalBottomRightPixelValue

2. Rotation:

- Rotation around the center:
  NewX = cos(angle) * (OriginalX - CenterX) - sin(angle) * (OriginalY - CenterY) + CenterX
  NewY = sin(angle) * (OriginalX - CenterX) + cos(angle) * (OriginalY - CenterY) + CenterY

3. Affine Transform:

- NewX = A * OriginalX + B * OriginalY + C
- NewY = D * OriginalX + E * OriginalY + F

4. Perspective Transform:

- NewX = (A * OriginalX + B * OriginalY + C) / (G * OriginalX + H * OriginalY + 1)
- NewY = (D * OriginalX + E * OriginalY + F) / (G * OriginalX + H * OriginalY + 1)

Processing Pipeline: This refers to the sequence of operations that the input image undergoes. In this case, the pipeline would involve passing the image through the Image Transformation Model first for the desired transformation, followed by any additional processing using OpenCV.

4. Results and Discussion

The paper leverages the OpenCV library to perform various artistic transformations on images. The code encompasses three distinct transformations: converting white-dominated images into vividly colored renditions, turning colored images into high-contrast monochromatic compositions, and rendering images in a sketch-like style.

4.1. White to Colored Transformation

This transformation employs the `cv2.applyColorMap` function from the OpenCV library. The function maps a grayscale image to a pseudo-coloured representation, creating an illusion of color in what was originally a black-and-white image. In this case, the 'COLORMAP_JET' color map was selected, but OpenCV provides a range of other maps to suit different artistic preferences. The result is a visually striking and vibrant image that evokes a sense of artistic expression.

4.2. Colored to White Transformation

This transformation seeks to simplify the visual elements of a colored image, emphasizing high-contrast edges. Initially, the colored image is converted into grayscale, which reduces it to a single channel. Then, a binary threshold is applied, isolating high-intensity regions. The resulting image features bold white contours on a black background, effectively distilling complex scenes into minimalist compositions that evoke a sense of clarity and simplicity.

4.3. Sketch Transformation:

To achieve a sketch-like effect, the code employs a series of operations. First, the image is converted to grayscale. Next, the grayscale image is inverted to produce a negative. Subsequently, a Gaussian blur is applied to the negative, simulating the blurring effect often seen in pencil sketches. The blurred negative is then inverted again, and the original grayscale image is divided by this inverted blur. The final result resembles a pencil sketch, with fine details highlighted against a textured background, evoking a sense of hand-drawn artistry.

Figure 2: Original Image

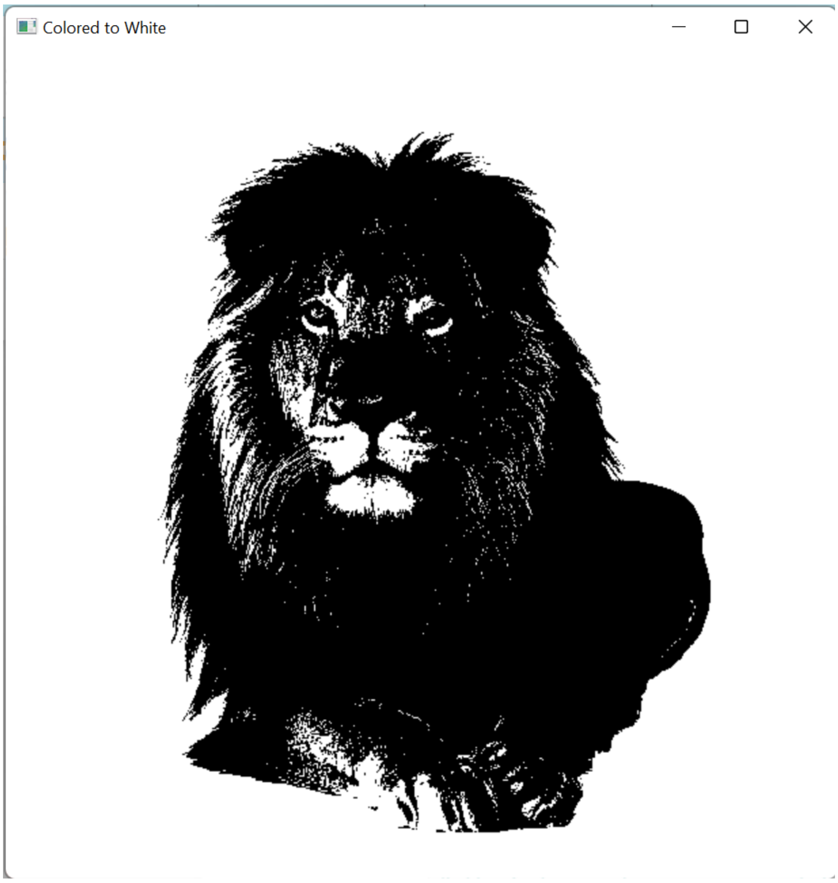

Figure 3: Black and White

Figure 4: Sketched image

Figure 5: Colored Image

Figure 6: Original Image

Figure 7: Colored Image

Figure 8: Black and White

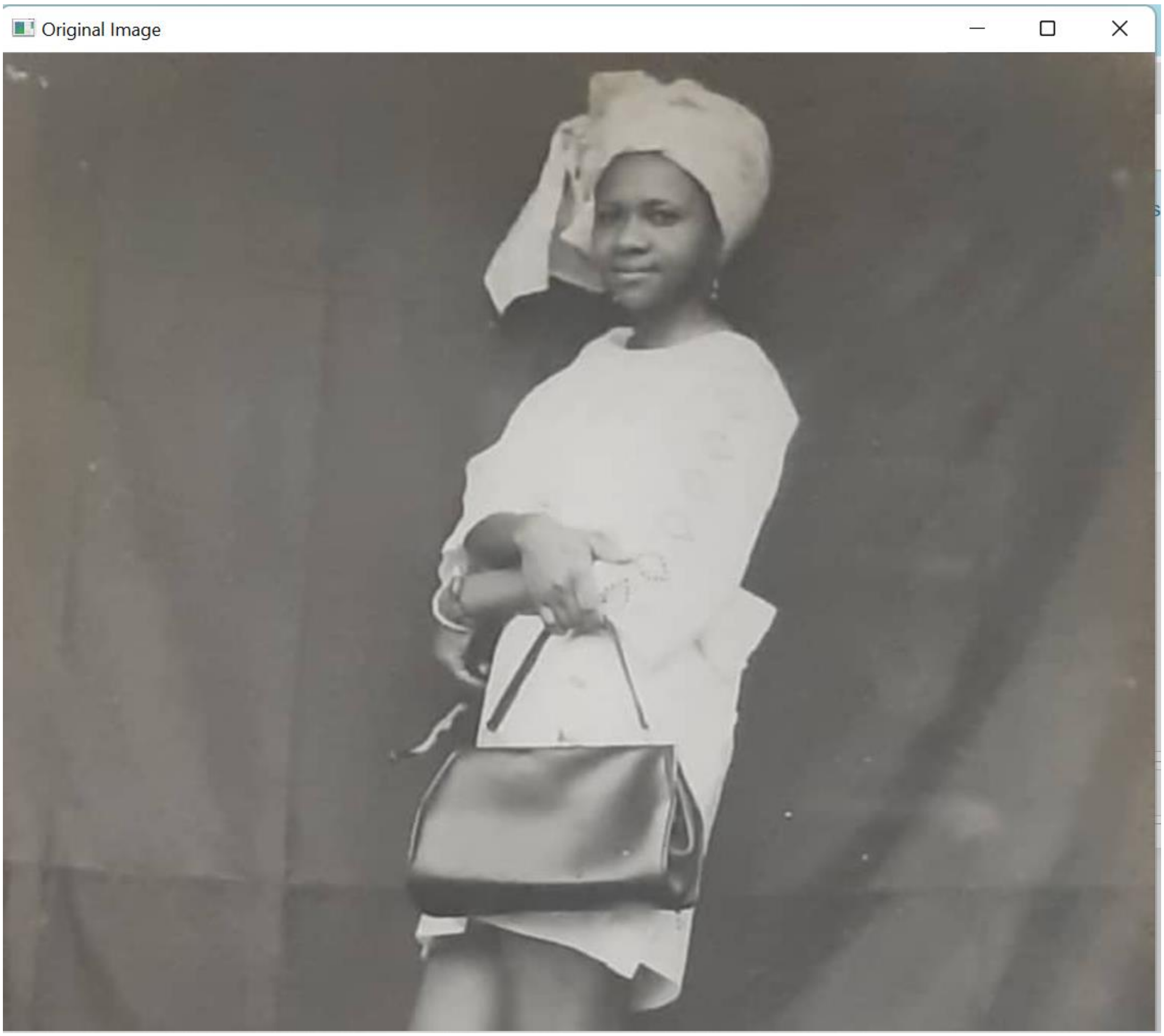

Figure 9: Original Image

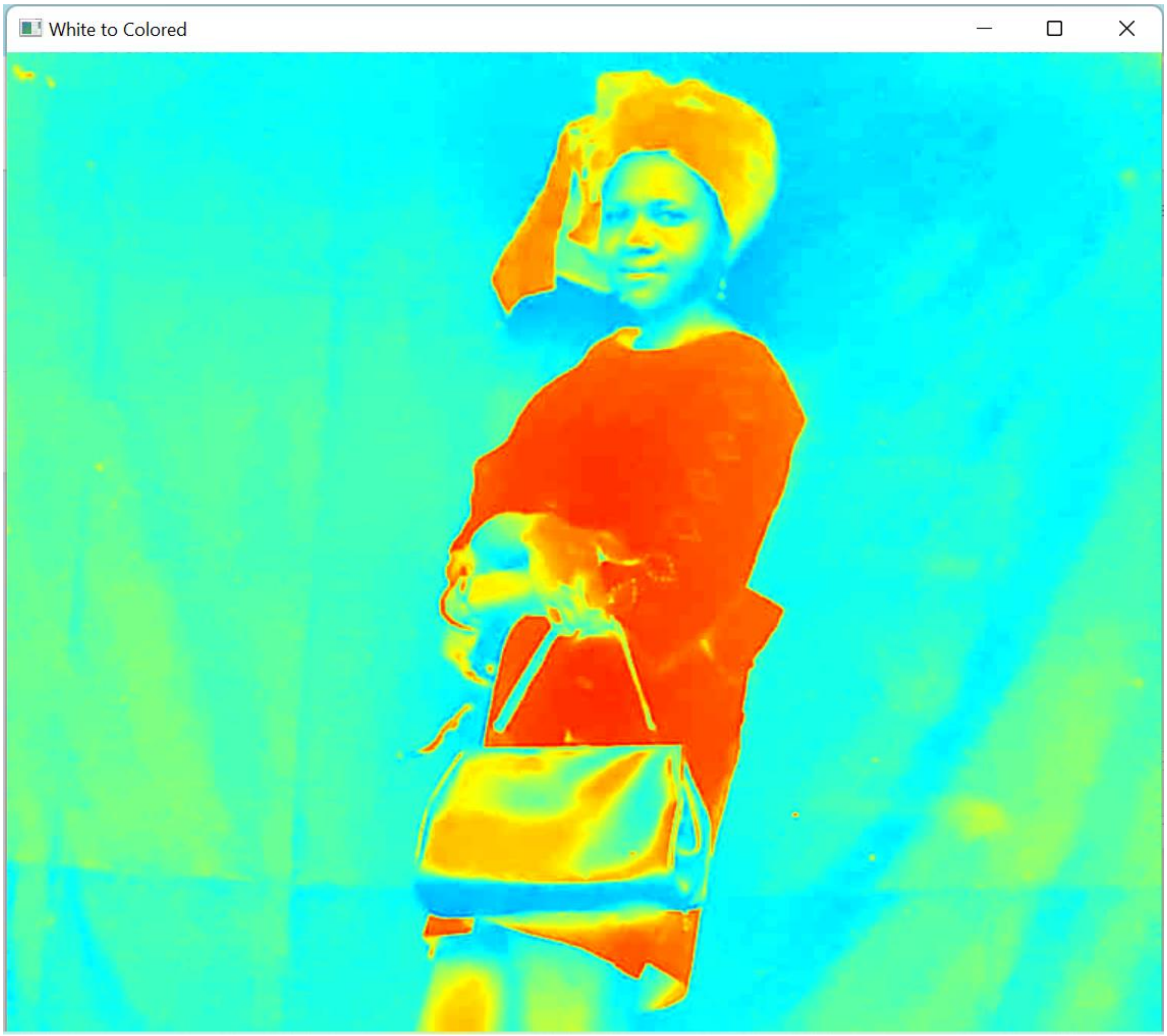

Figure 10: Coloured Image.

5. Conclusion

The utilization of computer vision in design is an innovation that enriches digital media and the field of design. This paper serves as a testament to the remarkable versatility and potency of the OpenCV library in the realm of image manipulation and artistic expression. By adeptly amalgamating essential image processing techniques, the library becomes a catalyst for crafting visually arresting transformations that traverse a spectrum of styles—from dynamic and vivid representations to refined, minimalist compositions and even intricate hand-drawn sketches. The code presented in this study acts as a gateway to an expansive realm of creative possibilities, offering designers and digital image enthusiasts an invaluable tool to produce distinctive and captivating visual content. The ability to seamlessly navigate between diverse artistic expressions underscores the library's significance as a cornerstone in the world of digital imagery, empowering users to explore and push the boundaries of their creative vision with unparalleled ease and innovation.

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