

Colourblind-Friendly Image Recolouring Using Generative Adversarial Networks

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Abstract—Color Vision Deficiency (CVD) affects approximately eight percentage of the global male population, significantly impairing the ability to perceive colors accurately. Dichromatic vision, one of the most prevalent forms of CVD, arises from the absence of specific cone cells in the retina, leading to difficulties in distinguishing between red-green or blue-yellow color spectrums. Traditional methods for improving color accessibility rely on static recolouring techniques, which lack adaptability and fail to generalize across diverse image datasets. This study introduces a method to improve color perception for CVD individuals by employing Generative Adversarial Networks (GAN). Using Pix2Pix architecture, the approach focuses on image recolouration, transforming input visuals to enhance color differentiation for CVD-affected users. The framework is tested on the publicly available Abstract Art Dataset. Evaluation metrics, including the Structural Similarity Index (SSIM), along with insights from user studies, validate the effectiveness of this method. The results showcase the potential of GAN-based techniques to surpass traditional recolouring methods.

Index Terms—Color vision deficiency, recolouration, GAN, Dichromates, colorblindness

I. INTRODUCTION

Color vision is a fundamental aspect of human perception that enables us to interpret and interact with the world in meaningful ways. Color vision deficit (CVD), commonly referred to as color blindness, affects approximately 0.4% female and 8% of the global male population's are in this category [1], [2]. Color blindness or CVD often goes unnoticed for years because people with the condition may adapt to their environment without realizing that they perceive colors differently. This is especially true for mild to moderate forms of CVD, where individuals may only have trouble distinguishing specific colors, such as red and green or blue and yellow. Since they may have grown up with these perceptions, they might assume everyone sees colors similarly.

It limits the ability to perceive and differentiate specific color ranges, particularly in individuals with dichromatic vision. These deficiencies significantly impact day-to-day tasks, including reading color-coded data, identifying signals, and other visually dependent activities. Figure 1, illustrates the concept of CVD for traffic light for normal trichomat, protanopia, deuteranopia and tritanopia, respectively.

By applying recolouration techniques, we aim to separate red and green hues effectively, enhancing distinguishability while maintaining visual naturalness.

The ability to perceive colors arises from the complex interaction of light with the human visual system, particularly the retina's cone cells. Any disruption in this process can lead to color vision deficiencies, that impact a person's daily activities and overall quality of life.

Human color vision relies on three types of cone cells in the retina: L-cones (sensitive to long wavelengths, associated with red), M-cones (sensitive to medium wavelengths, linked to green), and S-cones (sensitive to short wavelengths, related to blue) [3]. These cones form the basis of the LMS color space, where each type contributes to the perception of different parts of the visible spectrum.

In dichromatism, the absence of one type of cone limits its color perception, reducing the distinguishable gamut. Protanopia results from the absence of L-cones, while deuteranopia arises from the absence of M-cones. This leads to a significant overlap in perceived red and green hues, which diminishes contrast [3].

Another way to interpret color perception is through the opponent color theory, which models color as pairs of opposing channels: red-green, blue-yellow, and black-white. For individuals with Protanopia or Deuteranopia, the red-green opponent channel is severely impaired [3].

These blindnesses can be diagnosed using the Ishihara test, a widely recognized tool for detecting Color Vision Deficiency (CVD), particularly red-green blindness, which includes protanopia (insensitivity to red light) and deuteranopia (insensitivity to green light). The test consists of pseudoisochromatic plates displaying numbers or patterns embedded in dots of varying colors and brightness levels. Individuals with normal color vision can easily distinguish these figures, whereas those with red-green blindness may struggle or fail to identify them due to their inability to differentiate specific color wavelengths.

Our study addresses these deficiencies, particularly for Protanopia and Deuteranopia. These conditions affect red-green differentiation, creating challenges in distinguishing colors in natural and artificial scenes.

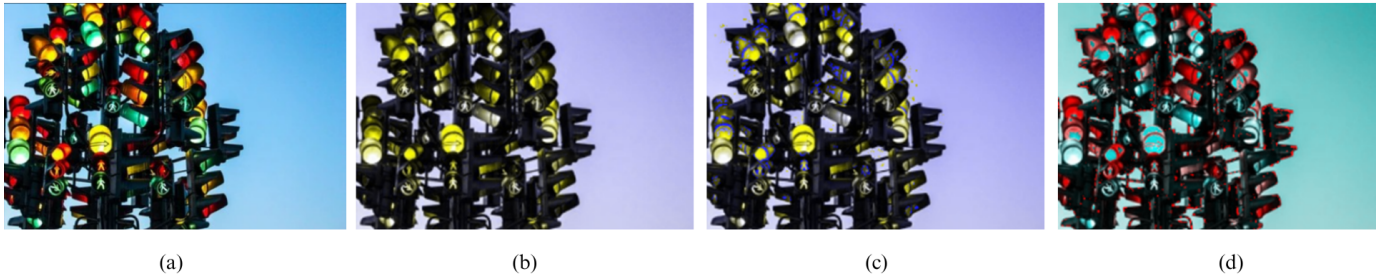


Fig. 1. An illustration of the color perception differences between protanopia and deuteranopia. (a) The visuals that people with normal vision see (Trichromat) (b) The visuals that people with protanopia see (c) The visuals that people with deuteranopia see (d) The visuals that people with tritanopia see.

II. LITERATURE REVIEW

The concept of color blindness was first documented by John Dalton in 1784 [4]. Dalton, a distinguished chemist, noted his difficulty in distinguishing between scarlet and green, as well as pink and blue. He theorized that this issue was due to the internal structure of his eyes, specifically hypothesizing that his vitreous humor had a blue tint. Following his death, his will instructed a post-mortem examination of his eyes, which revealed that his vitreous humor was, in fact, clear. As Dalton was both the first to scientifically study and personally experience red-green color blindness, the condition has since been named Daltonism in recognition of his contributions.

The LMS (Longwave, Middle wave, Shortwave) color model, which separates cone responses, is a more effective tool for colorimetric analysis compared to the CIE XYZ system, which obscures the connections between cone responses [5]. For example, in simulating protan vision, simply altering the CIE X component is insufficient because changes affect both long- and middle-wavelength cones. Using LMS allows precise manipulation for accurate simulation.

A computerized approach is proposed by Brettel et al. to replicate dichromatic vision for trichromatic observers, accurately representing the reduced color gamut and confusion of dichromats [5]. The simulation aims to recreate not only the color distortions but also the plausible appearance of colors as perceived by dichromats.

Blue and yellow hues show varying saturation levels. This method ensures that dichromats see no difference between original and simulated images, validating its fidelity.

The trichromatic theory explains color vision through three types of photoreceptors with different sensitivities, but fails to account for perceptual phenomena like opponent after-images [6]. Hering's opponent-color theory, which involves three opposing channels (white-black, red-green, yellow-blue), addresses these gaps. Combined, both theories offer a comprehensive understanding of color vision.

The replacement model was proposed by Machado et al. simulates dichromacy by substituting the spectral sensitivity function of one cone type with another [6]. For protanopia, the L-cone's sensitivity is replaced by the M-cone's, and vice versa for deuteranopia. However, the model requires rescaling

the replaced curves to preserve the area under the original cone's spectral sensitivity, improving accuracy in simulating color perception.

Kuhn et al. developed an algorithm based on spring-mass system to optimize colors in images and enhances contrasts for the colour blind people. The color gamut for each type of dichromacy is represented by a plane in the LMS color space, which is mapped to the perceptually uniform CIE Lab^* space [7]. A least-squares approach identifies the best plane representing the gamut. The algorithm involves three steps: first is quantizing the image to obtain a set of colours, second is optimizing the spring-mass based on these colors which were quantized in the previous step, and third is reconstructing the resultant colours. The optimization reduces to a 1D adjustment along the b^* axis, preserving luminance.

Jinmi Lee et al. proposed modifying the classical linear transform-based simulation method to model various degrees of color blindness using fuzzy parameters [1]. They introduced two new methods to correct color blindness. The method incorporates two modules: Correction and Control. The Correction module adapts to chromatic disturbances, and the Control module provides essential information through a graphical interface for further adjustment. In this study we have used this linear transformation technique for generating the recoloured images which are then passed to the GAN for its training.

Generative Adversarial Networks (GANs) are deep learning models comprising a generator and discriminator in a competitive framework [8]. The generator learns to produce realistic outputs, while the discriminator evaluates their authenticity. In recolouration tasks, GANs learn mappings from normal vision to simulated dichromatic vision, enabling targeted enhancements.

Jiang et al. introduced a novel Triple Latent-based disentanglement. Individuals with varying degrees of CVD (Color Vision Deficiency) have different sensitivities to distinguishable hues, requiring personalized color distribution generation [2]. To create images with diverse color distributions for specific needs, two objectives must be met: first, disentangling color representation, and second, controlling color distribution as specified. A novel triple-latent structure achieves this, with a contrastive group (z_1, z_2) for color representation disentanglement.

ment and a control group (z_{cvd}) for personalized generation, overcoming entangled dimensions in conventional GANs.

Li et al. evaluated image quality using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) with results showing that pix2pix-GAN produced the best performance overall [8]. The SSIM results indicated that images generated by pix2pix-GAN closely resembled the original images, leading to the highest similarity score. Although PSNR was also used for evaluation, it did not align with human visual perception, highlighting its limitations. Overall, pix2pix-GAN proved to be the most effective method for filling color-blind simulations, demonstrating the practicality of using deep learning for this task [9]. Hence we have used the Pix2Pix GAN architecture in this study. Pix2Pix, a specific type of GAN architecture, excels in paired image-to-image translation tasks. It employs a U-Net-based generator, which captures spatial details, and a PatchGAN discriminator, which focuses on local features to assess realism. By leveraging paired datasets, Pix2Pix learns pixel-wise mappings, making it particularly suitable for recolouration tasks where preserving fine details and natural aesthetics is crucial.

III. PROPOSED METHODOLOGY

Our methodology has three parts: simulating dichromatic vision, recolouring using linear transformation techniques, and generalising recolouration for unseen images using a GAN-based approach as shown in Figure 2. Every phase is intended to address a different facet of improving dichromatic people's visual perception.

Datasets

For the study, a publicly accessible dataset "Abstract Art Dataset"¹ with 1,000-images has been used. The selection of this dataset was based on its diverse and detailed colour patterns, which offer a strong basis for training the GAN to effectively generalise to unseen images with complex colour schemes.

The images in this dataset present diverse artistic styles and color compositions, making them ideal for testing and refining the model's ability to recolor images while maintaining natural aesthetics. By utilizing this dataset, we aimed to enhance the GAN's performance in generating visually pleasing and color-distinguishable images suitable for individuals with color vision deficiencies.

A. Simulation of Dichromatic Vision

A significant challenge in color science lies in accurately simulating dichromatic color perception, enabling individuals with normal trichromatic vision to understand how colorblind individuals perceive colors. The simulation of protanopia and deuteranopia is performed in three stages: conversion from RGB to LMS, application of dichromacy transformation matrices, and conversion back from LMS to RGB.

In the first step, the RGB values are transformed into the LMS color space. The corresponding equation image is shown in eq 1.

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 17.8824 & 43.5161 & 4.1194 \\ 3.4557 & 27.1554 & 3.8671 \\ 0.0300 & 0.1843 & 1.4671 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

The simulated dichromatic vision is obtained by applying the Protanopia (K_P) or Deuteranopia (K_D) transformation matrices to the LMS values. The corresponding equation images are shown in eq 2 and 3:

$$\begin{bmatrix} L_p \\ M_p \\ S_p \end{bmatrix} = \begin{bmatrix} 0 & 2.0234 & -2.5258 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} L \\ M \\ S \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} L_d \\ M_d \\ S_d \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0.4942 & 0 & 1.2483 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} L \\ M \\ S \end{bmatrix} \quad (3)$$

Finally, the transformed LMS values are converted back to RGB space eq 4:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 0.0809 & -0.1305 & 0.1167 \\ -0.0102 & 0.0540 & -0.1136 \\ -0.0004 & -0.0041 & 0.6935 \end{bmatrix} \begin{bmatrix} L \\ M \\ S \end{bmatrix} \quad (4)$$

These steps simulate the color perception of individuals with Protanopia or Deuteranopia. The resulting RGB images represent what a person with the respective color vision deficiency would perceive as Figure 2.

B. Recolouration for Dichromats

The recoloration process plays a vital role in improving visual accessibility for individuals with Color Vision Deficiency (CVD) as illustrated in Figure 2. Its primary objective is to restore distinguishable color contrasts in images while preserving their natural aesthetics. To achieve this, we apply specialized transformations to the RGB color space, tailoring the modifications to address specific dichromatic deficiencies. This approach ensures that the resulting recoloured images remain visually intuitive and appealing to viewers with and without CVD.

For individuals with protanopia, where the sensitivity to red (L-cones) is impaired, the recoloured image, denoted as $f_p = (f_0^r, f_0^g, f_0^b)$, is derived using linear transformations of the original RGB values. The equations for calculating the green and blue components are as follows:

$$\begin{aligned} f_0^g &= \frac{\alpha_p}{2} f_r + \left(2 - \frac{\alpha_p}{2}\right) f_g \\ f_0^b &= \frac{\alpha_p}{2} f_r + \left(2 - \frac{\alpha_p}{2}\right) f_b \end{aligned} \quad (5)$$

Here, f_r , f_g , and f_b represent the red, green, and blue components of the original image, while f_0^g and f_0^b are the modified green and blue components for Protanopia recolouration. The parameter α_p serves as a tuning factor that determines the extent of enhancement applied to the red-green spectrum.

¹<https://www.kaggle.com/datasets/goprogram/abstract-art>

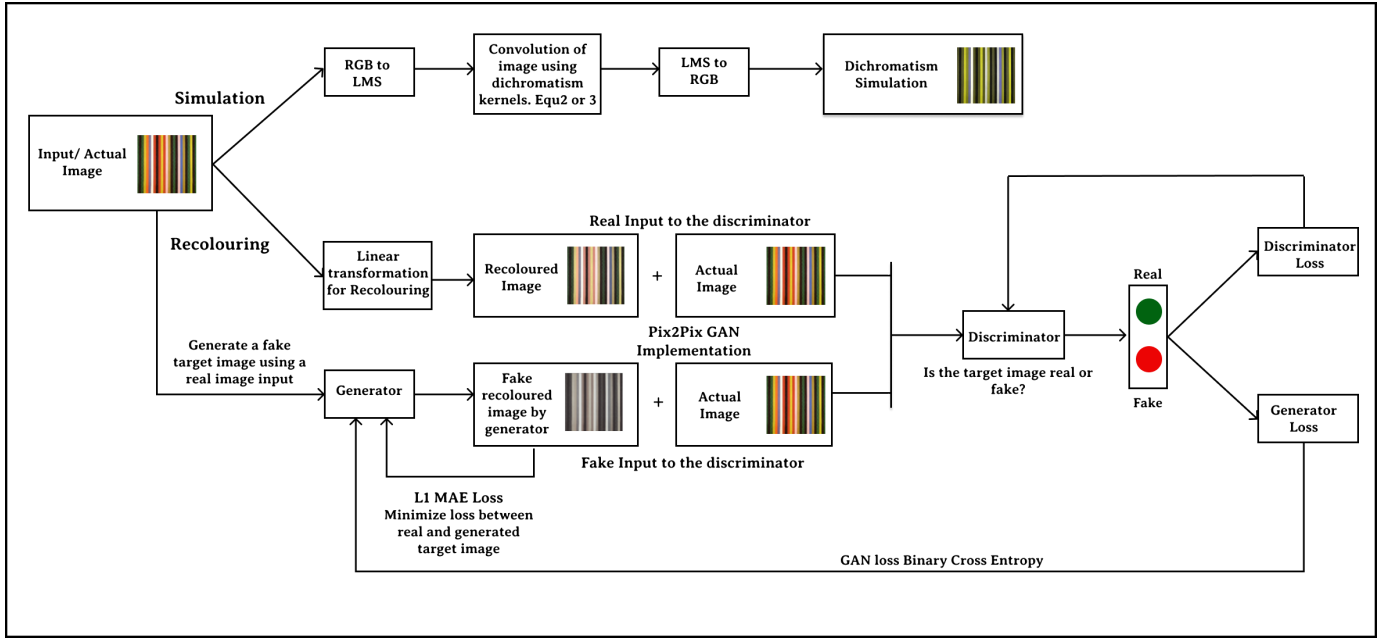


Fig. 2. Proposed methodology for Simulation of Colour Vision Deficiencies, Recolouration using linear transformations and Pix2Pix GAN architecture for generalization (Sample images are taken of Protanopia Deficiency).

For individuals with deuteranopia, characterized by a lack of sensitivity to green (M-cones), the recoloured image, denoted as $f_d = (f_0^r, f_g, f_0^b)$, is similarly computed. The equations for the red and blue components are as follows:

$$\begin{aligned} f_0^r &= \frac{\alpha_d}{2} f_g + \left(2 - \frac{\alpha_d}{2}\right) f_r, \\ f_0^b &= \frac{\alpha_d}{2} f_g + \left(2 - \frac{\alpha_d}{2}\right) f_b. \end{aligned} \quad (6)$$

In this case, f_0^r and f_0^b are the recoloured red and blue components, and α_d controls the green-red enhancement. These transformations adapt the color spectrum, ensuring that individuals with Deuteranopia can better distinguish colors without overly distorting the image for trichromatic viewers. The values of α_p and α_d are equal to 1 for absolute dichromat.

C. GAN-Based recolouration

Pix2Pix is a conditional GAN which is designed for tasks involving translation from one image to another image. Unlike normal GANs, that learn how to map from a random noise vector z to an output image y ($G: z \rightarrow y$), ConditionalGANs (cGANs) extend this concept by learning a mapping from an observed input image x and a noise vector z to the output image y ($G: \{x, z\} \rightarrow y$). In our case as shown in Figure 2 x is Actual image, z is Recoloured Image using the linear transformation and y is the fake image generated by the Generator.

Objective of Conditional GANs

The objective of a conditional GAN combines the adversarial loss and a conditional dependency. The adversarial loss

ensures that the generator G produces outputs that the discriminator D cannot distinguish from real images. Mathematically, the loss function for a cGAN can be expressed as:

$$L_{cGAN}(G, D) = \mathbb{E}_{x,y}[\log D(x, y)] + \mathbb{E}_{x,z}[\log(1 - D(x, G(x, z)))]. \quad (7)$$

Here:

- $D(x, y)$: Probability that (x, y) is a real pair.
- $G(x, z)$: The generated output conditioned on x and z .
- \mathbb{E} : Expectation over the data distribution.

The generator G aims to minimize this loss, while the discriminator D tries to maximize it, resulting in the following min-max optimization problem:

$$G^* = \arg \min_G \max_D L_{cGAN}(G, D). \quad (8)$$

Integration of Traditional Loss Functions

In addition to adversarial loss, it is beneficial to combine cGANs with traditional loss functions like L_2 or L_1 distance to ensure that the generated output is close to the ground truth. L_1 distance is particularly effective as it reduces blurriness compared to L_2 . The L_1 loss is defined as:

$$L_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x, z)\|_1]. \quad (9)$$

The final objective of the conditional GAN, incorporating the adversarial loss and the L_1 loss, is:

$$G^* = \arg \min_G \max_D (L_{cGAN}(G, D) + \lambda L_{L1}(G)), \quad (10)$$

where λ is a weighting factor that balances the contributions of the two losses.

Generator Architecture: U-Net with Skip Connections

Pix2Pix employs a U-Net architecture for the generator, designed for high-resolution image-to-image translation tasks. The U-Net consists of:

- **Encoder-Decoder Structure:** The input image is progressively downsampled to a bottleneck layer and then upsampled to reconstruct the output.
- **Skip Connections:** To bypass the bottleneck and preserve low-level spatial information, skip connections are added between corresponding encoder and decoder layers. These connections concatenate feature maps from the i th layer in the encoder with $n - i$ th layer in the decoder, where n is the total number of layers.

For image recoloration, this architecture allows the generator to retain structural details from the input while transforming its color properties.

Discriminator Architecture: PatchGAN

The discriminator in Pix2Pix, known as PatchGAN, focuses on modeling high-frequency details in local patches of the image rather than the entire image. This approach has several advantages:

- **Local Structure Modeling:** By operating on $N \times N$ patches, PatchGAN enforces realism at the scale of local features, ensuring sharper outputs.
- **Efficiency:** A smaller discriminator requires fewer parameters and computational resources, making it scalable for larger images.
- **Texture and Style Modeling:** PatchGAN effectively captures textural and stylistic details, as it treats each patch independently, similar to a Markov random field.

The final output of PatchGAN is the average response over all patches, providing a holistic evaluation of the generated image. [8]

IV. RESULTS

Our protanopia-focused results indicate significant enhancements in color distinction after recolouring. Figure 3 illustrates the original image, the simulation for protanopia, and the corrected image using our proposed recolouring methodology by Lee et. al [1]. The recolouring maintains visual fidelity while making reds more perceptible to individuals with protanopia.

The deuteranopia results demonstrated a similar improvement. As shown in Figure 3, the corrected images enable better discrimination between greens and adjacent colors. This is essential for people with deuteranopia, where M-cones (green-sensitive) are absent. The effectiveness of the GAN model in adapting image hues ensures that important visual details are preserved, while color shifts are applied to enhance clarity.

The results on Ishihara test plates are particularly noteworthy. Figures 4 illustrate the protanope's and deuteranope's perception before and after recolouring. As per Brettel et al. [5] we can also see the red part being darker in protanopia

simulation Figure 4 point (b1) as compared to that in deuteranopia simulation Figure 4 point (b2).

The statistical evaluation parameter for this study used is Structural Similarity Index (SSIM). It is a metric used to measure how much the two images are similar. It evaluates image quality based on structural information, focusing on luminance, contrast, and texture rather than pixel-wise differences. It measures perceptual similarity between images.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (11)$$

Where μ_x, μ_y are the mean intensity values of images x and y ; σ_x^2, σ_y^2 are variance of images x and y ; σ_{xy} is covariance between x and y and C_1 and C_2 are the stabilizing constants. The range of SSIM is [10]:

$$-1 \leq SSIM(x, y) \leq 1$$

SSIM value 1 represents identical images, 0 represents no structural similarity. Negative value shows strong dissimilarity.

We tested the model on 20 test abstract images and following is the SSIM Score table for both Protanopia and Deuteranopia. the results are as given in Table I

TABLE I
SSIM SCORES OF GAN IMAGE RECOLORATION MODEL

Image Number	SSIM Score Protanopia	SSIM Score Deuteranopia
1	0.9235928	0.9506183
2	0.8224718	0.8676517
3	0.8722834	0.8515755
4	0.9433624	0.9551803
5	0.8577222	0.9013119
6	0.9473457	0.9586063
7	0.9300492	0.9434787
8	0.9053294	0.8912536
9	0.9213264	0.9419389
10	0.844541	0.9224334
11	0.920498	0.9234792
12	0.956565	0.9485373
13	0.880649	0.8977783
14	0.948953	0.9581007
15	0.959669	0.9671972
16	0.950090	0.9645298
17	0.897669	0.9265367
18	0.887907	0.8925704
19	0.944630	0.948662
20	0.928994	0.939122
Average	0.9122	0.9275

Our model was trained on 1000 Abstract Images in 10 epochs using an NVIDIA GeForce RTX 3050 Laptop GPU (6GB VRAM) with CUDA Version 12.8. We have achieved an average SSIM Score of 0.9122 (91.22%) for the Protanopia GAN model and an average SSIM score of 0.9275 (92.75%) for the Deuteranopia GAN Model. These high SSIM scores indicate strong structural similarity between the generated and ground truth images, highlighting the effectiveness of our model.

Another key metric is the Fréchet Inception Distance (FID) score, a widely used measure for evaluating the quality of

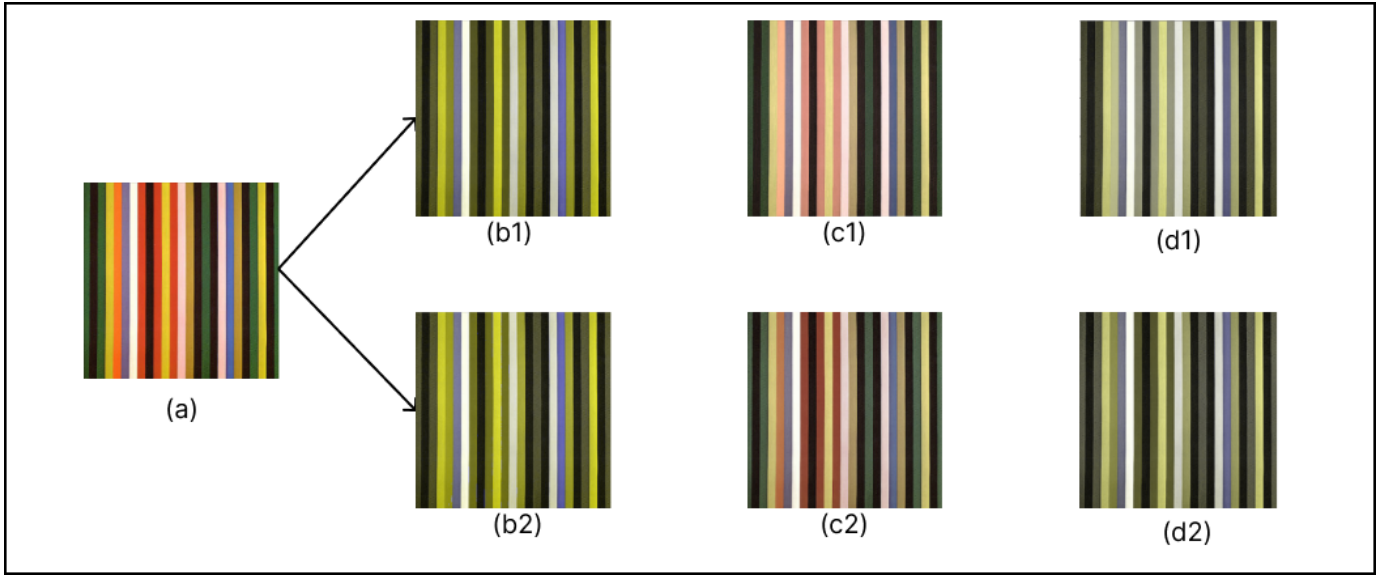


Fig. 3. Results on Abstract Art Dataset: (a) Original Image (b) Simulation of Dichromatic Vision (c) Recoloured image (d) Simulation of dichromatic vision after recolouring (1) Protanopia (2) Deuteranopia

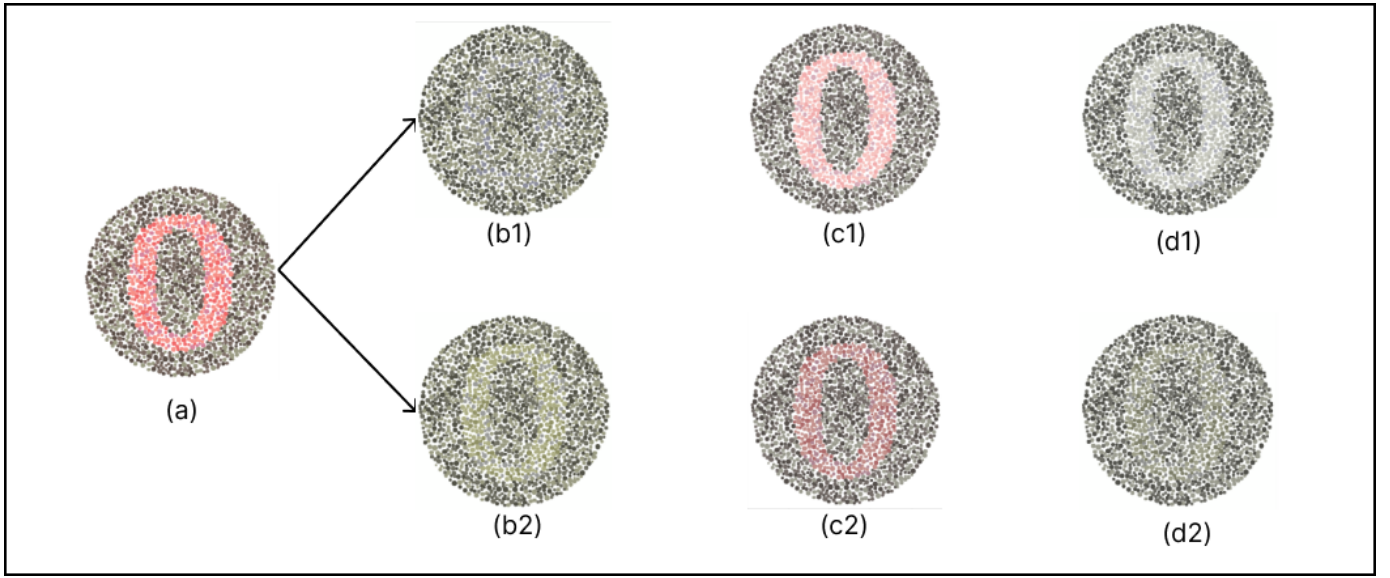


Fig. 4. Results on Ishihara Plates: (a) Original Image (b) Simulation of Dichromatic Vision (c) Recoloured image (d) Simulation of dichromatic vision after recolouring (1) Protanopia (2) Deuteranopia

generated images. It is computed by comparing the feature distributions of the generated images with those of the ground truth images [11].

$$\text{FID}(\mu_r, \Sigma_r, \mu_g, \Sigma_g) = \|\mu_r - \mu_g\|_2^2 + \text{Tr}(\Sigma_r + \Sigma_g - 2(\Sigma_r \Sigma_g)^{\frac{1}{2}}) \quad (12)$$

For the Protanopia GAN model, the FID score is 24.65, while for the Deuteranopia GAN model, it is 29.47. A lower

FID score reflects improved perceptual quality, further confirming the impact of GPU acceleration on model training.

As seen in Figure 5, with the computational power provided by the NVIDIA GeForce RTX 3050 GPU, the GAN recolouration model has been able to capture subtle colour variations effectively. This suggests that with further enhancement in computational resources, our model can generate high-quality recoloured images in real time without additional algorithmic processing.

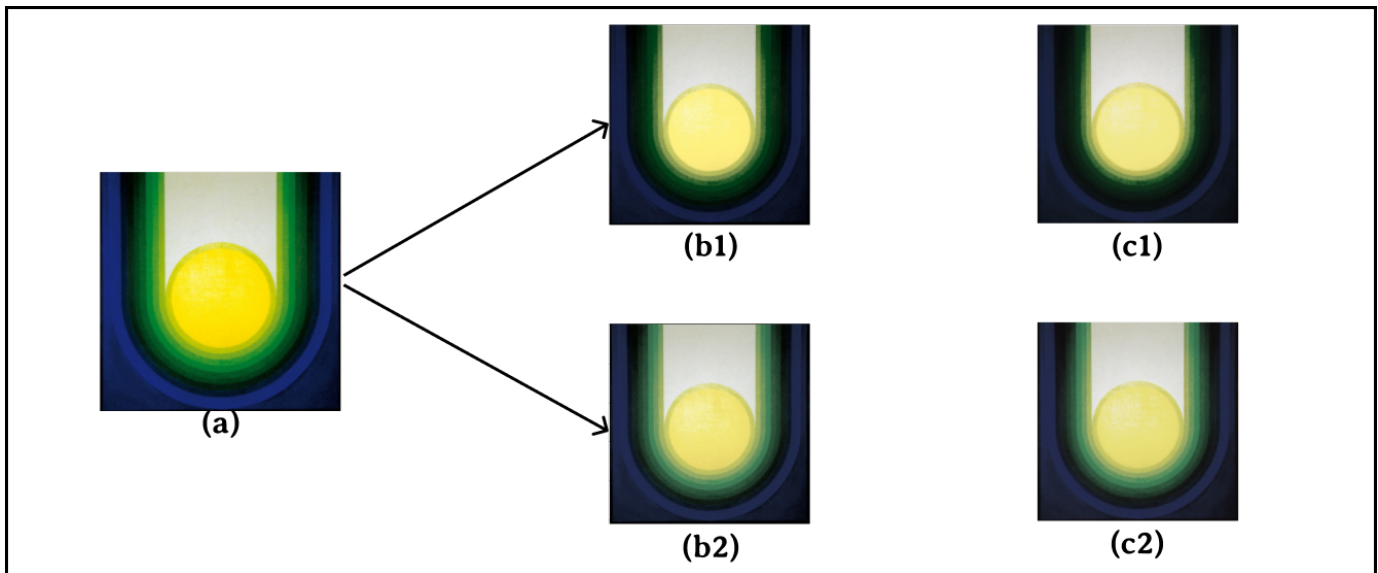


Fig. 5. Results from the GAN-based recolouring model on unseen image: (a) Original Image (b) Target Recoloured (c) GAN generated (1) Protanopia (2) Deuteranopia

V. CONCLUSION AND FUTURE WORK

GAN-based recolouration enhances color perception for individuals with dichromatic vision, surpassing traditional methods in adaptability and visual fidelity. By learning nuanced color transformations, GANs offer a promising path toward accessibility-focused technologies. However, extracting and preserving subtle color nuances requires significant computational power, especially for high-resolution images. Despite this, the study results highlight the potential of GAN-based recolouration in improving inclusivity across various applications.

Future work includes expanding support for Tritanopia recolouration and exploring real-time contrast enhancement for dichromats, enabling adaptive accessibility in live visual feeds. These advancements will further improve inclusivity in visual media. This approach has broad practical applications. In accessibility tools, it enhances CVD-friendly visualizations, making educational materials more inclusive. A key application is integrating recolouration into AR glasses, enabling real-time color adaptation for color-blind users. In design and media, it ensures UX/UI elements are accessible, fostering equitable digital experiences.

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