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Real-Time CVD-Friendly Content Generation via Personalized GAN Daltonization

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ABSTRACT

We propose a personalized, real-time framework for generating color vision deficiency (CVD)–friendly images that enhance color discriminability while preserving natural appearance and structural fidelity. The method integrates individualized CVD simulation with a conditional GAN that learns a neutral gray-layer representation, enabling perceptually adaptive color enhancement without introducing artifacts. A soft-light blending strategy further refines high-resolution results while maintaining real-time efficiency. Experiments on Flickr30K, DIV2K, and Ishihara test images demonstrate that our approach achieves superior color contrast preservation and comparable visual quality to state-of-the-art methods, while running over 10 FPS at 768×768 resolution. The results highlight the effectiveness of the proposed gray-layer–guided recoloring pipeline for accessible and perceptually consistent visualization in real-world applications.

KEYWORDS
color vision deficiency, image enhancement, generative adversarial networks

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INTRODUCTION

Color vision deficiency (CVD), also known as color blindness, is a common X-linked genetic condition affecting approximately 5% of the global population [1]. It can be categorized into red–green, blue–yellow, and total color blindness, each corresponding to difficulties in distinguishing specific wavelength ranges. Individuals with CVD often encounter challenges in daily activities, such as recognizing traffic signals or interpreting colorcoded visual information [2]. Despite its prevalence, there is currently no effective medical treatment for CVD [3].

In digital environments, most visual content is designed for normal trichromatic vision, which makes it difficult for CVD users to perceive critical visual cues. This limitation can lead to misinterpretation in applications such as data visualization, education, and safety-critical interfaces. To mitigate this issue, daltonization methods have been proposed to enhance color distinguishability for CVD users. Early approaches rely on rule-based or physiological models (e.g., Machado et al. [4]), which improve contrast for specific color pairs but often distort global color balance. More recent learning-based methods [5,6] achieve better perceptual consistency by modeling nonlinear color mappings. However, these approaches are typically computationally intensive and struggle to support real-time processing of high-resolution images.

To overcome these limitations, this study proposes a lightweight, real-time GAN-based daltonization framework for personalized CVD-friendly image enhancement. The framework integrates personalized CVD simulation matrices derived from user-specific assessments, a neutral gray layer computation to guide recoloring, and high-resolution inference with soft-light blending. This design enables fast and artifact-free recoloring while maintaining perceptual realism, making it suitable for applications in real-time settings, such as interactive visualization, digital education, and AR-assisted environments.

The main contributions of this work are summarized as follows:

1.Gray-layer-guided, artifact-suppressing recoloring: We propose a neutral gray layer representation that simplifies learning and guides the GAN to modify only perceptually relevant color information, preserving textures and reducing artifacts.

2.Lightweight, real-time GAN for high-resolution daltonization: Our conditional GAN framework enables fast and high-fidelity recoloring at full resolution while maintaining perceptual consistency, supporting real-time applications for CVD users across diverse digital content.

3.Robust evaluation and visualization: By combining personalized CVD simulation and soft-light blending, the method produces visually natural outputs that enhance color discriminability, providing a reliable solution for practical scenarios where immediate visual feedback is essential.

RELATED WORK

Color Vision Deficiency Assessment and Visual Simulation

Accurate diagnosis of CVD type and severity, along with mathematical modeling of an individual’s color perception, is essential for personalized daltonization. Existing CVD assessment methods can be categorized into three main types: general tests, computer-based tests, and genetic tests.

General tests include classical pseudoisochromatic plate tests [7] and hue arrangement tests such as the Farnsworth–Munsell 100 Hue (FM 100-Hue) Test [8]. In hue arrangement tests, participants are required to sort multiple color patches into seamless gradients. The number of ordering errors can be used to evaluate the participant's color discrimination ability and potential color vision deficiencies. Although widely applied in clinical settings, these methods cannot define a clear relationship between test results and the severity of CVD, making it impossible to derive an individual’s color perception model directly from the diagnosis.

With advances in computing and display technology, computer-based tests have become increasingly common. The Cambridge Colour Test [9] presents a letter “C” surrounded by a gray background, whose chromaticity continuously varies until the participant can barely detect the gap.

For visual simulation of CVD, most existing studies are based on Machado et al.‘s color transformation model [4], which linearly maps actual colors to simulate the perception of color-deficient individuals. Xu et al. [10] established transformation parameters by mapping easily confused color patches into the CVD color space and correlating them with normal observers’ sorting results. Shen et al. [5] further refined parameter estimation by having participants adjust one color patch until the color difference between two patches became indistinguishable. These methods form the foundation for personalized modeling of individual color perception, which is critical for effective real-time daltonization.

Color Perception Enhancement for CVD

To improve color perception for CVD individuals, colored glasses with specialized optical filters have been widely studied and commercialized. These glasses selectively block specific wavelengths to enhance red–green color perception, improving overall visual experience for users with red–green CVD [11–15]. However, commercially available solutions often block parts of the spectrum not affected by CVD, limiting their effectiveness in fully restoring color perception [16–17].

Daltonization-based image recoloring methods aim to both restore lost color discriminability and preserve naturalness. Traditional approaches optimize a cost function that minimizes the color difference between the original image and its recolored simulation for CVD viewers [18–19]. To preserve naturalness, Wang et al. [20] and Zhu et al. [21] introduced regularization constraints between the original and recolored images, while Rigos et al. [22] applied semantic segmentation to selectively recolor objects while keeping the rest unchanged. Jiang et al. [23] further developed personalized generation by decoupling and controlling color representations in the latent space.

Despite these advances, existing daltonization methods face two major limitations for real-time, high-resolution applications. First, most models are designed for static or offline image processing, making them computationally expensive and slow when handling high-resolution content. Second, many methods do not account for the full spectrum of individual CVD severity, limiting the ability to provide fully personalized and perceptually optimized color adaptation. These challenges motivate the development of lightweight, real-time frameworks that can deliver artifact-free, high-fidelity image enhancement for individual CVD users.

METHODS

Our proposed framework for generating CVD-friendly images consists of five main stages: dataset preparation, reference image selection via CVD simulation, neutral gray layer computation, conditional GAN training, and high-resolution inference with soft-light blending. The pipeline aims to enhance color distinction for individuals with color vision deficiency (CVD) while preserving natural appearance, local details, and high-fidelity textures in real-time daltonization scenarios.

Dataset Preparation

To construct a dataset suitable for training the CVD-specific recoloring model, it is essential to include images containing color combinations that are likely to be confused by individuals with color vision deficiencies. Each candidate image I_{ori} is first processed using a personalized CVD simulation based on physiologically motivated projection matrices P_{CVD} that account for both the type and severity of the deficiency.

Following the calibration method proposed by [5], a target CVD individual identifies pairs of colors that appear indistinguishable (confusing color pairs). These pairs are used to solve for the transformation matrix P_{CVD} under range and sum constraints via least-squares optimization. This ensures that each simulated image reflects the individual's color perception characteristics.

$$I_{CVD} = P_{CVD} \cdot I_{ori} \tag{1}$$

To quantify how well an image preserves perceptual color contrast under simulation, the Color Contrast Preservation Ratio (CCPR) [24] is computed between the simulated and original images:

$$CCPR(I_{CVD}, I_{ori}) \in [0,1]. \tag{2}$$

Images with $CCPR < \tau = 0.8$ are retained, while others are discarded. This selection ensures that the dataset focuses on perceptually meaningful color regions where recoloring can improve discriminability. The identification of confusing color regions is performed as an offline calibration step to estimate the user-specific projection matrix T . Once calibrated, the matrix is fixed and the subsequent image processing pipeline is fully automatic and real-time. We note that this manual calibration may limit scalability in large-scale deployment scenarios, and automating this process is an important direction for future work. All images are normalized in a perceptually uniform color space (CIELAB) prior to CCPR computation to align with human visual perception, and standard augmentations (random cropping, rotation, color jittering) are applied to enhance generalization. This filtering strategy significantly reduces the number of training samples compared to standard large-scale datasets. However, it improves data efficiency by focusing on perceptually challenging cases, which are more relevant for learning effective CVD-oriented color modulation.

Reference Image Selection via CVD Simulation

For each selected original image I_{ori} , multiple recolored candidates $\{I_{recolor,k}\}$ are generated following [25-26]. Each candidate is then processed through the personalized CVD simulation S_{CVD} to obtain the simulated perceptual images $\{I_{CVD,k}\}$.

Reference images are selected according to the CCPR threshold:

$$SelectedSet = \{I_{recolor,k} \mid CCPR(S_{CVD}(I_{recolor,k}), I_{ori}) > \tau\}. \tag{3}$$

Only recolorings with sufficient contrast preservation ($CCPR > \tau$) are included in the training set. Multiple qualifying recolorings may be kept to provide perceptual diversity, improving the robustness of the training data. This selection strategy balances contrast enhancement and naturalness, ensuring that high-resolution outputs maintain realistic visual appearance while improving discriminability for CVD observers.

Neutral Gray Layer Computation

To guide the recoloring process and reduce artifacts, a neutral gray layer G is computed instead of directly generating the recolored image. This design simplifies learning: the network focuses on perceptually relevant color modifications rather than modeling both textures and color shifts simultaneously.

The gray layer is defined as:

$$G = \frac{1}{2} \cdot \frac{(I_{ref} - I_{ori})^2}{(I_{ori} - I_{ori}^2)}, \quad G \in [0, 2] \tag{4}$$

The final output is reconstructed through soft-light blending:

$$I_{out} = 2 \odot G \odot I_{ori} + I_{ori}^2 - 2 \cdot I_{ori}^2 \odot G, \tag{5}$$

where $\odot$ denotes element-wise multiplication. This approach suppresses artifacts and preserves textures because the gray layer varies smoothly, allowing upscaling from low- to high-resolution without edge distortion. Conceptually, the gray layer acts as a nonlinear color adjustment map, emphasizing perceptually meaningful differences for CVD observers while leaving regions with sufficient contrast unchanged. Additionally, by predicting a smooth gray-layer modulation instead of full RGB values, the learning problem is substantially simplified, reducing model complexity and mitigating overfitting risks even with a relatively small but task-relevant dataset.

Unlike direct RGB generation, the proposed neutral gray layer constrains the network to learn a smooth modulation map, effectively reducing high-frequency artifacts introduced by adversarial training. This design implicitly improves both structural consistency (reflected in SSIM) and perceptual contrast preservation (reflected in CCPR), as the network focuses on modifying only perceptually ambiguous regions while preserving original textures.

Conditional GAN Training

A conditional GAN (cGAN) is trained to map low-resolution original images I_{LR} to corresponding gray layers G_{LR} :

$$\hat{G}_{LR} = G(I_{LR}). \tag{6}$$

The discriminator D distinguishes between generated $\hat{G}_{LR}$ and ground truth G_{LR} . The objective function combines adversarial and L1 reconstruction losses:

$$L = E[logD(G_{LR}, I_{LR})] + E[log(1 - D(\hat{G}_{LR}, I_{LR}))] + \lambda \parallel G_{LR} - \hat{G}_{LR} \parallel_1 . \tag{7}$$

The adversarial term enforces perceptual realism, while the L1 term encourages accurate gray-layer reconstruction. Combined with the gray-layer formulation, this design constrains the optimization to low-frequency modulation, reducing artifact-prone direct color generation.

High-Resolution Inference

During inference, a high-resolution input I_{HR} is first downsampled to I_{LR} . The generator produces $\hat{G}_{LR}$, which is upsampled to $\hat{G}_{HR}$ through smooth interpolation. The final high-resolution recolored output is obtained by:

$$I_{HR,out} = 2 \cdot \hat{G}_{HR} \odot I_{HR} + I_{HR}^2 - 2 \cdot I_{HR}^2 \odot \hat{G}_{HR}. \tag{8}$$

This framework leverages low-resolution training for efficiency while maintaining artifact-free, high-quality results at full resolution. By integrating personalized CVD simulation matrices P_{CVD} throughout, the recoloring process remains individual-specific, ensuring perceptually optimized enhancement for users with different color vision deficiencies.

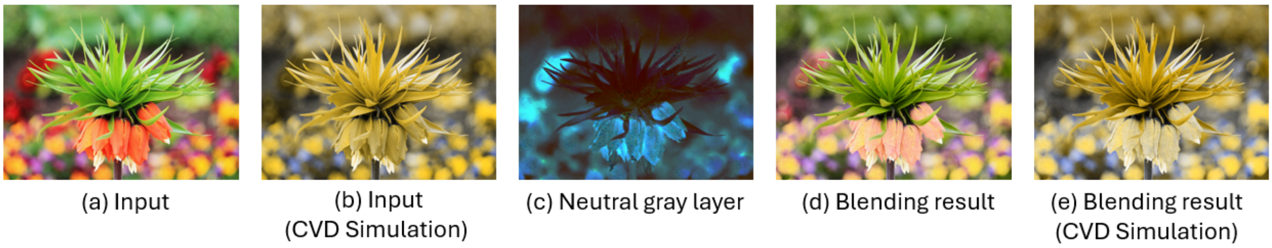
(a) Input
(b) Input (CVD Simulation)
(c) Neutral gray layer
(d) Blending result
(e) Blending result (CVD Simulation)

Figure 1. Visualization of representative visual results of proposed recoloring pipeline

Figure 1 shows representative visual results: the original image (Input), its simulated appearance for a CVD observer (Input CVD simulation), the learned Neural Gray Layer, the blended output (Blending result), and the corresponding CVD-simulated version (Blending result CVD simulation). The generated gray layer effectively highlights contrast regions that are critical for color differentiation without altering the overall style or mood of the scene.

EXPERIMENTS

To validate the effectiveness of our real-time CVD-friendly daltonization framework, we conducted a series of experiments focusing on quantitative evaluation, perceptual quality, and real-time performance. The experiments aim to assess whether the personalized GAN-based recoloring improves color distinguishability for individuals with varying types and severities of CVD while preserving naturalness in high-resolution images.

Experimental Setup

The training dataset comprises high-resolution images from the Flickr30K dataset, covering diverse indoor, outdoor, and synthetic scenes with varied color distributions. Additionally, we curated a test set by selecting images from the DIV2K dataset and incorporating 62 Ishihara test images [27] to evaluate the model's performance across different CVD types. Each image was processed through personalized CVD simulations to generate candidate recolorings, and reference images were selected according to the CCPR threshold ($\tau=0.1$), as described in Section 3.2. Finally, we have 430 training pairs and 140 testing pairs. It is worth noting that the dataset size is intentionally constrained by a perceptual filtering strategy rather than limited data availability. Specifically, training pairs are selected based on personalized CVD simulation and CCPR thresholds, ensuring that only perceptually ambiguous and informative samples are retained. This reduces redundancy while increasing task relevance, as the model focuses on cases where color discrimination is genuinely challenging for CVD observers. All images were normalized in the CIELAB color space to ensure perceptual uniformity. Low-resolution versions (256×256) were used for cGAN training, while the full-resolution images were reserved for evaluation and inference. Here, 'personalized' refers to the incorporation of user-specific color perception parameters through calibrated simulation models rather than subjective user studies; conducting large-scale evaluations with real CVD participants is beyond the scope of this work and will be explored in future research. The generator follows a U-Net–style architecture with multi-scale feature extraction and skip connections to preserve fine textures and local details [28]. The discriminator is a patch-based network that evaluates local realism, ensuring that generated gray layers maintain perceptually plausible transitions. The network is trained with a combination of adversarial loss and L1 reconstruction loss, with $\lambda=100$ balancing the two terms. Quantitative evaluation is performed using the CCPR and the Structural Similarity Index (SSIM). CCPR measures enhancement in perceptual discriminability for CVD observers, while SSIM evaluates overall structural fidelity and naturalness. Performance in real-time scenarios is evaluated in terms of inference speed and memory usage.

Results

The proposed method achieves substantial improvement in CCPR across all CVD types compared to baseline daltonization techniques and conventional rule-based daltonization methods.

Figure 2 shows qualitative comparisons between our method and two state-of-the-art approaches, including Shen method [5] and Wang method [6]. As illustrated, our daltonization results achieve comparable color distinguishability for CVD users to the existing SOTA methods, effectively enhancing the perceptual separability of confusing color regions. Unlike Wang's method, which tends to generate noticeable texture artifacts in highly saturated areas, our approach preserves fine structural details and avoids unnatural visual distortions. In addition, thanks to the lightweight network design and efficient blending strategy, our method supports real-time inference, making it suitable for practical applications such as interactive or embedded CVD-friendly visualization systems.

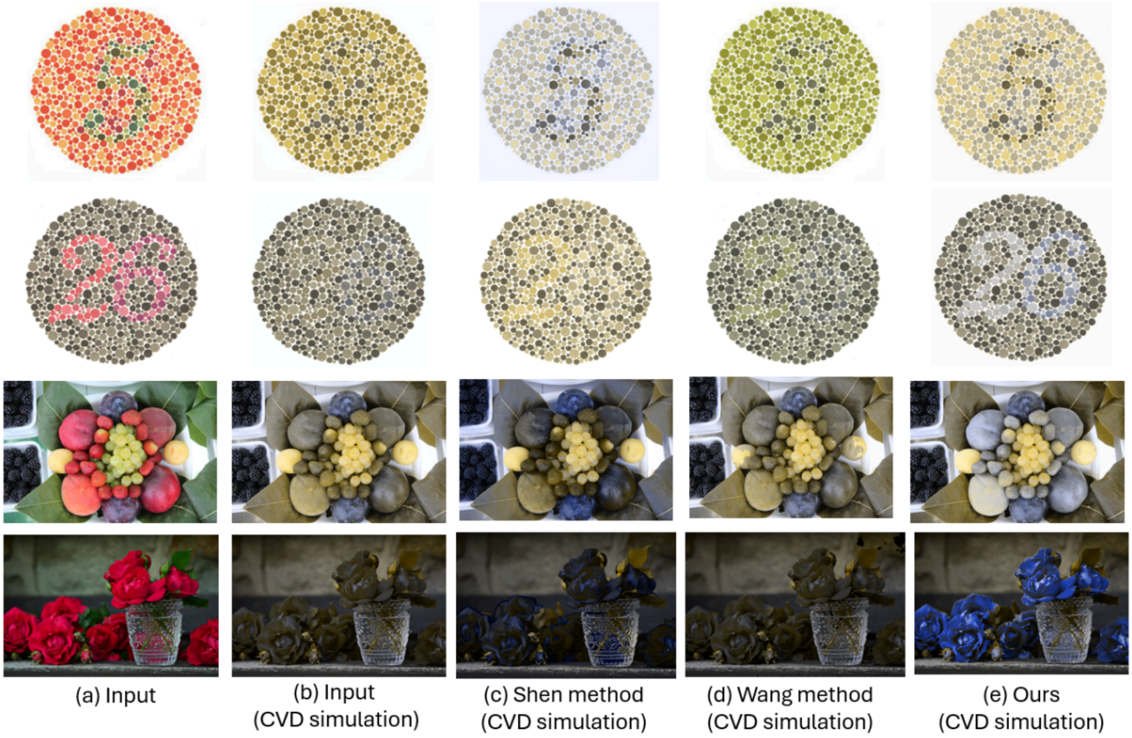

Figure 2. Qualitative comparisons between our method and several state-of-the-art approaches

To quantitatively evaluate perceptual enhancement and structural fidelity, we adopt two complementary metrics: the Color Contrast Preservation Ratio (CCPR) and the Structural Similarity Index (SSIM). CCPR quantifies the degree to which recolored images improve perceptual color separability for CVD observers, while SSIM measures the preservation of structural consistency and natural appearance. As summarized in Table 1, our method achieves a CCPR of 0.881, surpassing Shen's (0.865) and Wang's (0.827) methods, indicating stronger perceptual discriminability under CVD simulation. In terms of SSIM, our framework attains 0.771, comparable to state-of-the-art approaches, confirming that the proposed gray-layer design enhances contrast without compromising texture fidelity or introducing artifacts. This improvement is attributed to the gray-layer–based modulation, which limits the solution space of the GAN and avoids direct high-frequency color generation.

Table 2 reports the processing time for each stage of our CVD-friendly recoloring pipeline under different input resolutions. The total latency includes three components: model inference, image resizing, and soft-light blending. As shown, the total processing time remains below 0.08 s for resolutions up to 768×768, corresponding to a throughput of approximately 12–13 FPS. Even at higher resolutions (1280×1280), the system maintains interactive performance with a latency of 0.138 s per frame. Both Shen and Wang methods consume more than 0.5s at 512×512 resolution. The statistics demonstrates that the use of low-resolution gray layer prediction followed by smooth upscaling significantly reduces computational load without sacrificing visual quality.

Table 1. Quantitative comparison between state-of-the-art methods and our method.

	Shen method	Wang method	Ours
CCPR	0.865	0.827	0.881
SSIM	0.773	0.764	0.771

Table 2. Average inference and post-processing time per image at different resolutions.

Resolution	Inference (s)	Resize (s)	Soft light blending (s)	Total (s)
256 x 256	0.0200	-	0.0041	0.024
512 x 512	0.0200	0.0097	0.0148	0.044
768 x 768	0.0200	0.0158	0.0340	0.069
1280 x 1280	0.0200	0.0212	0.0972	0.138

CONCLUSION

This work presented a personalized, real-time framework for CVD-friendly image recoloring that enhances color distinguishability while preserving structural and perceptual naturalness. By integrating individualized CVD simulation, contrast-based reference selection, and conditional GAN–driven gray-layer generation with soft-light blending, the proposed method effectively decouples color enhancement from texture modeling, suppressing artifacts and maintaining high visual fidelity.

Quantitative and qualitative evaluations on DIV2K, and Ishihara datasets demonstrate that the method achieves higher CCPR and comparable SSIM to state-of-the-art approaches, with substantially lower latency. The lightweight design enables real-time inference at up to 13 FPS for 768×768 inputs, supporting practical deployment in interactive and embedded visualization systems.

LIMITATION AND FUTURE WORK

Although effective, several limitations remain. The current framework targets static images and does not enforce temporal consistency in videos, which may cause flickering in dynamic scenes. The personalized calibration of CVD simulation matrices also relies on manually identified color pairs, limiting scalability. Future work will explore automatic or feedback-based calibration and temporal modeling for video recoloring.

We also note that the proposed method is not applicable to total color blindness (achromatopsia), where no chromatic information can be perceived, and thus recoloring-based approaches provide limited benefit.

Moreover, while quantitative metrics confirm perceptual improvements, large-scale user studies are needed to assess subjective comfort and usability. Extending this framework to AR/VR and mobile platforms, along with model compression for on-device inference, represents a promising direction toward accessible, real-time CVD-aware visual experiences.

Author Contributions

Conceptualization, Zhenyu Xiao and Xinghong Hu; methodology, Xinghong Hu; software, Taizhi Wang; validation, Shaoying Tan and Wuyao Shen; formal analysis, Mingpu Xu; resources, Zhenyu Xiao and Wuyao Shen; writing—original draft preparation, Sichuang Xu; writing—review and editing, Zhenyu Xiao, Xinghong Hu, and Wuyao Shen; visualization, Taizhi Wang; supervision, Zhenyu Xiao; project administration, Zhenyu Xiao; funding acquisition, Xinghong Hu. All authors have read and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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