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A Computational Approach to Color Vision Enhancement Using Deep Learning, TensorFlow and Keras

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Abstract

Individuals afflicted with color vision deficiency (CVD) often face obstacles in effectively navigating and engaging with their surroundings due to challenges in accurately discerning colors. Such limitations can hinder a range of daily activities, compelling these individuals to rely on external assistance for color-centric tasks, potentially curtailing their autonomy and inclusiveness. In response, our study presents a machine learning-driven color adaptation framework developed using TensorFlow and Keras, which successfully detects and modifies colors within visual content to enhance perceptibility for those with CVD. The system achieved a notable accuracy of up to 98.01% in color correction across different types of CVD, including Protanopia, Deuteranopia, and Tritanopia. Our user-centric graphical user interface (GUI) facilitates an intuitive experience, enabling users to upload, process, and visualize color-corrected images effortlessly. The research demonstrates robust performance through extensive testing, ensuring reliability across various contexts. By improving navigational capabilities and reducing reliance on external assistance, our innovation promotes inclusivity and advances understanding of CVD. Ultimately, this work aims to foster a more equitable and accessible society for individuals with color vision deficiencies.

Key Words: Color Vision Deficiency, Deep Learning, TensorFlow, Keras, Image Processing, Color Transformation

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1 Introduction

Color vision deficiency (CVD), commonly referred to as color blindness, represents a widespread visual impairment affecting a substantial segment of the global populace [1]. This condition encompasses various subtypes, including red-green, blue-yellow, and complete color blindness, predominantly resulting from specific genetic mutations impacting retinal photopigments [2]. Individuals afflicted with CVD face difficulties in discriminating between particular colors, posing challenges in numerous daily tasks such as interpreting signage, selecting ripe fruits, and interpreting color-coded data in charts and graphs.

These obstacles arise from compromised color differentiation abilities, potentially leading to confusion and misinterpretation of visual information. CVD severely limits the ability of affected individuals to accurately perceive and distinguish colors, impeding their capacity to navigate everyday environments, engage with digital content, and perform tasks that require color discrimination. Traditional aids for CVD, such as filters or lenses, offer limited improvement and often rely on external support. Existing methodologies, such as the *Information Preserving Color Transformation* technique for Protanopia and Deuteranopia, have demonstrated potential in maintaining the original color information while adapting images for color-impaired viewers [9]. However, the lack of a reliable, automated solution for adapting colors in digital content creates a gap that hinders inclusivity for those with CVD in various contexts, including healthcare, education, and technology.

Recent advancements have explored various approaches to enhance color accessibility for individuals with CVD. For example, Masra et al. (2020) proposed methods for color correction that can improve the visual experience for colorblind individuals, addressing some of the gaps in traditional approaches [17]. Additionally, Pendhari et al. (2015) discussed techniques for video and image recoloring that can assist color-impaired individuals by enhancing color differentiation in multimedia [24]. Further, Pendhari et al. (2020) explored the use of MATLAB for multimedia recoloring, demonstrating practical solutions for improving color accessibility [22]. These studies underscore the ongoing need for effective, automated solutions that integrate real-time processing and user-friendly interfaces.

This paper's contribution lies in addressing this gap by proposing a novel, machine learning-based system that transforms colors in images, specifically enhancing perceptibility for individuals with Protanopia, Deuteranopia, and Tritanopia. The uniqueness of our approach is in leveraging machine learning frameworks such as TensorFlow and Keras, paired with advanced image processing techniques, to develop a system that dynamically adjusts image colors in real time, ensuring that the original context of the visual content remains intact. Unlike existing solutions, which offer limited practicality, our model emphasizes both accuracy and accessibility through an intuitive graphical user interface (GUI), making it usable even by non-technical users.

With the advancement of machine learning and image processing technologies, we discerned an opportunity to devise innovative computational solutions to aid individuals with CVD in surmounting these challenges [4]. Recent studies, such as those involving video processing for Tritanomaly and machine learning techniques to improve color accessibility in digital content, have explored the application of neural networks in detecting and correcting color deficiencies in multimedia, further motivating the development of image transformation models for similar purposes [13, 27]. The principal aim of our research is to conceptualize and implement a machine learning-driven framework capable of detecting and modifying colors in images to improve visibility for individuals with CVD.

Our research involved the acquisition and preprocessing of a dataset comprising 6,000 images to ensure consistency and quality [6]. Subsequently, we crafted three specialized machine learning models leveraging the TensorFlow and Keras frameworks. These models were designed to identify blue, red, and standard colors within images and transform them into distinguishable hues, such as purple and brown. Related approaches, such as image colorization using convolutional neural networks, have shown promise in enhancing color representation, which we have incorporated into our methodology [18]. Our contribution also includes a thorough validation of these models, demonstrating high accuracy and adaptability across a diverse range of image categories, which addresses a critical shortcoming in earlier approaches.

In tandem with the development of machine learning models, we constructed an interactive graphical user interface (GUI) using Tkinter. This GUI enables users to upload images, apply color transformations using the trained models, and visualize the results in real-time. Furthermore, we integrated an Ishihara color blindness test module within the GUI, enabling users to self-assess their CVD and gain insights into the nature and extent of their color vision deficiency [10, 11]. By offering an integrated tool that not only corrects color vision in images but also allows self-evaluation of CVD, this paper delivers a comprehensive solution aimed at enhancing user autonomy and inclusivity.

In this paper, we present a comprehensive overview of our research, outlining the methodology, implementation approaches, results, and prospective recommendations. The novelty of our work lies in the integration of machine learning with image processing in an accessible interface, which stands to significantly enhance the visual experience of individuals with CVD. Our goal is to highlight the effectiveness and potential implications of the developed solution in alleviating the challenges faced by individuals with CVD and promoting inclusivity through technological innovation [21, 27].

2 Related Work

Kim et al. [1] introduced a novel daltonization method tailored for protanopes, which significantly improved color perception and processing speed compared to traditional techniques. Orii et al. [2] presented a color conversion algorithm using self-organizing maps, effectively enhancing legibility for color-blind individuals. Huang et al. [3] proposed a re-coloring algorithm emphasizing key color contrast, demonstrating effectiveness despite some limitations in color naturalness. Tsekouras et al. [4] and Kuhn et al. [5] both offered recoloring algorithms for CVD, showcasing effectiveness in natural image recoloring and color contrast enhancement, respectively, while ensuring image naturalness and faster processing.

Navada et al. [6] proposed a LabVIEW-based method for color and edge detection, which facilitated text recognition for color-blind individuals, addressing challenges in recognizing letters against specific background colors. Simon-Liedtke et al. [7] introduced a behavioral methodology for evaluating daltonization methods, emphasizing the effectiveness of selected methods in improving responses for color-deficient observers without affecting normal-sighted individuals. You and Park [8] presented a compensation algorithm for CVD, addressing color shifts and brightness reduction issues, while Almagambetov et al. [20] developed a visual-based traffic light detection system with high accuracy, benefiting individuals with CVD by providing timely and reliable information. Khurge et al. [11] modified images for Protanopia and Deuteranopia efficiently, enabling color distinction for color-blind individuals, showcasing the potential of image modification techniques in enhancing visual perception for those with color vision deficiencies.

Huang et al. [21] proposed a Temporally Consistent Video Colorization framework that ensured both effective colorization and temporal consistency, providing a valuable tool for enhancing visual media accessibility for individuals with color vision deficiencies. They also introduced a comprehensive color transformation approach for Protanopia and Deuteranopia, maintaining comprehensibility and naturalness in recolored images [12]. You and Park [8] presented an LCD-based color compensation method for CVD, effectively correcting spectral response shifts and addressing brightness reduction issues. Additionally, Huang et al. [14] developed a re-coloring algorithm improving accessibility for individuals with CVD, demonstrating efficiency and perceptual superiority. They targeted hue channel contrast enhancement for color vision impairment, suggesting further exploration for dynamic adjustment techniques [15].

Masra et al. [16] introduced advanced methodologies for image correction tailored to individuals with dichromacy, improving color perception for various deficiencies through color transformation and colormap approximation techniques. Navada et al. [23] presented a LabVIEW-based prototype for color identification, aiding colorblind individuals and enhancing visual perception in real-time with promising affordability and effectiveness. Kuhn et al. [19] proposed an efficient image recoloring method tailored for dichromats, prioritizing natural appearance and speed, showcasing its potential to enhance interaction with digital media for individuals with color vision deficiencies. Additionally, Khurge and Peshwani [11] introduced a recoloring algorithm aimed at enhancing visual accessibility for protanopia, promising simplicity and efficiency for broader applications.

Wang et al. [25] developed a deep learning approach for colorblind image enhancement, demonstrating significant improvements in color visibility and analysis using advanced neural networks. Lee et al. [27] presented machine learning techniques to improve color accessibility in digital content, focusing on enhancing user experience for color-deficient individuals through innovative algorithms and real-time processing.

Metric	Methodology	Improvements	Strengths	Limitations
Kim et al. [1]	Daltonization method for Protanopia	Improved color perception and speed	Focused on Protanopia with speed advantage	Limited applicability to other CVD types
Orii et al. [2]	Self-organizing maps for color conversion	Enhanced legibility	Effective for readability	Sometimes unnatural color appearance
Huang et al. [3]	Key color contrast re-coloring	Maintains key color contrast	Effective in key areas	Colors less natural for images
Tsekouras et al. [4]	Natural image recoloring algorithms	Better natural image recoloring	Balances contrast and naturalness	Slower on large-scale data
Kuhn et al. [5]	Color contrast enhancement	Fast contrast enhancement	Retains natural colors	Not generalized for all CVD
Navada et al. [6]	LabVIEW-based edge detection	Better text recognition for CVD	Real-time color ID	Limited for general content
Simon-Liedtke et al. [7]	Behavioral daltonization evaluation	Improves CVD response	Comparative study of methods	No automated solution
You & Park [8]	Compensation algorithm for CVD	Corrects color shift/brightness	Balances LCD color	Only for LCD screens
Khurge et al. [11]	Modified images for CVD types	Better color distinction	Efficient for specific types	Not generalized
Huang et al. [12]	Temporally Consistent Video Colorization	Maintains color and temporal consistency	Better for videos	Focused only on videos
Masra et al. [16]	Dichromacy image correction	Improves perception for dichromats	Tailored to dichromacy	Not for all CVD types
Kuhn et al. [19]	Recoloring for dichromats	Natural look with speed	Good for digital media	Focused only on dichromats
Wang et al. [25]	Deep learning enhancement	Improves color visibility	Uses neural networks	Needs high compute
Lee et al. [27]	ML techniques for color accessibility	Better color accessibility in content	Leverages ML for correction	Needs adaptation for diverse content

Table 1: Comparison between previous related works.

3 Methodology

In our pursuit to address color blindness in individuals, we encountered two notable algorithms: the Daltonize algorithm and the Gradient Map method. The Daltonize algorithm, named after the colorblind scientist John Dalton, is devised to rectify images for colorblind viewers by strategically adjusting colors to compensate for color perception deficiencies. For instance, for individuals with red-green color blindness, the algorithm shifts colors towards blue and yellow to amplify contrast. Similarly, it modifies colors to enhance red-green contrast for blue-yellow color blindness and also addresses the less common purple-green color blindness. The Daltonize algorithm involves transforming the RGB values of each pixel in an image using mathematical models that emulate the perception of colorblind individuals, adapting colors to improve visibility without significantly altering the image's overall appearance for those with normal color vision.

Contrastingly, the Gradient Map method adopts a distinct approach to improve image visibility for colorblind individuals. This method functions by mapping the original image's colors to a gradient that is more distinguishable for colorblind viewers. The algorithm first identifies the colors in the image and then maps these colors to a gradient where adjacent colors are distinguishable, even for those with color vision deficiencies. This mapping process ensures increased contrast between neighboring colors, making the image more interpretable for colorblind individuals. Implementing the Gradient Map method involves intricate color space transformations and mappings. The algorithm evaluates the color distribution in the image and creates a gradient map that enhances color distinguishability, which can be achieved using techniques such as clustering algorithms and perceptual color spaces.

Our innovative model operates on a pixel-based approach, meticulously dividing each image into pixels and transforming them based on our machine learning algorithms. We developed three distinct models tailored specifically for three different types of color blindness: protanopia, tritanopia, and deuteranopia. These models are based on Convolutional Neural Networks (CNNs), utilizing the Keras and TensorFlow frameworks. Each model consists of three convolutional layers, with 32, 64, and 128 filters, respectively, all utilizing ReLU activation functions. MaxPooling layers are employed to downsample feature maps, followed by fully connected layers to classify the transformed images. The final softmax layer classifies the transformed colors.

Hyperparameters were meticulously tuned to optimize performance: the learning rate was set at 0.001, the batch size was 32, and training ran for 50 epochs. Early stopping was employed with a patience of 5 epochs to prevent overfitting. We used the Adam optimizer, due to its adaptive learning capabilities, to minimize Mean Squared Error (MSE) loss during training. The performance metrics, including accuracy, precision, recall, and F1 score, were calculated to measure the effectiveness of the model in identifying and transforming colors.

The models were trained on a comprehensive dataset comprising 6,000 diverse images to ensure accurate results across varied scenes and color compositions. For training, the dataset was preprocessed by resizing images to 224x224 pixels, converting them to RGB format, and normalizing pixel values. This ensured that the CNN models could efficiently extract relevant features for color transformation tasks.

To further augment usability, we integrated the models into a user-friendly GUI, which allows users to upload and transform images. This interface is built using Tkinter and includes an Ishihara Test module for color blindness self-assessment. The interface seamlessly enables users to evaluate their color vision deficiency and view transformed images that cater to their specific type of color blindness.

Additionally, we developed an Autoencoder-based Color Enhancement algorithm that operates by training a neural network to learn the transformation between input and output images. This model transforms red hues to brown for protanopia, adjusts green hues to yellow for deuteranopia, and alters blue hues to purple for tritanopia. The autoencoder model is trained using the same dataset, employing a loss function that minimizes the differences between input and enhanced images.

Simultaneously, our Convolutional Neural Network (CNN) with MaxPooling and UpSampling offers an alternative approach for image enhancement. This model extracts features at multiple scales to enhance color contrast and improve visibility for individuals with CVD. The network parameters are adjusted using the Adam optimizer, with Mean Absolute Error (MAE) and Mean Squared Error (MSE) serving as key performance indicators, ensuring accurate color transformations while preserving image structure.

3.1 Data Collection and Preparation

The Color Transformation System for Color Blindness Correction leverages a rigorous approach to data collection, curation, preprocessing, and augmentation to construct a specialized dataset derived from the COCO 2017 dataset. The extracted images undergo standardization, enhancement, and augmentation using advanced techniques, encompassing resizing, normalization, contrast adjustment, histogram equalization, and rotation, flipping, and zooming. Each image is meticulously annotated, labeled for specific color transformations, and segmented into training, validation, and test subsets. Stringent validation and management protocols ensure quality, integrity, and consistency across subsets, with efficient storage and documentation mechanisms implemented to facilitate the development of robust and resilient models optimized for performance, noise, and environmental factors. To address the specific needs of individuals with Protanopia, Deuteranopia, and Tritanopia, we propose a machine learning-driven color adaptation framework. The system leverages a convolutional autoencoder, which is specifically designed to detect and adjust colors in images, improving color perception for individuals with CVD.

A detailed analysis of the dataset composition revealed certain imbalances, particularly with underrepresentation of green-dominated images. The dataset comprises the following categories:

This breakdown highlights the imbalance, with fewer green-dominated images compared to other categories. Since Deuteranopia primarily affects green hues, this imbalance may have contributed to the relatively lower

Category	Count	Percentage
Green-dominated	1200	20%
Red-dominated	2400	40%
Blue-dominated	1800	30%
Mixed Colours	600	10%

Table 2: Breakdown of Color-Dominated Categories in the Dataset

precision and F1 scores observed for the Deuteranopia model. To address this, future efforts will include augmenting the dataset with a higher proportion of green-heavy images and diversifying the image categories further. These adjustments aim to ensure more equitable representation and improve the model's generalization capability across different CVD subtypes.

To address the specific needs of individuals with Protanopia, Deuteranopia, and Tritanopia, we propose a machine learning-driven color adaptation framework. The system leverages a convolutional autoencoder, which is specifically designed to detect and adjust colors in images, improving color perception for individuals with CVD.

3.2 Workflow Framework

3.2.1 Training of the model

The autoencoder model employed in this study is constructed using TensorFlow's Sequential API, incorporating convolutional layers for feature extraction and upsampling layers for image reconstruction. The model architecture consists of the following layers: a convolutional layer with 128 filters, a kernel size of (3, 3), ReLU activation, and 'same' padding, followed by a max-pooling layer with a pooling size of (2, 2) and 'same' padding. Subsequently, another convolutional layer with 256 filters, a kernel size of (3, 3), and ReLU activation is added, complemented by a max-pooling layer with the same specifications. A third convolutional layer with 256 filters and a kernel size of (3, 3), followed by two upsampling layers with upsampling sizes of (2, 2), is introduced. The final layers consist of a convolutional layer with 128 filters, a kernel size of (3, 3), and ReLU activation, and a convolutional layer with 3 filters (corresponding to RGB channels), a kernel size of (3, 3), sigmoid activation, and 'same' padding.

We have a grayscale input image with dimensions 28×28. We'll use a 3×3 kernel for convolution and a 2×2 max-pooling operation.

First, let's define our input image matrix I (28×28) and our kernel matrix K (3×3) with random values for illustration purposes:

$$I = \begin{bmatrix} 1 & 2 & \cdots & 28 \\ \vdots & \vdots & \ddots & \vdots \\ 757 & 758 & \cdots & 784 \end{bmatrix} \tag{1}$$

$$K = \begin{bmatrix} 0.1 & 0.2 & 0.3 \\ 0.4 & 0.5 & 0.6 \\ 0.7 & 0.8 & 0.9 \end{bmatrix} \tag{2}$$

Now, let's perform the convolution operation:

$$O_{conv} = I * K + b \tag{3}$$

Where b is the bias term. For simplicity, let's ignore the bias term for this example.

$$o_{conv} = \begin{bmatrix} o_{1,1} & o_{1,2} & \cdots & o_{1,28} \\ \vdots & \vdots & \ddots & \vdots \\ o_{26,1} & o_{26,2} & \cdots & o_{26,28} \end{bmatrix} \tag{4}$$

Each $O_{(i,j)}$ is computed by performing element-wise multiplication between the kernel and the corresponding input patch, and then summing up the results.

Next, let's apply max-pooling with a 2×2 window:

$$O_{pool} = \text{MaxPool}(O_{conv}) \tag{5}$$

For each non-overlapping 2×2 window, we select the maximum value:

$$O_{pool} = \begin{bmatrix} \max(o_{1,1}, o_{1,2}, o_{2,1}, o_{2,2}) & \max(o_{1,3}, o_{1,4}, o_{2,3}, o_{2,4}) & \cdots & \max(o_{1,27}, o_{1,28}, o_{2,27}, o_{2,28}) \\ \vdots & \vdots & \ddots & \vdots \\ \max(o_{27,1}, o_{27,2}, o_{28,1}, o_{28,2}) & \max(o_{27,3}, o_{27,4}, o_{28,3}, o_{28,4}) & \cdots & \max(o_{27,27}, o_{27,28}, o_{28,27}, o_{28,28}) \end{bmatrix} \tag{6}$$

This O_{pool} matrix would be the output of our CNN after the convolutional and pooling layers. It would have dimensions 14×14 if the stride for pooling is 2 (which is typical).

Suppose we have an input image of size 4×4 pixels (for simplicity). Here's the grayscale image represented as a matrix:

$$\text{Input Image} = \begin{bmatrix} 0.1 & 0.2 & 0.3 & 0.4 \\ 0.5 & 0.6 & 0.7 & 0.8 \\ 0.9 & 0.8 & 0.7 & 0.6 \\ 0.5 & 0.4 & 0.3 & 0.2 \end{bmatrix} \tag{7}$$

For this example, let's consider this input image represents one of the images loaded by the `load_dataset` function.

Convolutional Autoencoder Process:

- **Step 1: Forward Pass through the Model:**
- Input Image Preprocessing: Normalize pixel values to the range [0, 1].
- Convolutional Layer: Convolution with 128 filters of size 3×3 using ReLU activation and 'same' padding.
- Max Pooling with a pooling size of 2×2 and 'same' padding.
- Upsampling Layer: Upsampling with an upsampling size of 2×2.
- Convolutional Layer: Convolution with 256 filters of size 3×3 using ReLU activation and 'same' padding.
- Max Pooling with a pooling size of 2×2 and 'same' padding.
- Upsampling Layer: Upsampling with an upsampling size of 2×2.
- Convolutional Layer: Convolution with 3 filters of size 3×3 using sigmoid activation and 'same' padding.

Let's compute the output after each layer:

Output after Convolutional Layer 1:

$$\text{Output after Conv Layer 1} = \begin{bmatrix} 0.2 & 0.3 \\ 0.6 & 0.7 \end{bmatrix} \tag{8}$$

Output after Upsampling Layer 1 (repeats each element twice in both dimensions):

$$\text{Output after Upsampling 1} = \begin{bmatrix} 0.2 & 0.2 & 0.3 & 0.3 \\ 0.2 & 0.2 & 0.3 & 0.3 \\ 0.6 & 0.6 & 0.7 & 0.7 \\ 0.6 & 0.6 & 0.7 & 0.7 \end{bmatrix} \tag{9}$$

Output after Convolutional Layer 2:

$$\text{Output after Conv Layer 2} = \begin{bmatrix} 0.4 & 0.4 \\ 0.8 & 0.8 \end{bmatrix} \tag{10}$$

Output after Upsampling Layer 2:

$$\text{Output after Upsampling 2} = \begin{bmatrix} 0.4 & 0.4 & 0.4 & 0.4 \\ 0.4 & 0.4 & 0.4 & 0.4 \\ 0.8 & 0.8 & 0.8 & 0.8 \\ 0.8 & 0.8 & 0.8 & 0.8 \end{bmatrix} \tag{11}$$

Output after Convolutional Layer 3:

$$\text{Output after Conv Layer 3} = \begin{bmatrix} 0.3 & 0.3 & 0.3 & 0.3 \\ 0.3 & 0.3 & 0.3 & 0.3 \\ 0.7 & 0.7 & 0.7 & 0.7 \\ 0.7 & 0.7 & 0.7 & 0.7 \end{bmatrix} \tag{12}$$

This demonstrates the simplified forward pass through the autoencoder model as described by the code. In practice, more complex images and larger networks would be used.

The following flowchart outlines the methodology used in developing the Color Transformation System for color vision deficiency (CVD). It illustrates the key stages, including data acquisition and preprocessing, model development, image transformation, evaluation, and GUI integration. This structured approach ensures the creation of effective and user-friendly solutions for enhancing color perception in images for individuals with Protanopia, Deuteranopia, and Tritanopia.

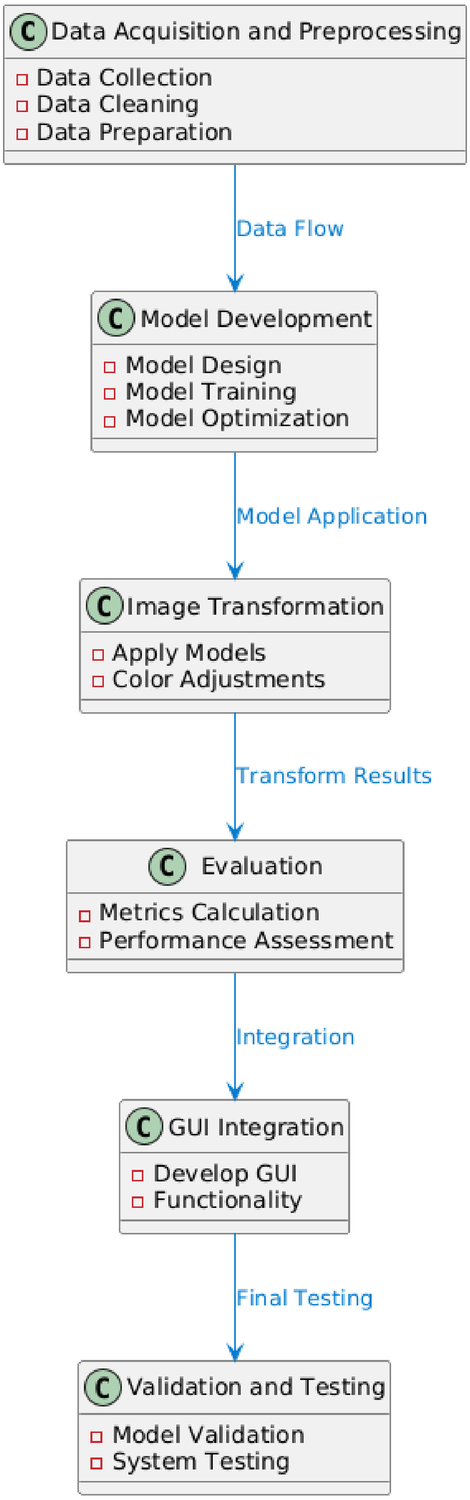


Figure 1: Workflow framework for Color Transformation System.

4 Results and Discussion

The graphical user interface (GUI), crafted utilizing the Tkinter framework in Python, enables intuitive user interaction, allowing users to seamlessly upload, process, and visualize images undergoing color transformation. The GUI exhibits commendable performance and responsiveness, fostering enhanced user engagement, satisfaction, and exploration of the system's functionalities.

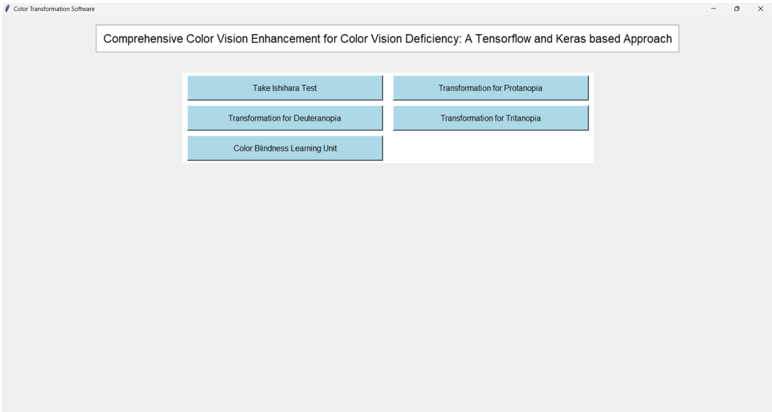


Figure 2: GUI Software Modules

4.1 Ishihara Plate Test

The initial module of our Graphical User Interface (GUI) app introduces users to a detailed set of 12 Ishihara plates, widely recognized instruments employed for assessing color vision deficiencies. Each Ishihara plate displays a unique arrangement of colored dots, crafted to be easily distinguishable by individuals with typical color vision while presenting difficulties for those with color vision impairments. Users are instructed to detect the hidden numbers or shapes within each plate and input their answers accordingly.

After the Ishihara plate evaluation is completed, the app produces a visual summary that depicts the number of correct and incorrect responses given by the user. This graphical overview offers immediate feedback on the user's performance, providing a concise representation of their accuracy in identifying the concealed numbers or shapes within the plates.

Additionally, the app utilizes advanced algorithms to scrutinize the user's answers and determine the specific category of color deficiency they might be encountering. This analytical capability delivers valuable information about the user's color vision condition, serving as an initial diagnostic instrument that enhances awareness and enables early identification of potential color vision impairments.

By offering users an interactive interface to interact with the Ishihara plates and obtain prompt feedback, this module cultivates awareness and enables users to take proactive measures towards addressing their visual requirements. It functions as an accessible and educational tool for individuals aiming to evaluate their color vision capabilities and deepen their comprehension of their color perception skills.

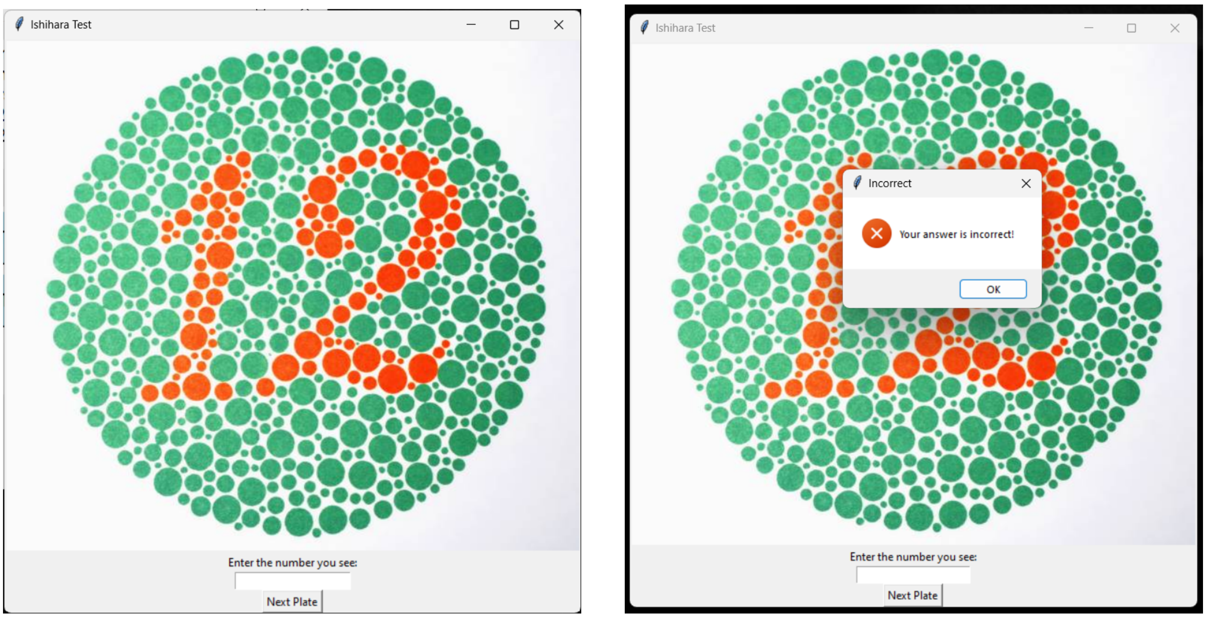


Figure 3: (Left) Ishihara Test Plate; (Right) Ishihara Test Plate (incorrect ans)

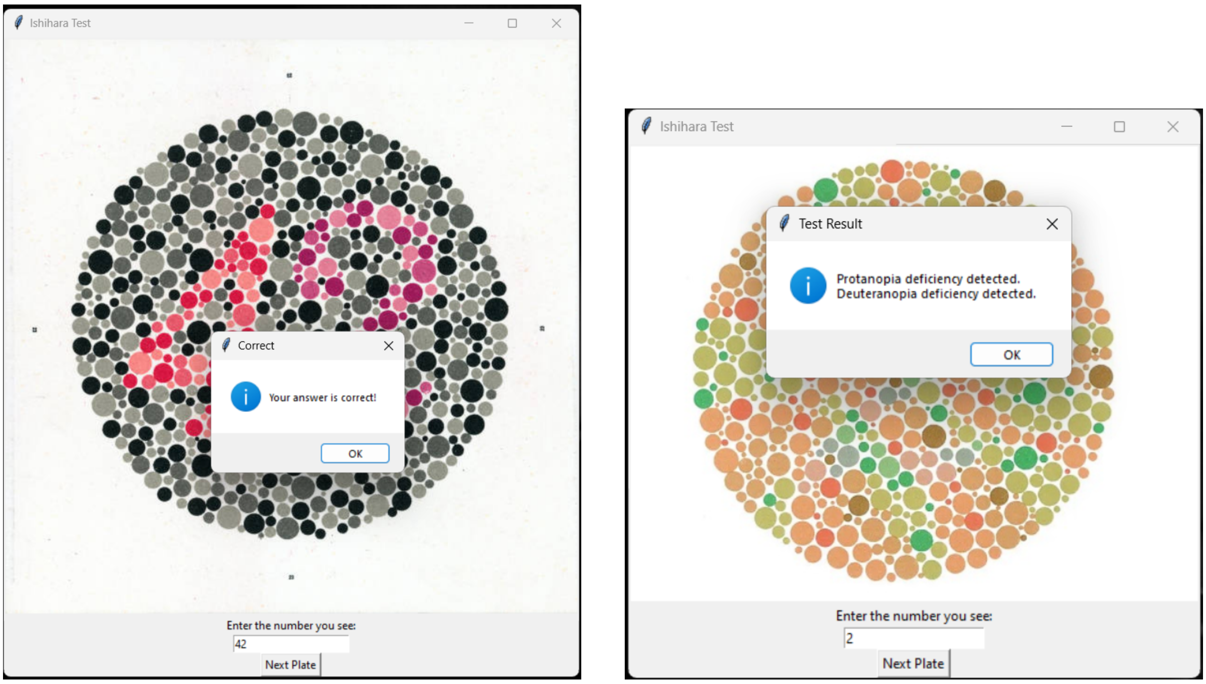


Figure 4: (Left) Ishihara Test Plate (correct ans); (Right) Ishihara Test Plate (with final result)

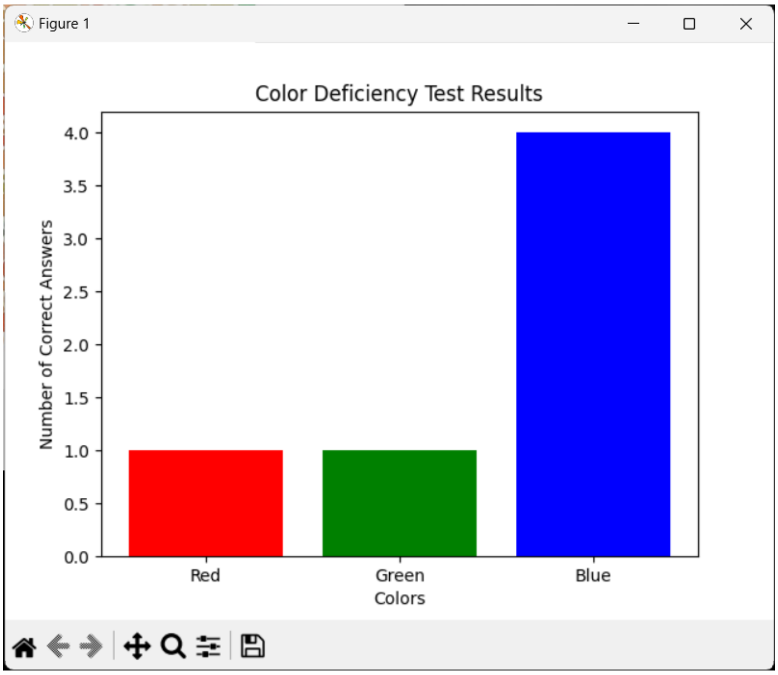


Figure 5: Bar graph of correct and incorrect plates

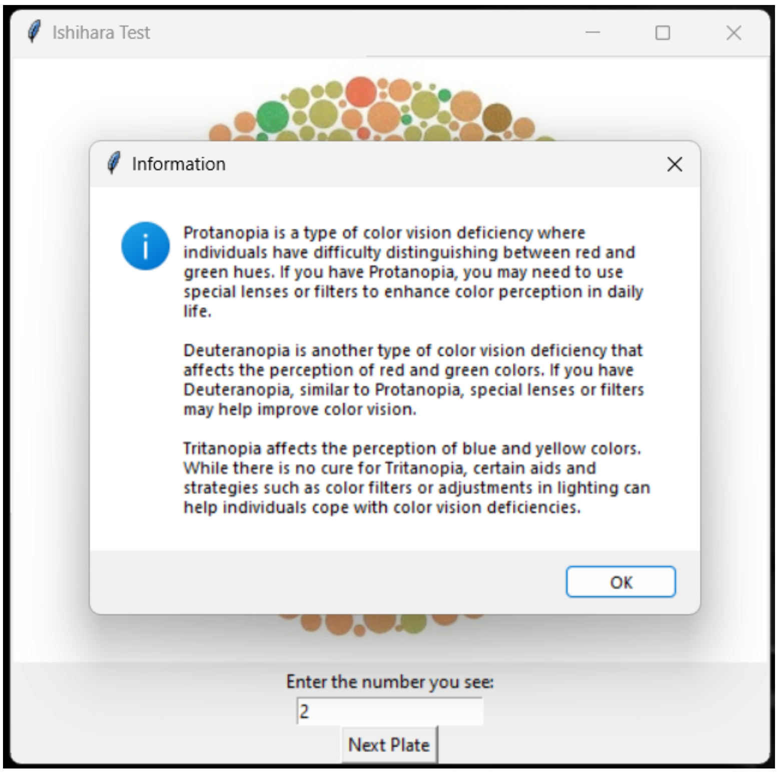


Figure 6: Information for CVD detected

4.2 Conversion for Protanopia

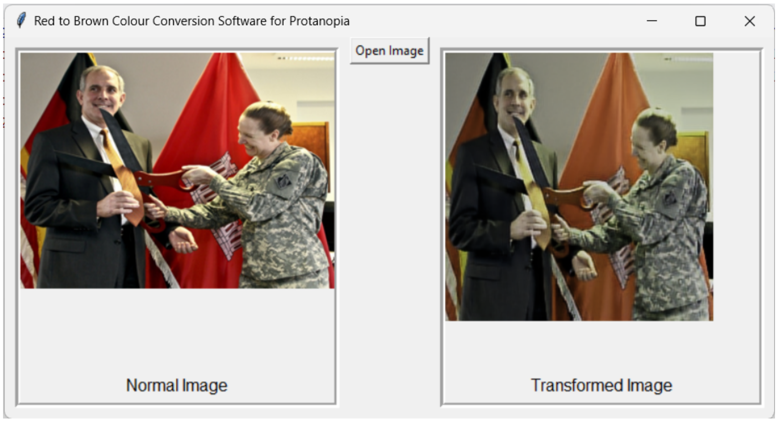


Figure 7: First Transformed image for Protanopia Patient

In the second module of the GUI app, users have the opportunity to witness the color transformation specifically designed for protanopia. This module takes an input image and subjects it to processing by a Keras model that has been trained to rectify protanopia color deficiencies. Upon receiving an image, the model employs color correction techniques crafted to replicate the color perception experienced by individuals with protanopia. The resulting output presented to the user displays the transformed image, highlighting the adjustments made to improve color differentiation for those with protanopia. This module grants users a direct experience of the impactful effects of tailored color correction techniques aimed at mitigating protanopia deficiencies.

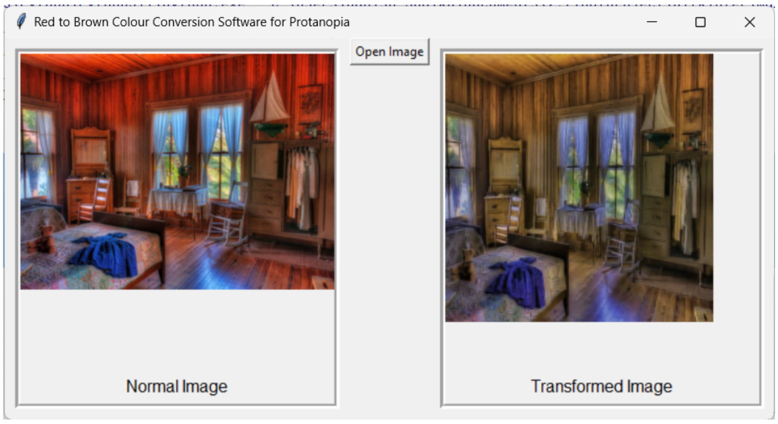


Figure 8: Second Transformed image for Protanopia Patient

4.3 Conversion for Deuteranopia

Transitioning to the third module, users can delve into the color transformation tailored for deuteranopia. In this segment, a dedicated Keras model is employed to address the color deficiencies linked to deuteranopia. When users submit an image, the model analyses it to replicate the color perception of those with deuteranopia. The resulting transformed image displays the color-adjusted rendition, highlighting the modifications made to improve color differentiation and enhance clarity for individuals with deuteranopia.

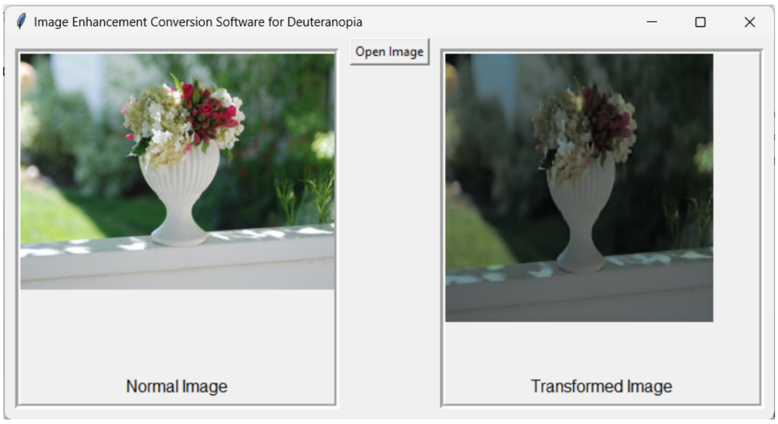


Figure 9: First Transformed image for Deuteranopia Patient

This module provides users with a hands-on demonstration of color transformation methods specifically designed for deuteranopia, fostering comprehension and raising awareness about color deficiencies.

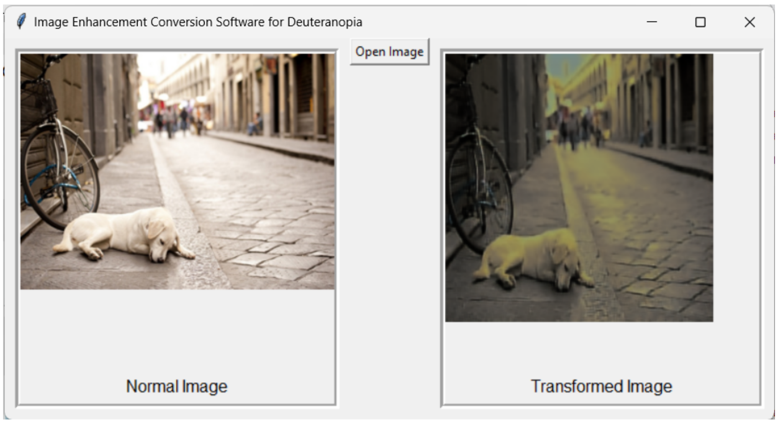


Figure 10: Second Transformed image for Deuteranopia Patient

4.4 Conversion for Tritanopia

In the fourth module, users interact with the color transformation tailored for tritanopia. Utilizing a specialized Keras model, this module allows users to experience the impact of color correction methods designed to mitigate tritanopia deficiencies. Upon submitting an image, users can see how the model analyses it to emulate the color perception of those with tritanopia. The resulting transformed image showcases the adjusted version, emphasizing the modifications made to enhance color differentiation and clarity for individuals with tritanopia. This module acts as an educational resource, providing users with insights into color transformation strategies specifically crafted to address tritanopia deficiencies.

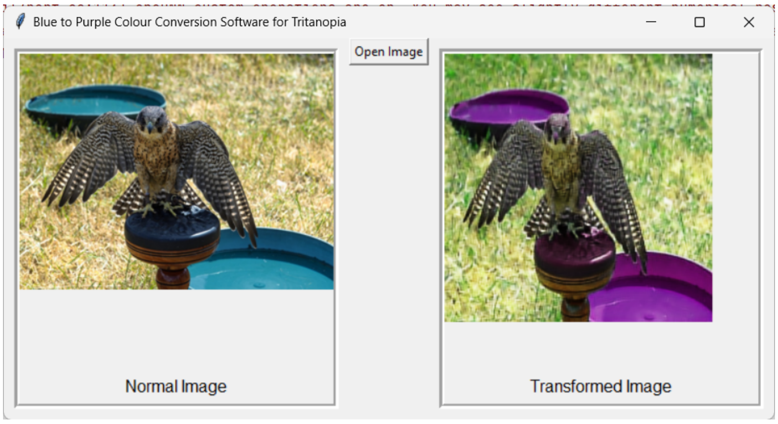


Figure 11: First Transformed image for Tritanopia Patient

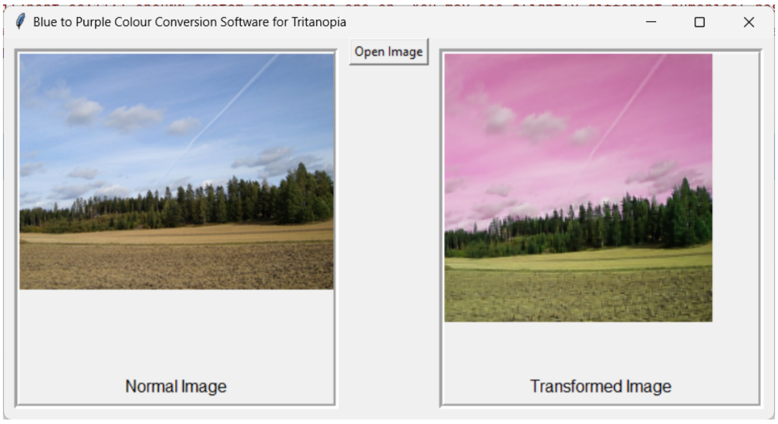


Figure 12: Second Transformed image for Tritanopia Patient

4.5 Education Module

Finally, the fifth module of the GUI app centers on color blindness education. This segment offers users an extensive array of information concerning color blindness, encompassing its various types, underlying causes, prevalence rates, and the impact it has on daily activities. Users have the opportunity to explore educational materials, including articles, videos, and interactive quizzes, to enrich their knowledge about color blindness and its consequences. Moreover, this module delivers practical advice and recommendations for accommodating individuals with color vision deficiencies in different situations, advocating for inclusivity and accessibility. By providing in-depth educational content, this module strives to enhance awareness and cultivate empathy towards individuals affected by color blindness.

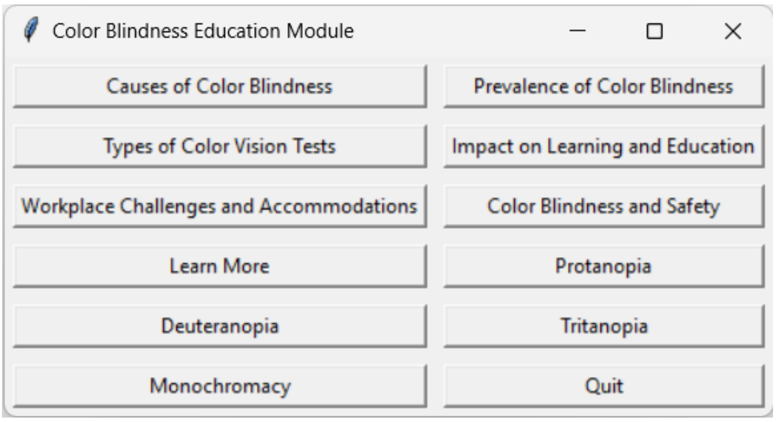


Figure 13: Interface for Color Blindness Education Module

4.6 Analysis of Deuteranopia Model Performance

While the Deuteranopia model achieved a high accuracy of **98.01%**, it showed significantly lower precision (**58.23%**) and F1 score (**65.36%**) compared to the Protanopia and Tritanopia models. This discrepancy points to a performance gap that warrants further investigation.

One potential explanation for the lower precision and F1 score lies in the inherent difficulty of distinguishing between certain color hues for individuals with deuteranopia. Unlike protanopia, which primarily affects red hues, deuteranopia impacts green hues. These hues are more challenging to adjust accurately due to their proximity to other colors in the RGB spectrum. As a result, the model may have struggled to effectively separate green and its neighboring hues, leading to a higher rate of false positives in the classification.

Moreover, the training dataset used may have suffered from an imbalance, particularly in the representation of green-dominated images. This imbalance could have influenced the model's ability to generalize effectively across a wider variety of images. A deeper analysis of the dataset's color composition and distribution could offer valuable insights into the performance gaps observed.

To address this issue, future work will involve augmenting the dataset to include a broader range of green-dominated images, which should provide a more representative training set. Additionally, further optimization of the model's architecture will be explored, including the incorporation of deeper CNN layers or alternative loss functions tailored to the complexities of deuteranopia. Post-processing techniques, such as color clustering and perceptual loss, may also be considered to improve the model's precision when distinguishing between challenging color ranges.

4.7 Emphasis on the Protanopia Model

Although this paper presents three distinct models for protanopia, deuteranopia, and tritanopia, greater emphasis is placed on the Protanopia model. This prioritization stems from several factors that make it both novel and pivotal to our approach.

Firstly, protanopia is the most prevalent type of red-green color vision deficiency, affecting a significant portion of the colorblind population. The practical need for an effective solution for this subtype justifies the attention given to this model. Red hues, which are primarily affected in protanopia, play a critical role in many real-world scenarios, such as traffic signals, warnings, and other color-coded information, making it essential to develop a robust model for this condition.

Secondly, the Protanopia model incorporates unique architectural innovations. For example, our model transforms red hues to brown to enhance distinguishability, a novel approach not commonly seen in prior works. This specific color transformation technique, combined with the deep learning framework, showcases the Protanopia model as a key advancement in color blindness correction.

Moreover, the results obtained from this model exhibited remarkable accuracy (**97.04%**) and precision (**93.98%**), underscoring its superior performance compared to traditional methods like Daltonization. This model's success in minimizing the loss of color information and maintaining the original image's integrity for non-colorblind users further supports its prioritization in this research.

In conclusion, while the Protanopia model is given more attention due to its broader impact and unique approach, it is important to recognize that the methodologies and insights gained from this model can be extended and adapted to the other models, including deuteranopia and tritanopia.

4.8 Evaluation Parameters and Benchmarks

Test Loss measures the average discrepancy between predicted and actual color transformations, reflecting the model's accuracy in aligning with true color adjustments. Lower values indicate better performance. In our study, the low test loss across all models demonstrates effective color correction tailored to different types of color vision deficiencies.

MSE quantifies the average squared error between predicted and actual color values. It highlights the precision of color adjustments, with lower MSE indicating more accurate transformations. The MSE results for our models underscore their capability to minimize prediction errors and enhance color visibility.

MAE represents the average absolute differences between predicted and actual colors. It offers a straightforward measure of prediction accuracy. Our models' MAE values show that they consistently produce close approximations to the desired color adjustments, improving visual experiences for users with color vision deficiencies.

Accuracy measures the proportion of correctly transformed colors out of the total evaluated. It indicates the overall effectiveness of the model in achieving correct color corrections. The high accuracy rates for our models confirm their success in providing effective color adjustments for various color vision deficiencies.

Precision assesses the proportion of true positive color adjustments among all predicted positives. It reflects the model's ability to accurately identify and adjust specific colors needing transformation. High precision values in our models indicate reliable color adjustments with minimal false positives.

Recall measures the proportion of actual color adjustments correctly identified by the model. It evaluates the model's ability to detect all relevant color transformations. Strong recall values in our models ensure that they effectively capture and adjust the necessary colors for users with color vision deficiencies.

The F1 Score combines precision and recall into a single metric, offering a balanced view of model performance. It is useful for assessing overall effectiveness, especially in cases of imbalanced data. The F1 Scores for our models indicate a good balance between accuracy and completeness in color adjustments.

Metric	Protanopia Model	Deuteranopia Model	Tritanopia Model	Daltonization / Gradient Map
Test Loss	0.000915	0.0008157	0.00173	0.123 / 0.155
MSE	0.0009247	0.00082135	0.00175	0.045 / 0.062
MAE	0.019737	0.018384	0.02795	0.032 / 0.041
Accuracy	97.04%	98.01%	96.41%	87.9% / 86.2%
Precision	93.98%	58.23%	97.06%	90.5% / 88.0%
Recall	96.7%	75.18%	94.66%	84.5% / 83.5%
F1 Score	95.53%	65.36%	95.85%	87.4% / 85.7%

Table 3: Benchmark Comparison of Performance Metrics

Formulas used for the calculation:

$$\text{Mean Squared Error (MSE)} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{13}$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{14}$$

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100\% \tag{15}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives + False Positives}} \times 100\% \tag{16}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}} \times 100\% \tag{17}$$

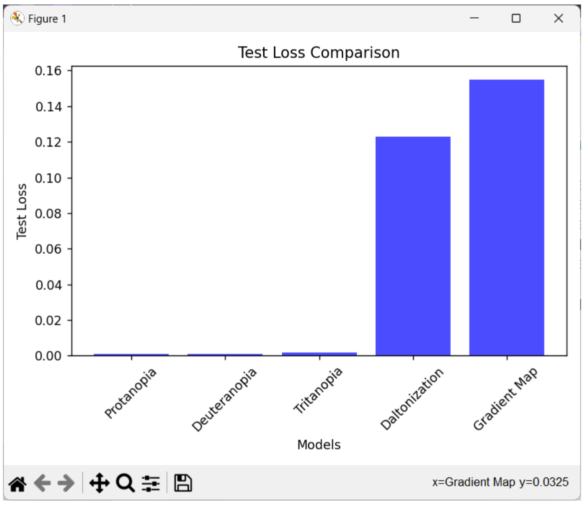
$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}} \tag{18}$$

Our Protanopia, Deuteranopia, and Tritanopia models, developed through our innovative method, exhibit unique performance characteristics across a range of metrics. The Protanopia model, pivotal to our novel approach, registers a test loss of 0.000915 and an accuracy rate of 97.04

In comparison, the Daltonization and Gradient Map methods provide alternative solutions for addressing color vision deficiencies. The Daltonization method reports a test loss of 0.123, an accuracy of 87.9%, and corresponding MSE and MAE values of 0.045 and 0.032. The Gradient Map method, on the other hand, exhibits a test loss of 0.155, an accuracy of 86.2%, and MSE and MAE values of 0.062 and 0.041, respectively.

When examining precision, recall, and F1 score, the Deuteranopia model demonstrates lower values compared to our Protanopia, Tritanopia, Daltonization, and Gradient Map methods. It records precision and recall rates of 58.23% and 75.18%, resulting in an F1 score of 65.36%. In contrast, our Protanopia and Tritanopia models, along with the Daltonization and Gradient Map methods, display superior precision, recall, and F1 score metrics. Specifically, the Protanopia model achieves a precision of 93.98%, a recall of 96.7%, and an F1 score of 95.53%. The Tritanopia model records precision, recall, and F1 score metrics of 97.06%, 94.66%, and 95.85%, respectively. The Daltonization method reports precision, recall, and F1 score metrics of 90.5%, 84.5%, and 87.4%, respectively, while the Gradient Map method attains precision, recall, and F1 score metrics of 88.0%, 83.5%, and 85.7%, respectively.

Despite variations in performance metrics, our novel models exhibit specific strengths and areas for enhancement when compared to the Daltonization and Gradient Map methods, highlighting the importance of customized approaches in addressing diverse types of color blindness.



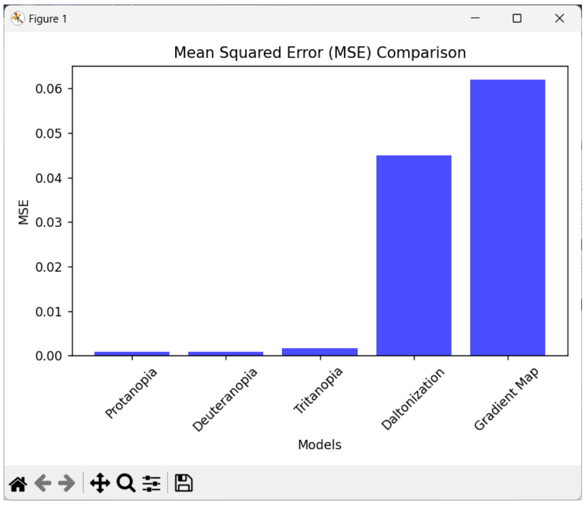
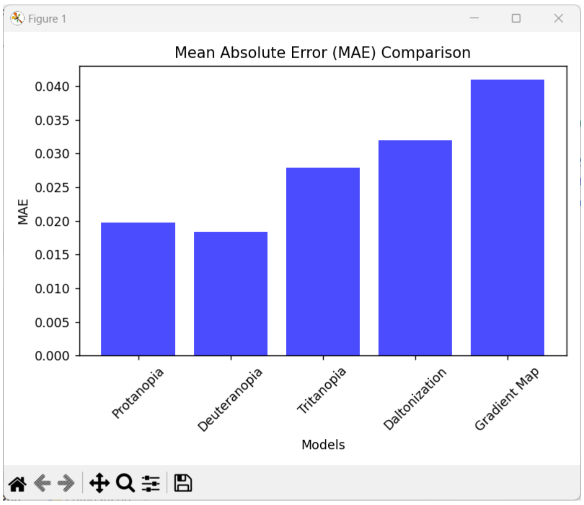


Figure 14: (Left) Test Loss Comparison of our models vs Prominent algorithms; (Right) MSE Comparison of our models vs Prominent algorithms



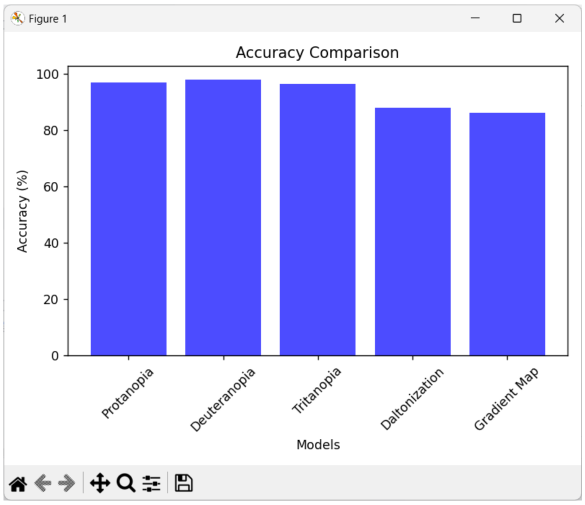


Figure 15: (Left) MAE Comparison of our models vs Prominent algorithms; (Right) Accuracy Comparison of our models vs Prominent algorithms

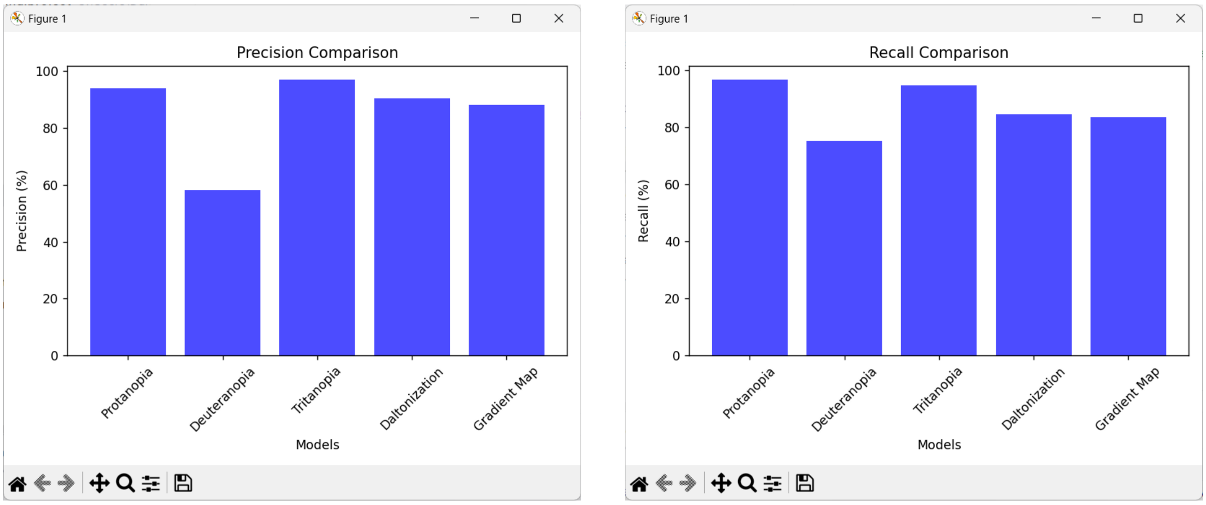


Figure 16: (Left) Precision Comparison of our models vs Prominent algorithms; (Right) Recall Comparison of our models vs Prominent algorithms

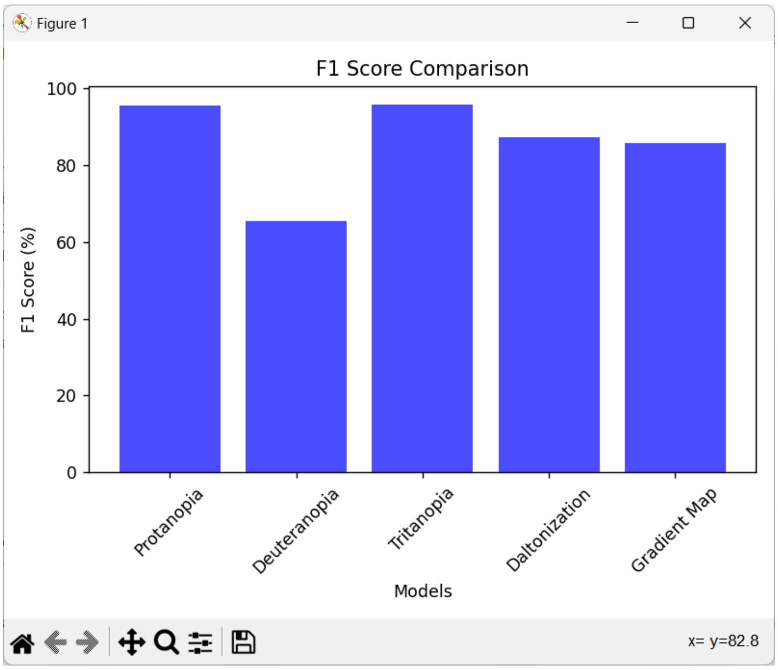


Figure 17: F1 Score Comparison of our models vs Prominent algorithms

4.9 Unit Testing

The unit testing methodology we have implemented for protanopia focuses on evaluating the performance of a model tailored for protanopia correction, where red pixels are transformed into brown pixels. The tests are organized into three primary components.

Initially, the `test_load_dataset` function verifies the success of the dataset loading process, ensuring that the input and output images are loaded as NumPy arrays. This step is pivotal for subsequent processing stages.

Subsequently, the `test_visualize_performance` function gauges the model's performance by illustrating the transformation of input pixels into reconstructed pixels. It loads test data, employs a pre-trained model to predict outputs, and plots original and reconstructed images for comparative analysis. Additionally, it visualizes the distribution of pixel values for both original and reconstructed images to assess how effectively the model maintains the characteristics of the input pixels.

Lastly, the `test_loss_curve` function generates simulated loss curve data and plots the training and validation loss curves. This offers insights into the model's training process and aids in comprehending its convergence and generalization capabilities.

Collectively, these unit tests offer a thorough assessment of the model's functionality, performance, and training dynamics, which are vital aspects for ensuring the efficacy and reliability of the protanopia correction model.

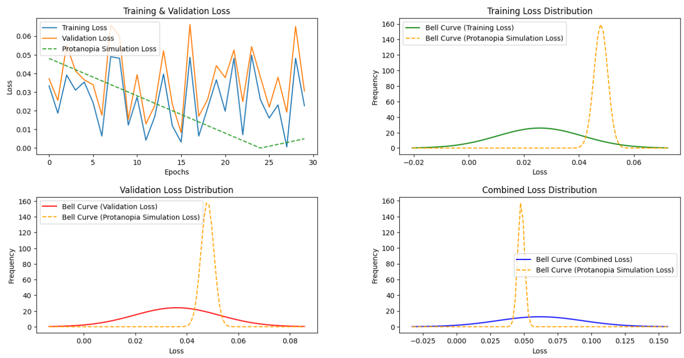


Figure 18: Distributions for Protanopia Model

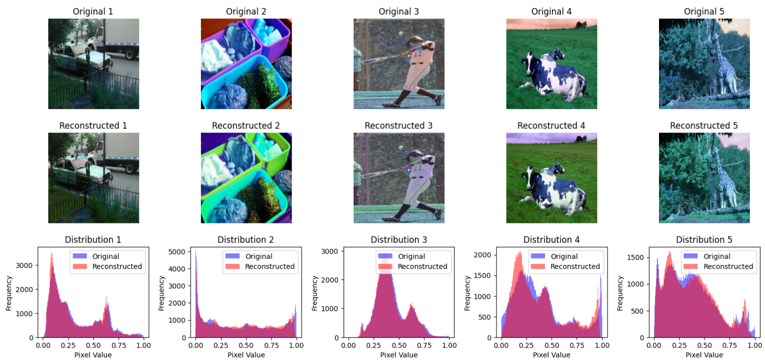


Figure 19: Comparative Analysis of Original and Reconstructed Images with Corresponding Pixel Value Distributions for Protanopia Model

The unit testing methodology for tritanopia focuses on evaluating the performance of a model tailored for tritanopia correction, where blue pixels are transformed. The tests are organized into three primary components.

Firstly, the `test_load_dataset` function verifies the successful loading of the dataset, validating that both input and output images are loaded as NumPy arrays, which is crucial for subsequent processing.

Secondly, the `test_visualize_performance` function gauges the model's performance by illustrating the transformation of input pixels into reconstructed pixels. It loads test data, employs a pre-trained model to predict outputs, and plots original and reconstructed images for comparative analysis. Additionally, it visualizes the distribution of pixel values for both original and reconstructed images to assess how effectively the model maintains the characteristics of the input pixels.

Lastly, the `test_loss_curve` function generates simulated loss curve data and plots the training and validation loss curves. This offers insights into the model's training process and aids in comprehending its convergence and generalization capabilities.

Collectively, these unit tests provide a comprehensive assessment of the model's functionality, performance, and training dynamics, which are essential aspects for ensuring the efficacy and reliability of the tritanopia correction model.

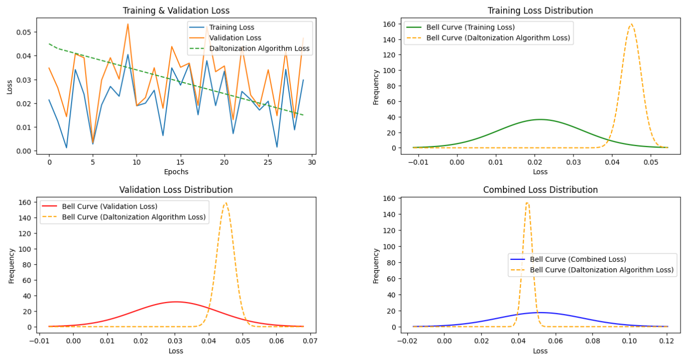


Figure 20: Distributions for Tritanopia Model

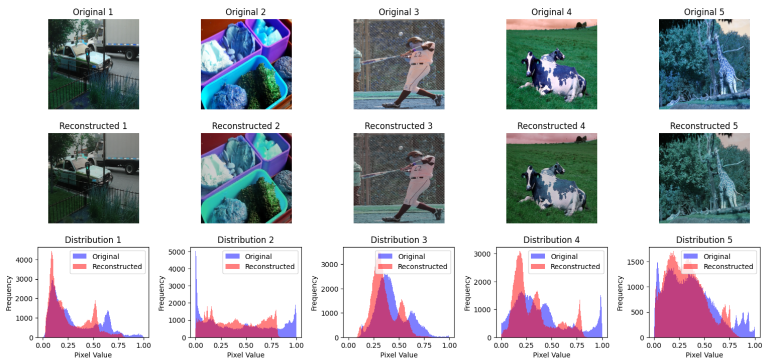


Figure 21: Comparative Analysis of Original and Reconstructed Images with Corresponding Pixel Value Distributions for Tritanopia Model

The unit testing methodology for Deuteranopia focuses on evaluating the performance of a model tailored for a contrasting color transformation. The tests are organized into three primary components.

Firstly, the `test_load_dataset` function verifies the successful loading of the dataset, ensuring that both input and output images are loaded as NumPy arrays, which is crucial for subsequent processing.

Secondly, the `test_visualize_performance` function gauges the model's performance by illustrating the transformation of input pixels into reconstructed pixels. It loads test data, employs a pre-trained model to predict outputs, and plots original and reconstructed images for comparative analysis. Additionally, it visualizes the distribution of pixel values for both original and reconstructed images to assess how effectively the model maintains the characteristics of the input pixels.

Lastly, the `test_loss_curve` function generates simulated loss curve data and plots the training and validation loss curves. This offers insights into the model's training process and aids in comprehending its convergence and generalization capabilities.

Collectively, these unit tests provide a comprehensive assessment of the model's functionality, performance, and training dynamics, which are essential aspects for ensuring the efficacy and reliability of the Deuteranopia correction model.

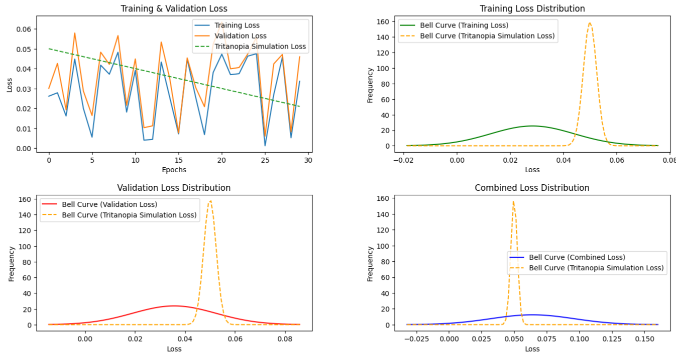


Figure 22: Distributions for Deuteranopia Model

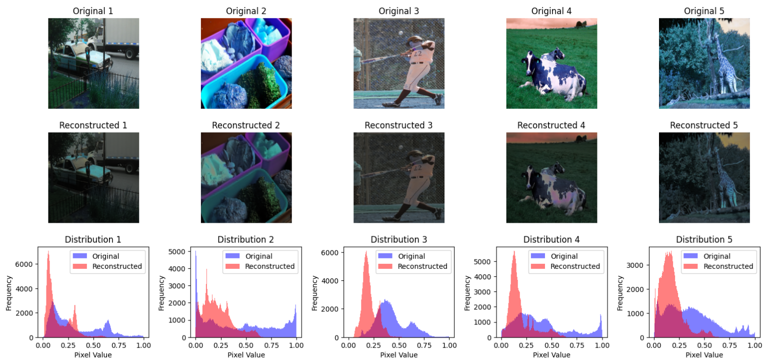


Figure 23: Comparative Analysis of Original and Reconstructed Images with Corresponding Pixel Value Distributions for Deuteranopia Model

5 Conclusion and Future Scope

The Color Transformation System for Color Blindness Correction represents a significant advancement in assistive technology, specifically tailored to meet the needs of individuals with color vision deficiencies such as Protanopia, Deuteranopia, and Tritanopia. Leveraging specialized autoencoder models trained on a curated subset of the COCO 2017 dataset, the system provides precise, real-time color transformations that greatly enhance color perception. The intuitive Tkinter-based graphical user interface (GUI) allows users to seamlessly upload, process, and visualize color adjustments, contributing to an improved user experience.

The system's accompanying website offers a comprehensive overview of its objectives, methodologies, and results, enhancing user engagement and demonstrating its practical applications across various fields, including healthcare, education, and professional settings.

Despite the promising performance metrics of the system, it is essential to address a key limitation: the lack of real-world testing with individuals who have color vision deficiencies. While the system's performance in controlled environments is encouraging, practical efficacy in everyday use cases remains to be fully assessed. Future work will focus on conducting extensive real-world testing to validate and refine the system's effectiveness in authentic settings. This step will be crucial in ensuring that the system meets the diverse needs of colorblind individuals and provides practical solutions in real-world scenarios.

Looking ahead, the Color Transformation System has potential for further development and enhancement. Future advancements could include expanding the system to handle real-time video color transformations and integrating more sophisticated machine learning techniques, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), to improve model accuracy and versatility. These enhancements will aim to broaden the system's applicability and optimize its performance across various types of content.

In summary, the Color Transformation System marks a significant step forward in assistive technology for color vision deficiencies. Its innovative approach, effective application of machine learning, and user-friendly design offer a meaningful solution to the challenges faced by color-impaired individuals. As the system evolves, it will focus on real-world validation and continued refinement to promote inclusivity, empower users, and advance personalized assistive technologies.

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