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Aiding Color Vision Deficiency with Image Recognition and Machine Learning

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ABSTRACT: This research tackles the challenge of colorblindness, affecting millions, by developing a machine learning system that translates images for easier visualization by individuals with red-green color deficiency (Deuteranopia). The system first mimics Deuteranopic vision through machine learning training, then reverses this process to enhance red and green hues in images, making them more distinct and recognizable for colorblind individuals. Tests confirm the system's effectiveness in simulating normal color perception. Beyond science, this project emphasizes empathy and inclusion, aiming to create a more accessible world. It demonstrates the significant potential of machine learning in aiding colorblind vision, paving the way for future iterations addressing broader forms of colorblindness and further refinement with larger datasets.

KEYWORDS: Robotics and Intelligent Machines; Machine Learning; Cognitive Systems; Color Vision Deficiency; Deuteranopia.

Introduction

Imagine seeing a world where red might blur with green or yellow fades into brown. This is the everyday reality for millions of people with color vision deficiency, often called color blindness. Affecting more than 3% or 12 million Americans, it's a challenge that many need to understand fully.[1] The struggle of colorblind individuals to navigate a world designed for the color-seeing majority is often overlooked.[2] Imagine choosing matching clothes, understanding traffic lights, or appreciating colorful artwork. These are just a few of the daily obstacles faced by people with color blindness. While special glasses and filters can offer some help, they often fall short. These solutions may partially enhance the distinction of certain color perceptions, but they don't fully address the limitations faced by colorblind individuals. For instance, colorblind glasses use tinted lenses to selectively filter out specific wavelengths of light, which cannot restore normal color vision. The commercial products available (e.g., EnChroma, Pilestone, etc.) tend to be expensive, making them inaccessible to everyone. To overcome these challenges, innovative approaches leveraging technological advancements are essential.[3]

This project explores a new approach using two powerful tools: image recognition and machine learning. The main goal of this project is to build a system that can automatically "translate" images, making it easier to provide colorblind-friendly images. This work achieves the goal of providing colorblind-friendly images with the following three techniques. First, the system is trained using ML to "see" like someone with color vision deficiency.[4] This involves mimicking how they perceive colors and the challenges they face. Second, once the system understands the colorblind vision, it can "reverse" this process. It will process test images and adjust their color compositions to be more distinct and recognizable for colorblind people. The output images of this reverse prediction will be overly vibrant to the eyes of individuals with normal vision. Finally, the system is tested to see how accurately these predicted images "mimic" the colors the individuals with normal vision perceive.[5] It turns out to be very close, indicating that the developed system is valuable for improving daily life and accessibility for millions.

This research has several potential contributions. First, it introduces novel approaches to addressing colorblindness by proposing a simple yet innovative use of ML. Second, unlike traditional ML methods, we employ closed-loop validation instead of relying solely on hold-out datasets for prediction accuracy tests. By iteratively validating predictions within the same dataset, it conserves data points and avoids unnecessary exclusion. Third, leveraging the existing Wolfram function contributes to the broader Wolfram community. Showcasing my new model fosters knowledge sharing and encourages others to explore similar applications. Finally, this project is more than just a science experiment; it is about empathy and inclusion. By bridging the gap between colorblindness and normal vision, this project aims to create a more accessible and vibrant world for everyone.[6]

Methods

This study employs machine learning techniques to generate images tailored for individuals with colorblind vision. The process involves a four-step pipeline for image optimization. First, unstructured image data, representing normal and Deuteranopia-adapted vision, is transformed into structured datasets by extracting color features (*Data Preparation*). Subsequently, a machine learning model is trained on these pre-labeled datasets to capture the intricacies of color perception among colorblind individuals. This trained model is then used to predict colorblind-friendly test image versions (*Model Training and Validation*). Thirdly, an inverse function of the model is employed to reverse the process, estimating how individuals with normal vision perceive images that appear to those with color vision deficiencies (*Inverse Model*). Lastly, closed-loop

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validation procedures are conducted to assess the accuracy of the inverse model in predicting how colorblind individuals perceive images, thus providing a promising means of simulating normal vision (*Closed-Loop Validation of the Inverse Model Prediction*). Further details on the outcomes and implications of each step are elaborated in the next section.

This study focuses on Deuteranopia, a specific type of colorblindness. Reference is made to the Ishihara color test, designed to assist individuals who struggle to differentiate between red and green.[7] This test, developed by Dr. Shinobu Ishihara in 1917, identifies four forms of color vision deficiency related to red and green perception: Deuteranopia, Protanomaly, Protanopia, and Deuteranomaly.

Result and Discussion

Let us explore how colorblindness alters our visual perception. Remember, my images are labeled with three values: red, green, and blue (RGB). When someone with Deuteranopia sees a picture, these 3-dimensional (3D) values get altered. To generate the color values of the Deuteranopia vision, a Wolfram Language function called ImageEffect, which simulates different forms of color blindness, is used. When the images are run through this function, the colors change quite a bit. The reds became less intense, almost blending in with the greens and blues. This shows that people with Deuteranopia might not see colors as vibrant and distinct as those with normal vision.

To picture this, imagine a 3D graph like Figure 1. Its axes are red, green, and blue, each going from 0 to 1. Five colored dots are plotted on this graph, varying the red value from 0.2 to 0.7 while keeping green and blue fixed at 0.3 and 1.0, respectively. An arrow connects each dot to a second dot, showing how the color would appear to someone with Deuteranopia. These arrows tell us something interesting. They point down and slightly inwards, meaning the red value decreases, while green and blue decrease slightly. As expected, people with Deuteranopia tend to see less vibrant colors overall, especially reds. For those readers interested, the 'Coblis Color Blindness Simulator' also provides a tool to simulate colorblind images, but it processes one image at a time.

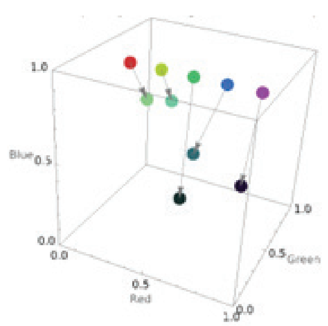


Figure 1: How color perception changes in Deuteranopic vision in a 3D graph in RGB space. The changes in five sample dots indicate that people with Deuteranopia tend to see less vibrant colors, especially reds.

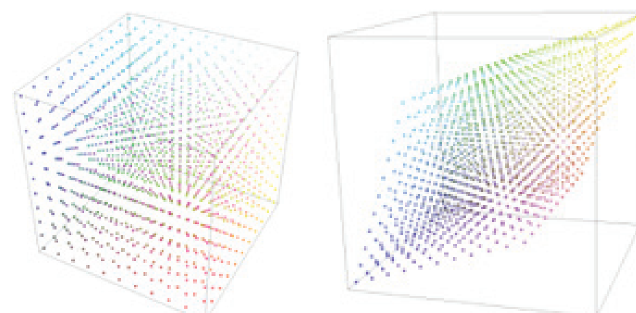
In the following subsections, I break down the process of preparing my data and an ML model to use with it. Then, I describe how my model's inverse function can help people with Deuteranopia see colors differently.

Data Preparation:

Two distinct datasets are generated: everyday and colorblind perceptions of a diverse palette. The first data set represents normal vision and is constructed by sampling points within the 3D color space defined by RGB values, ensuring uniform coverage of the visible spectrum. Each point in this dataset is then transformed into its corresponding Deuteranopic vision using the Wolfram Language ImageEffect function, generating the second dataset, reflecting the colorblind interpretation of the original palette.

Figure 2 visually depicts both datasets dotted within the 3D RGB space. As expected, the color points representing Deuteranopic vision cluster towards the center compared to the normally distributed points. This visually confirms the diminished vibrancy and color differentiation experienced by individuals with Deuteranopia.

Both datasets, comprising over 1,300 labeled data points, serve as the foundation for training the ML model. The RGB labels associated with each point provide the training data for my model to learn and later apply during the color correction process.



(A) Normal vision dataset (B) Deuteranopic vision dataset

Figure 2: Two training datasets visualized in the 3D RGB space: Normal vision data points show a uniform distribution of RGB hues (Panel A), and Deuteranopic vision data points cluster towards the center (Panel B).

A separate dataset of test images is compiled to evaluate the performance of the trained ML model. Specifically, 500 images of apples were randomly chosen from a publicly available dataset in the Wolfram library. I intentionally chose the images of apples due to the contrast between the red and green hues present in apples, which would amplify the difference between standard and Deuteranopic vision. This test dataset provides a robust platform for demonstrating the model's color correction efficacy. Figure 3 showcases a representative sample image, presenting the original version and its Deuteranopic counterpart generated by the Wolfram ImageEffect function. As expected, the colorblind version exhibits less vibrant colors than the original image.

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(A) Original image (B) ImageEffect output

Figure 3: Sample pair of images representing a normal vision (Panel A) versus Deuteranopic vision (Panel B). The colorblind version exhibits less vibrant colors than the original image.

Model Training and Validation:

The two color-feature datasets prepared in the previous section serve as the foundation for training the ML model. In essence, the model learns to map the 3D RGB color features of standard vision images onto the corresponding features of their Deuteranopic counterparts. Through this process, the model is established between the two training datasets. Utilizing this learned knowledge, my model can now predict the Deuteranopic version of a standard vision image, essentially acting as a color correction tool. This prediction phase begins with feeding the model a standard vision apple image from the test dataset. The model extracts the image's color features and, by leveraging its learned associations, transforms them into the color features of the corresponding Deuteranopic image. Therefore, the machine learning model operates as a predictive tool, converting standard vision images into their Deuteranopic counterparts, offering a simulated view for individuals with Deuteranopia.

The flowchart in Figure 4 summarizes the process.[8] It is essential to acknowledge that my model builds upon the principles of supervised ML. However, it incorporates modifications tailored to address the challenge of colorblind vision simulation and these modifications are detailed in the flowchart below.

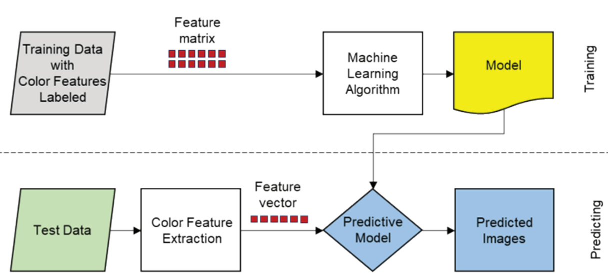
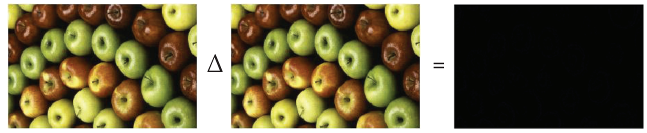


Figure 4: Flowchart of the model in a supervised ML framework.

Using the 500 apple images from the test dataset, the model generates corresponding colorblind versions. For a representative sample, this predicted image is compared to a colorblind version caused by the Wolfram ImageEffect function. Figure 5 offers these two images side-by-side. Additionally, it presents a third image showcasing the pixel-by-pixel difference in color features between the predicted image and the reference image generated by ImageEffect. A completely black image in this difference map indicates perfect unity between the two colorblind photos, meaning the model's prediction perfectly matches the established function's output. My model accurately simulates Deuteranopic vision.



(A) Model prediction (B) ImageEffect output (C) Difference of images = (A) - (B)

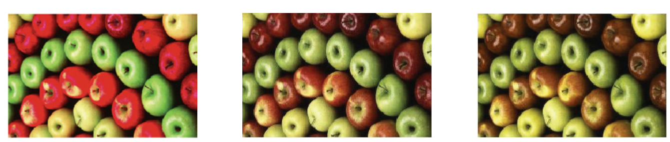
Figure 5: Validation of model prediction: The image predicted by my model (Panel A) is compared to a colorblind version (Panel B), and the pixel-by-pixel difference in color features between these two images (Panel C) indicates perfect congruence.

Inverse Model:

While the existing Wolfram function ImageEffect can simulate the vision of color-blind individuals, my ML model does not merely present how normal images appear to the colorblind individuals' eyes. Instead, this research aims to generate alternative images that appear normal when viewed by color-blind people. The key contribution of my new model lies in its algorithm, which can be flexibly manipulated to enhance their visual experiences, such as by inverting the original algorithm.

Thus, this section explores the concept of an inverse function of my model. My model is now applied to predict the standard vision counterpart of a colorblind image. In essence, I address an interesting question: "Given an image as seen normal by someone with Deuteranopia, how would someone with normal vision perceive the same image?". The predicted image generated by the inverse function should represent what individuals with normal vision see when presented with an image perceived normal by the colorblind.

Recalling that colorblind vision often exhibits reduced vibrancy and chromatic differentiation, the inverse function should enhance those qualities, producing a more vivid and color-rich image. Figure 6 demonstrates this concept alongside the original image. As expected, the inverse model prediction displays heightened color vibrancy compared to the authentic and Deuteranopic images. This inverse function opens doors for exciting future avenues. It offers individuals with Deuteranopia a view of the richer color spectrum experienced by individuals with normal vision.



(A) Inverse model prediction (B) Original image (C) Model prediction

Figure 6: Predicted images using inverse model versus original model: The image indicated by the inverse model (Panel A) displays heightened color vibrancy than the original image (Panel B), and the image predicted by my original model (Panel C) shows less vibrancy than the original image.

Closed-Loop Validation of the Inverse Model Prediction:

This section validates the efficacy of the inverse model in predicting normal vision for individuals with Deuteranopia. Specifically, the overly vibrant image generated by the inverse model is fed back into the original model. Ideally, this "closed-loop" process should produce a colorblind version resembling the original image. Suppose my model successfully reproduces

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the original image from its overly vibrant counterpart. In that case, it suggests that my inverse model has accurately predicted the image perceived as usual by the colorblind individual.

Figure 7 presents the model's predicted output from the closed-loop process alongside the original image and a pixel-by-pixel difference map. While some slight color-feature discrepancies are visible as faint hues in the background, the overall dark black image signifies high similarity between the predicted and original versions. This successful closed-loop validation provides strong evidence for the accuracy of the inverse model's predictions. This result demonstrates its potential to offer individuals with Deuteranopia a simulated view of the vibrant world experienced by those with normal vision.

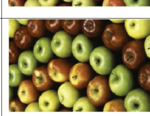
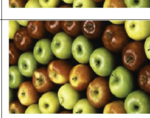
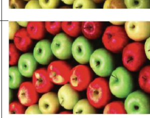
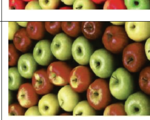
(A) Closed-loop output (B) Original image (C) Difference of images = (A) - (B)

Figure 7: Validation of inverse model prediction: The image produced from the closed-loop process (Panel A) is compared to the original image (Panel B), and the pixel-by-pixel difference in color features between these two images (Panel C) signifies high similarity.

This closed-loop validation suggests that providing individuals with Deuteranopia augmented images predicted by the inverse model, with enhanced color vibrancy, could allow them to experience a similar level of color richness as those with normal vision. By strategically amplifying certain color features, we could bridge the gap in color perception and allow individuals with Deuteranopia to share the joy of color vibration. This finding underscores the promising potential of applying ML models to modify images for colorblind individuals. As demonstrated in this research, the model exhibits a compelling ability to manipulate color values in images, making them more distinguishable and potentially enhancing the visual experience for those with color vision deficiency.

Lastly, Table 1 provides a comprehensive overview of the sample test images utilized throughout this research, accompanied by informative notes detailing their origin and purpose.

Table 1: List of sample test images.

Image Label	Image	Note
Original image		A sample image from Test Data with a sample size of 500
ImageEffect output		The output of the Wolfram Function ImageEffect with a link of "Deuteranopia," where input is the Original image
Model prediction		Prediction output of my model, where input is the Original image
Inverse model prediction		Prediction output of the inverse function of my model, where input is the Original image
Closed-loop output		Prediction output of my model, where input is Inverse model prediction

Conclusion

This research develops an ML model that shows promise in addressing Deuteranopia, a common form of red-green colorblindness affecting millions globally. The resulting image exhibits enhanced red and green hues, bringing them close to an everyday color experience. Future iterations could incorporate additional forms of colorblindness like Protanopia and Tritanopia to address these broader challenges. Despite not achieving an entirely accurate solution, this study demonstrates the significant potential of ML in aiding colorblind vision. The model's accuracy could be further refined with access to more extensive and diverse datasets during training.

Moreover, the proposed model has practical implications for improving color perception among colorblind individuals. For instance, we can embed the proposed inverse algorithm into smart glasses, biasing what users see in real-time. These smart glasses offer an enhanced vision experience with superior functionality compared to existing colorblind glasses, which filter a limited range of wavelengths. Additionally, our algorithm can be applied to mobile apps. Consider the existing app 'Color Blind Pal,' which currently assists colorblind users by identifying color names using the phone camera's vision. Our model could enhance this app's capabilities by incorporating a novel feature: real-time manipulation of the image captured by the phone camera to simulate normal vision for colorblind individuals. This solution provides a portable color vision aid without requiring a separate purchase, unlike physical glasses.

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