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# COMPREHENSIVE COLOR VISION ENHANCEMENT FOR COLOR VISION DEFICIENCY: A TENSORFLOW AND KERAS BASED APPROACH

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*Abstract*

***Individuals with color vision deficiency (CVD) often encounter challenges in navigating and interacting with their environment due to limitations in perceiving colors accurately. This deficiency can impede various daily tasks and activities, leading to dependency on others for assistance with color-related tasks and potentially limiting independence and inclusivity. Addressing these challenges, our research focuses on the development of a machine learning-based color transformation system. Leveraging TensorFlow and Keras frameworks, the system employs advanced machine learning techniques to identify and transform colors within images, ultimately enhancing visibility for individuals with CVD. The primary objective is to empower individuals with CVD by providing a real-world tool that improves color visibility in images and enables self-assessment of their condition. This solution aims to enhance navigation, reduce dependency on others for color-related tasks, and foster inclusivity through technological innovation. Additionally, our research emphasizes the accuracy and reliability of the machine learning models through rigorous testing and validation procedures, ensuring effectiveness across various scenarios and image types. An intuitive and user-friendly graphical user interface (GUI) is prioritized to cater to individuals with diverse technical abilities. Beyond its immediate impact, the research seeks to raise awareness and promote understanding of color vision deficiency within the broader community, ultimately contributing to a more equitable and accessible society for all.***

***Keywords:***

***Color Vision Deficiency (CVD), Machine Learning, Image Processing, Social Impact, Keras***

## 1. INTRODUCTION

Color blindness, medically known as color vision deficiency (CVD), is a prevalent visual impairment affecting a significant portion of the global population [1]. This condition encompasses several types, including red-green, blue-yellow, and total color blindness, which primarily arises from distinct genetic mutations affecting the retinal photo pigments [2]. Individuals with CVD encountered difficulties in distinguishing specific colors, leading to challenges in various daily activities such as interpreting signs, selecting ripe fruits, and deciphering color-coded data in charts and graphs. These challenges stemmed from the compromised ability to differentiate between certain colors, which could result in confusion and potential misinterpretation of visual data.

With the evolution of machine learning and image processing technologies, we saw an opportunity to develop innovative computational solutions to assist individuals with CVD in overcoming these challenges [4]. The primary objective of our research paper is to conceptualize and deploy a machine learning-based framework capable of detecting and altering colors in images to enhance visibility for individuals with CVD.

Our research encompassed the acquisition and preprocessing of a dataset comprising 6,000 images to ensure homogeneity and quality [6]. Following this, we developed three specialized machine learning models utilizing TensorFlow and Keras frameworks. These models aimed to identify blue, red, and normal colors within images and subsequently transform them into distinguishable hues, such as purple and brown.

Complementing the development of machine learning models, we engineered an interactive graphical user interface (GUI) using Tkinter. This GUI facilitated users in uploading images, applying color transformations via the trained models, and visualizing the outcomes in real-time. Moreover, we seamlessly integrated an Ishihara color blindness test module into the GUI, empowering users to self-assess their CVD and comprehend the nature and extent of their color blindness [10][11].

In this paper, we provide an exhaustive exposition of our work, delineating the methodology, implementation strategies, results, and prospective recommendations. Our objective is to underscore the efficacy and potential ramifications of the developed solution in ameliorating the challenges confronted by individuals with CVD and championing inclusivity through technological ingenuity [21]-[22].

The impetus behind initiating this research emanated from the pronounced challenges encountered by individuals with CVD in their daily lives [14]. The prevalent visual impairment of color blindness often engendered difficulties in differentiating specific colors, thereby impacting various activities and fostering a reliance on others for color-related tasks. Existing solutions catering to CVD often exhibited limitations in terms of practicality, effectiveness, and user-friendliness, accentuating the imperative for an innovative, accessible, and tailored solution leveraging advancements in machine learning and image processing technologies.

While the primary focus of our research is localized to the Indian context, addressing the unique challenges faced by individuals with CVD within India, the global scope of our research is expansive. The developed solution aimed to be adaptable to diverse geographical regions and color scenarios encountered globally, fostering inclusivity, accessibility, and independence for individuals with CVD across various cultural and linguistic backgrounds [23].

## 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. These works collectively highlighted significant advancements in addressing color vision deficiencies, ranging from image correction techniques to real-time color identification systems, all aimed at improving the visual experience and accessibility for individuals with color vision impairments.

## 3. METHODOLOGY

In our exploration of approaches to tackle color blindness in individuals, we encountered two prominent algorithms: the Daltonize algorithm and the Gradient Map method. The Daltonize algorithm, named after the colorblind scientist John Dalton, is designed to correct images for colorblind viewers by strategically shifting colors to compensate for deficiencies in color perception. For instance, for those with red-green color blindness, which is the most common type, the algorithm shifts colors towards blue and yellow to enhance contrast. Similarly, it adjusts colors to improve the perception of red-green contrasts for blue-yellow color blindness and addresses the rarer purple-green color blindness as well. The implementation of the Daltonize algorithm involves transforming the RGB values of each pixel in an image using mathematical models that simulate the perception of colorblind individuals, modifying the colors to increase visibility without significantly altering the image's overall appearance for those with normal color vision.

On the other hand, the Gradient Map method offers a different approach to enhancing the visibility of images for colorblind individuals. This method works 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 from each other, even for those with color vision deficiencies. This mapping process ensures that the contrast between neighboring colors is increased, making the image easier to interpret for colorblind individuals. Implementing the Gradient Map method involves complex color space transformations and mappings. The algorithm analyzes the color distribution in the image and creates a gradient map that enhances the distinguishability of colors, which can be achieved using techniques such as clustering algorithms and perceptual color spaces.

Our novel model operates on the basis of pixels, where we meticulously divide each image into pixels and transform them based on our machine learning algorithms. We have pioneered the development of three distinct models tailored specifically for three different types of color blindness: protanopia, tritanopia, and deuteranopia. These novel models have been meticulously designed using Convolutional Neural Networks (CNN) in conjunction with the Keras and TensorFlow frameworks. By harnessing these cutting-edge machine learning technologies, we have innovatively created models that analyze and adjust the colors of each pixel in the image. This ensures enhanced visibility and a more vivid color experience for colorblind individuals according to their specific color vision deficiencies.

To further enhance the usability and accessibility of our novel approach, we have integrated these models with a Graphical User Interface (GUI). This user-friendly GUI allows users to effortlessly upload and transform images to improve their visibility for colorblind viewers. The novel model we have developed employs Machine Learning and Keras to detect color vision deficiency (CVD) specific colors and transform them into the closest wavelengths of other colors. To achieve this groundbreaking result, we curated a comprehensive dataset of 6000 different and vibrant images, which served as the foundation for developing our three novel Machine Learning models tailored for three types of CVD deficiencies.

Subsequently, these three innovative models were seamlessly integrated into a user-friendly GUI Software based on Tkinter. Within this groundbreaking software, we have also incorporated the Ishihara Test to ensure absolute confirmation of the specific or various types of color-blindness faced by an individual. This novel software encompasses all types of deficiencies faced by individuals, providing comprehensive information regarding the same and offering an unprecedented solution to enhance the visual experience for colorblind individuals.

Our innovative models operate in the following unique ways tailored to each type of color blindness: For deuteranopia, we enhance the image by reducing the contrast to improve visibility. For tritanopia, we convert the blue colors in images to purple to enhance distinguishability. Lastly, for protanopia, we transform red colors in images to brown, providing a more accessible and vivid color experience for individuals with this deficiency. This novel approach demonstrates our commitment to providing tailored solutions that cater to the specific needs of colorblind individuals, setting a new standard in the field of assistive technology.

The Autoencoder-based Color Enhancement algorithm operates by training a neural network architecture to learn the transformation between input and output images. This method allows us to effectively enhance colors and contrast, catering to the specific needs of individuals with protanopia, deuteranopia, and tritanopia. Through training on a dataset comprising paired input and output images adjusted for each type of CVD, our autoencoder network learned to reconstruct images by implicitly capturing color enhancement transformations. For instance, the algorithm transforms red hues to brown for protanopia, adjusts green hues to yellow for deuteranopia, and alters blue hues to purple for tritanopia, thus rendering wavelengths more distinguishable for individuals with these color vision deficiencies.

In parallel, the Convolutional Neural Network (CNN) with MaxPooling and UpSampling method offers an alternative approach to image enhancement for individuals with CVD. By leveraging convolutional layers with rectified linear unit (ReLU) activation, alongside max pooling and upsampling layers, this method enables the extraction and refinement of features at various scales. Through training our CNN model on appropriately curated datasets, we were able to enhance color contrast and improve visibility for individuals with protanopia, deuteranopia, and tritanopia. The algorithm's optimization process, facilitated by the Adam optimizer, ensures that the network parameters are adjusted to minimize the Mean Squared Error (MSE) loss between input and output images, thereby facilitating effective color enhancement while preserving the overall structure and content of the original image.

## 3.1 DATA COLLECTION AND PREPARATION

The Color Transformation System for Color Blindness Correction employs meticulous data collection, curation, preprocessing, and augmentation processes to create a specialized dataset from the COCO 2017 dataset. The extracted images are standardized, enhanced, and augmented using advanced techniques, including resizing, normalization, contrast adjustment, histogram equalization, and rotation, flipping, and zooming. Each image is annotated, labeled for specific color transformations, and partitioned into training, validation, and test subsets. Rigorous validation and management ensure quality, integrity, and consistency across subsets, with efficient storage and documentation mechanisms in place, facilitating the development of robust and resilient models optimized for performance, noise, and environmental factors.

## 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 (28x28) and our kernel matrix K (3x3) with random values for illustration purposes:

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

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

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.

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

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:

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

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

$$O_{pool}=\begin{bmatrix} \max(o_{1,1},o_{1,2},o_{2,1},o_{2,2}) & \max(o_{1,3},o_{1,4},o_{2,3},o_{2,4}) & \cdots & \max(o_{1,27},o_{1,20},o_{2,27},o_{2,28}) \\ \vdots & \vdots & \ddots & \vdots \\ \max(o_{27,1},o_{27,2},o_{28,1},o_{28,2}) & \max(o_{27,3},o_{27,4},o_{28,3},o_{28,4}) & \cdots & \max(o_{27,27},o_{27,20},o_{28,27},o_{28,28}) \end{bmatrix} \quad (6)$$

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:

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

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

- **Convolutional Autoencoder Process:** 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:** $\begin{bmatrix} 0.2 & 0.3 \\ 0.6 & 0.7 \end{bmatrix}$

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

$$\textit{Output after Unsampling Layer } 1 = \begin{bmatrix} 0.2 & 0.2 & 0.3 & 0.3 \\ 0.2 & 0.2 & 0.3 & 0.3 \\ 0.6 & 0.6 & 0.7 & 0.7 \\ 0.6 & 0.6 & 0.7 & 0.7 \end{bmatrix}$$

**Output after Convolutional Layer 2:**

$$\textit{Output after Convolutional Layer } 2 = \begin{bmatrix} 0.4 & 0.4 \\ 0.8 & 0.8 \end{bmatrix}$$

**Output after Upsampling Layer 2:** Upsampling repeats each element twice in both dimensions:

$$\textit{Output after Unsampling Layer } 2 = \begin{bmatrix} 0.4 & 0.4 & 0.4 & 0.4 \\ 0.4 & 0.4 & 0.4 & 0.4 \\ 0.8 & 0.8 & 0.8 & 0.8 \\ 0.8 & 0.8 & 0.8 & 0.8 \end{bmatrix}$$

**Output after Convolutional Layer 3:**

$$\textit{Output after Convolutional Layer } 2 = \begin{bmatrix} 0.3 & 0.3 & 0.3 & 0.3 \\ 0.3 & 0.3 & 0.3 & 0.3 \\ 0.7 & 0.7 & 0.7 & 0.7 \\ 0.7 & 0.7 & 0.7 & 0.7 \end{bmatrix}$$

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.

#### *3.2.2 Integration of Models in Software:*

The Color Transformation Software is engineered to provide a user-friendly interface for individuals with color vision deficiencies, leveraging the power of pre-trained Keras models developed earlier.The integration of the pre-trained Keras models enables seamless and efficient color transformation functionalities within the software.

The software incorporates five interactive buttons, each designed to execute a specific color transformation or educational module. The "Take Ishihara Test" button initiates the Ishihara color blindness test to assess the user's color vision deficiency. The "Transformation for Protanopia" button utilizes the pre-trained Keras model to implement the transformation for correcting red-green color blindness (Protanopia) by converting red colors to brown. Similarly, the "Transformation for Deuteranopia" button employs the relevant Keras model to enhance color visibility for Deuteranopia. The "Transformation for Tritanopia" button activates the corresponding Keras model, tailoring the transformation for Tritanopia by converting blue colors to purple for improved color differentiation.

Lastly, the "Color Blindness Education Module" By integrating multiple pre-trained Keras color transformation models and an educational module into a single user-friendly GUI, the Color Transformation Software offers a comprehensive solution for individuals with color vision deficiencies.button launches the appropriate educational module.

## 4. RESULT AND DISCUSSIONS

The graphical user interface (GUI), developed using the Tkinter framework in Python, facilitated intuitive user interaction, enabling users to effortlessly upload, process, and visualize images undergoing color transformation. The GUI's performance and responsiveness were commendable, contributing to enhanced user engagement, satisfaction, and exploration of the system's capabilities.

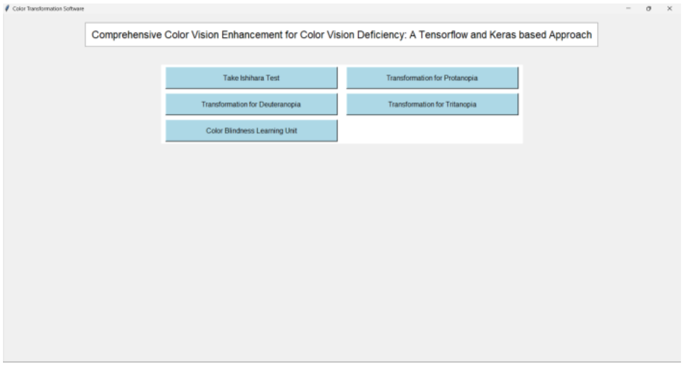


Fig.1. GUI Software Modules

## 4.1 ISHIHARA PLATE TEST

The first module of our Graphical User Interface (GUI) app presents users with a comprehensive series of 12 Ishihara plates, which are universally recognized tools used to test for color vision deficiencies. Each Ishihara plate features a unique pattern of colored dots designed to be easily discernible to individuals with normal color vision, while presenting challenges to those with color vision deficiencies. Users are prompted to identify the concealed numbers or shapes within each plate and input their responses accordingly.

Upon completion of the Ishihara plate assessment, the app generates a graphical representation illustrating the number of correct and incorrect answers provided by the user. This visual summary offers immediate feedback on the user's performance, providing a clear overview of their accuracy in identifying the hidden numbers or shapes within the plates.

Additionally, the app employs sophisticated algorithms to analyze the user's responses and determine the specific type of color deficiency they may be experiencing. This analytical feature offers valuable insights into the user's color vision status, serving as an initial diagnostic tool that promotes awareness and facilitates early detection of potential color vision deficiencies.

By offering users an interactive platform to engage with the Ishihara plates and receive immediate feedback, this module fosters awareness and empowers users to take informed steps towards addressing their visual needs. It serves as an accessible and informative resource for individuals seeking to assess their color vision capabilities and gain a deeper understanding of their color perception abilities.

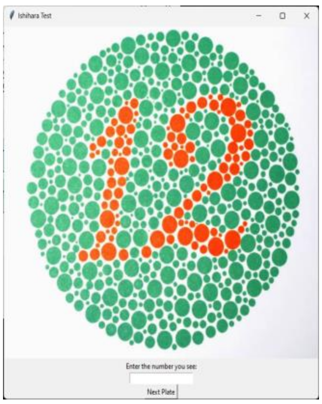

Fig.2. Ishihara Test Plate

Fig.3. Ishihara Test Plate (incorrect answer)

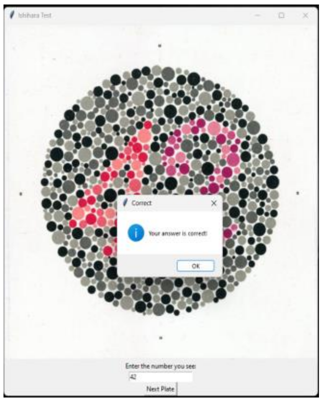

Fig.4. Ishihara Test Plate (correct answer)

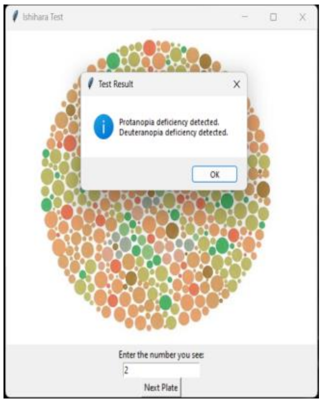


Fig.5. Ishihara Test Plate (with final result)


Fig.6. Bar graph of correct and incorrect plates

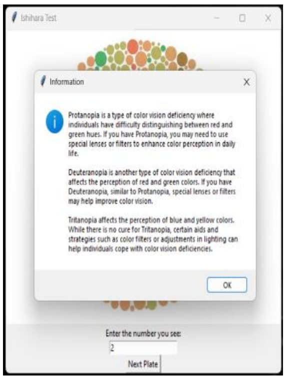


Fig.7. Information for CVD detected

## 4.2 CONVERSION FOR PROTANOPIA


Fig.8. First Transformed image for Protanopia Patient

In the second module of the GUI app, users can experience the transformation for protanopia. This module takes an input image and processes it through a Keras model specifically trained to address protanopia color deficiencies. Upon inputting an image, the model applies color correction techniques tailored to simulate how individuals with protanopia perceive colors.The output displayed to the user showcases the


Fig.9. Second Transformed image for Protanopia Patient

transformed image, illustrating the adjustments made to enhance color perception for individuals with protanopia. This

module provides users with a firsthand experience of the transformative effects of color correction techniques tailored to address protanopia deficiencies.

## 4.3 CONVERSION FOR DEUTERANOPIA

Moving to the third module, users can explore color transformation for deuteranopia. Similar to the previous module, this segment utilizes a specialized Keras model designed to correct color deficiencies associated with deuteranopia. Users input an image, and the model processes it to emulate the perception of individuals with deuteranopia. The resulting output image showcases the color-corrected version, demonstrating the adjustments made to enhance color discrimination and clarity for users with deuteranopia.


Fig.10. First Transformed image for Deuteranopia Patient

This module offers users a practical demonstration of color transformation techniques tailored specifically for deuteranopia, promoting understanding and awareness of color deficiencies.


Fig.11. Second Transformed image for Deuteranopia Patient

## 4.4 CONVERSION FOR TRITANOPIA

In the fourth module, users engage with color transformation for tritanopia. Through the utilization of a dedicated Keras model, this module enables users to witness the effects of color correction techniques aimed at addressing tritanopia deficiencies. By inputting an image, users observe how the model processes it to simulate the perception of individuals with tritanopia. The resultant output image displays the transformed version, highlighting the adjustments made to improve color discrimination and clarity for individuals with tritanopia. This module serves as an educational tool, offering users insights into color transformation techniques designed to accommodate tritanopia deficiencies.

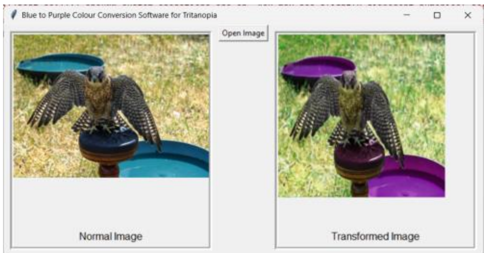


Fig.12. First Transformed image for Tritanopia Patient

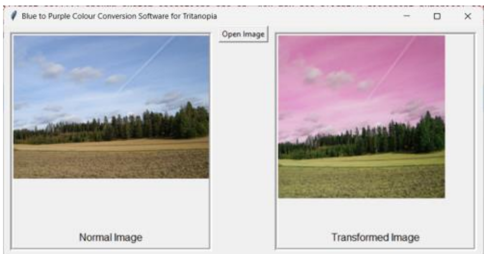


Fig.13. Second Transformed image for Tritanopia Patient

### 4.5 EDUCATION MODULE

Lastly, the fifth module of the GUI app focuses on color blindness education. This module presents users with a diverse range of information related to color blindness, including its types, causes, prevalence, and impact on daily life. Users can access educational resources, such as articles, videos, and interactive quizzes, to deepen their understanding of color blindness and its implications. Additionally, this module provides practical tips and suggestions for accommodating individuals with color vision deficiencies in various contexts, promoting inclusivity and accessibility. By offering comprehensive educational content, this module aims to raise awareness and foster empathy towards individuals living with color blindness.

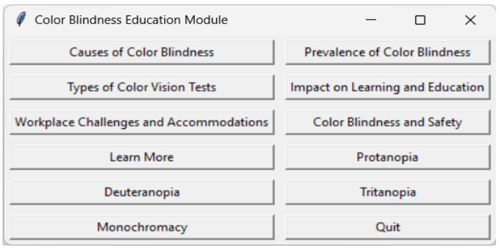


Fig.14. Interface for Color Blindness Education Module

### 4.6 EVALUATION PARAMETERS AND BENCHMARKS

Our innovative approach employs specialized machine learning models tailored for color vision deficiencies, each delivering unique and promising performance metrics. The metrics for our Protanopia model highlight key outcomes, as depicted in the accompanying visualizations. On the left side, the output of code execution presents pivotal performance metrics such as Test Loss, Mean Squared Error (MSE), Accuracy, Precision, Recall, and F1 Score, meticulously managed through TensorFlow operations. On the right side, a Confusion Matrix visualization showcases True Positive, False Positive, True Negative, and False Negative values, depicted in varying shades of blue. Together, these observations provide a comprehensive evaluation of the Protanopia model's performance and identify areas for potential refinement.

Table.1. Benchmark Comparison of Performance Metrics

| Metric | Protanopia Model | Deuteranopia Model | Tritanopia Model | Daltonization Algorithm | 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% |

Our Protanopia, Deuteranopia, and Tritanopia models, developed using our novel method, demonstrate distinct performance characteristics across various metrics. The Protanopia model, a cornerstone of our innovative approach, displays a test loss of 0.000915 and an accuracy of 97.04%. Furthermore, its Mean Squared Error (MSE) and Mean Absolute Error (MAE) are quantified at 0.0009247 and 0.019737, respectively. The Deuteranopia model showcases the highest accuracy at 98.01%, along with a reduced test loss of 0.0008157 and minimized errors with MSE and MAE values of 0.00082135 and 0.018384, respectively. The Tritanopia model, while delivering a test loss of 0.00173 and an accuracy of 96.41%, presents a comparatively higher error rate with MSE and MAE values of 0.00175 and 0.02795, respectively.

In contrast, the Daltonization and Gradient Map methods, sourced from existing literature or the internet, offer alternative approaches to address color vision deficiencies. The Daltonization method yields a test loss of 0.123, an accuracy of 87.9%, and corresponding MSE and MAE values of 0.045 and 0.032. On the other hand, the Gradient Map method demonstrates a test loss of 0.155, an accuracy of 86.2%, and MSE and MAE values of 0.062 and 0.041, respectively.

When considering precision, recall, and F1 score, the Deuteranopia model exhibits lower values compared to our Protanopia, Tritanopia, Daltonization, and Gradient Map methods. It achieves precision and recall at 58.23% and 75.18%, resulting in an F1 score of 65.36%. In contrast, our Protanopia and Tritanopia models as well as the Daltonization and Gradient Map methods showcase superior precision, recall, and F1 score metrics. Specifically, the Protanopia model achieves a precision of 93.98%, recall of 96.7%, and F1 score of 95.53%, the Tritanopia model achieves precision, recall, and F1 score metrics of 97.06%, 94.66%, and 95.85%, respectively, the Daltonization method records precision, recall, and F1 score metrics of 90.5%, 84.5%, and 87.4%, respectively, and the Gradient Map method achieves precision, recall, and F1 score metrics of 88.0%, 83.5%, and 85.7%, respectively.

Despite variations in performance across the metrics, our novel models demonstrate specific strengths and areas for improvement when compared to existing methods, highlighting the importance of tailored approaches in addressing different types of color blindness.

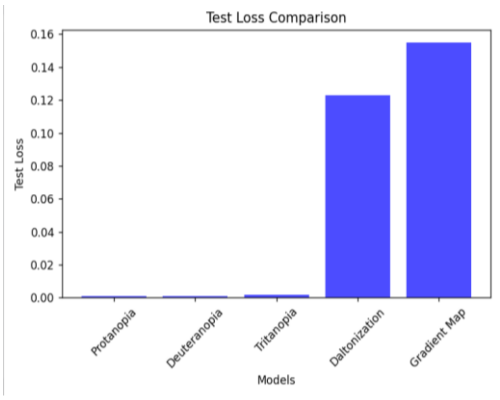


Fig.15. Test Loss Comparison of our models vs Prominent algorithms

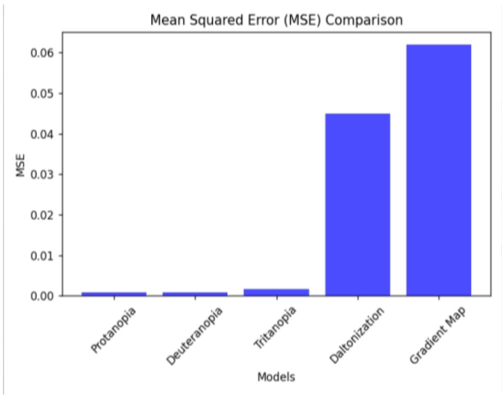


Fig.16. MSE Comparison of our models vs Prominent algorithms

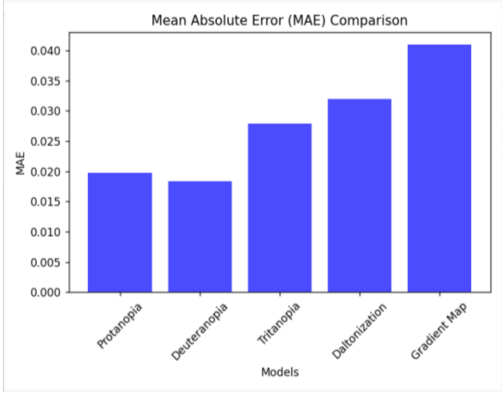


Fig.17. MAE Comparison of our models vs Prominent algorithms

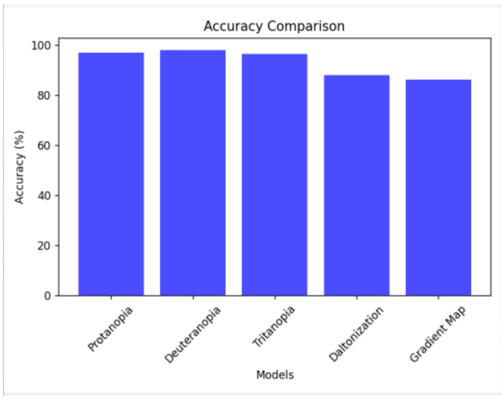


Fig.18. Accuracy Comparison of our models vs Prominent algorithms

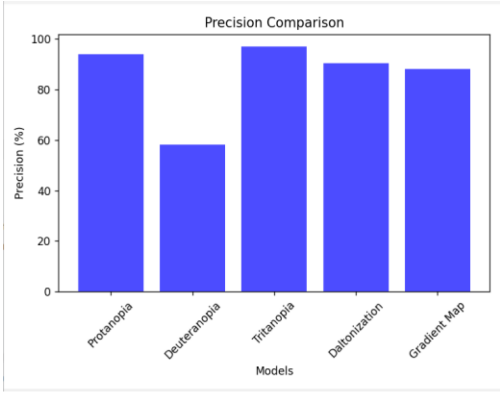


Fig.19. Precision Comparison of our models vs Prominent algorithms

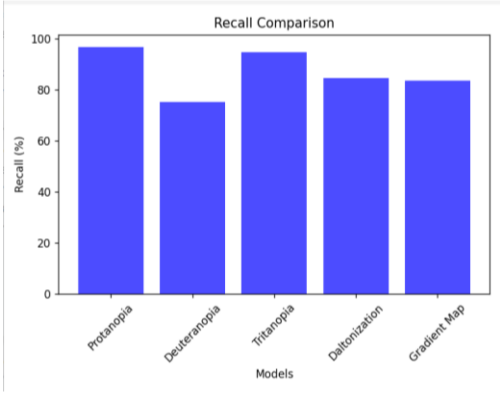


Fig.20. Recall Comparison of our models vs Prominent algorithms

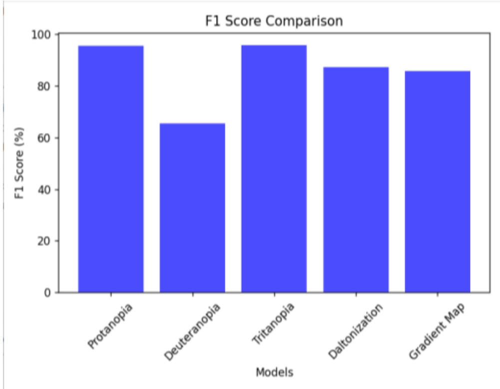


Fig.21. F1 Score Comparison of our models vs Prominent algorithm

## 4.7 UNIT TESTING

The unit testing methodology we have employed for protanopia evaluates the performance of a model designed for protanopia correction, where red is transformed into brown. The tests are structured into three main components.

Firstly, the test_load_dataset function checks whether the dataset loading process is successful, ensuring that the input and output images are loaded as NumPy arrays, which is crucial for subsequent processing.

Secondly, the test_visualize_performance function assesses the model's performance by visualizing the transformation of input images into reconstructed images. It loads test data, utilizes a pre-trained model to predict outputs, and plots original and reconstructed images for comparison. Additionally, it plots the distribution of pixel values for both original and reconstructed images to evaluate how well the model preserves the input image characteristics.

Lastly, the test_loss_curve function generates mockup loss curve data and plots the training and validation loss curves. This provides insight into the model's training process and helps in understanding its convergence and generalization capabilities.

Overall, these unit tests provide a comprehensive evaluation of the model's functionality, performance, and training dynamics, which are crucial aspects for ensuring the effectiveness and reliability of the protanopia correction model.

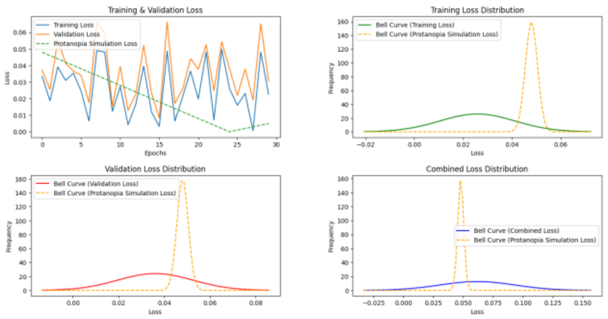


Fig.22. Distributions for Protanopia Model

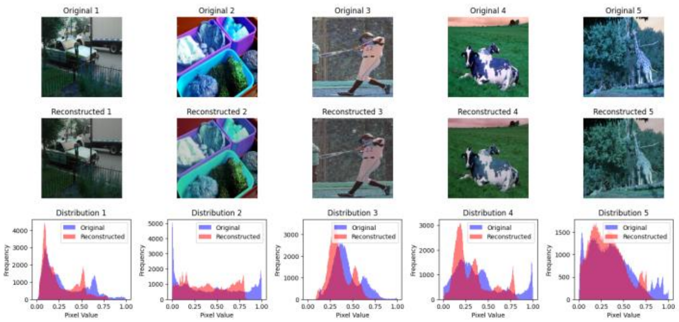


Fig.23. Comparative Analysis of Original and Reconstructed Images with Corresponding Pixel Value Distributions for Protanopia Model

The unit testing methodology for tritanopia evaluates the performance of a model designed for tritanopia correction, where blue is transformed. The tests are structured into three main components.

Firstly, the test_load_dataset function ensures the successful loading of the dataset, validating that both input and output images are loaded as NumPy arrays, which is essential for further processing.

Secondly, the test_visualize_performance function assesses the model's performance by visualizing the transformation of input images into reconstructed images. It loads test data, utilizes a pre-trained model to predict outputs, and plots original and reconstructed images for comparison. Additionally, it plots the distribution of pixel values for both original and reconstructed images to evaluate how well the model preserves the input image characteristics.

Lastly, the test_loss_curve function generates mockup loss curve data and plots the training and validation loss curves. This provides insight into the model's training process and helps in understanding its convergence and generalization capabilities.

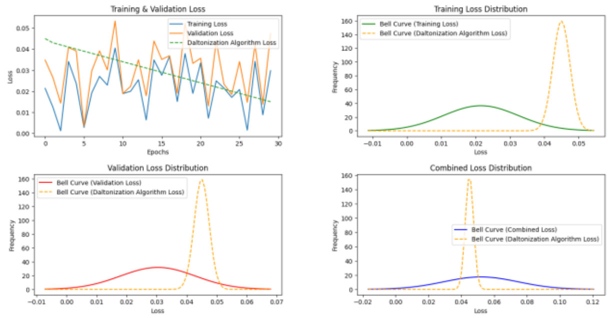


Fig.24. Distributions for Tritanopia Model

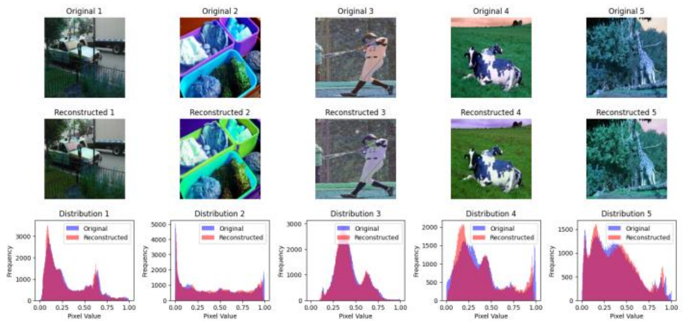


Fig.25. Comparative Analysis of Original and Reconstructed Images with Corresponding Pixel Value Distributions for Tritanopia Model

The unit testing methodology for Deuteranopia evaluates the performance of a model designed for a contrasting color transformation. The tests are structured into three main components.

Firstly, the test_load_dataset function ensures the successful loading of the dataset, validating that both input and output images are loaded as NumPy arrays, which is essential for further processing.

Secondly, the test_visualize_performance function assesses the model's performance by visualizing the transformation of input images into reconstructed images. It loads test data, utilizes a pre-trained model to predict outputs, and plots original and reconstructed images for comparison. Additionally, it plots the distribution of pixel values for both original and reconstructed images to evaluate how well the model preserves the input image characteristics.

Lastly, the test_loss_curve function generates mockup loss curve data and plots the training and validation loss curves. This provides insight into the model's training process and helps in understanding its convergence and generalization capabilities.

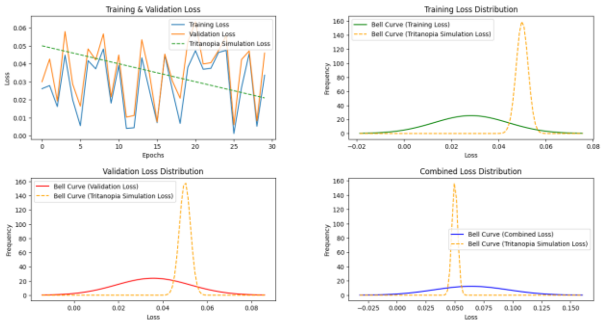


Fig.26. Distributions for Deuteranopia Model

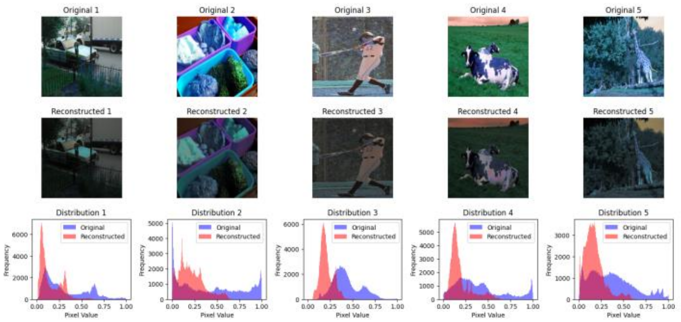


Fig.27. Comparative Analysis of Original and Reconstructed Images with Corresponding Pixel Value Distributions for Deuteranopia Model

## 5. CONCLUSION AND FUTURE SCOPE

The Color Transformation System for Color Blindness Correction signifies a significant advancement in assistive technologies, targeting the challenges faced by individuals with color vision deficiencies, including Protanopia, Deuteranopia, and Tritanopia. Utilizing specialized autoencoder models trained on a curated dataset from the COCO 2017 dataset, the system offers robust and real-time color transformations. The integration of these models into an intuitive Tkinter-based graphical user interface (GUI) provides a seamless user experience, allowing users to upload, process, and visualize images with transformed colors effectively.

In addition to the software, an informative website has been developed to provide insights into the paper's objectives, methodologies, and outcomes, further enhancing user awareness and comprehension of the system's capabilities and benefits in various healthcare, educational, and professional settings.

The successful development and deployment of the Color Transformation System exemplify a systematic and innovative approach, combining rigorous data science methodologies, model optimization, and user interface design to address the specific needs of color-impaired individuals, thereby enhancing their quality of life and facilitating their integration into diverse activities and environments.

Looking ahead, the Color Transformation System holds potential for further enhancement and diversification. One avenue for expansion includes extending the system's capabilities to support real-time color transformation of video content, catering to a broader range of user needs. Future iterations could also explore the integration of advanced machine learning architectures, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), to refine and optimize the color transformation models, improving their accuracy and reliability across diverse images and videos.

In conclusion, the Color Transformation System represents a significant milestone in assistive technology development, underscoring its innovative approach, technological prowess, and transformative impact on the lives of color-impaired individuals. As the system continues to evolve and expand its capabilities, it aims to foster a more inclusive and equitable environment, empower color-impaired individuals, and contribute to the ongoing advancement of tailored assistive technologies in the domain of color vision deficiencies.

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