CHAPTER I
INTRODUCTION

This chapter explains the background of the issue of color correction in images, particularly in relation to the simulation of color vision impairments, as well as the rationale for selecting deep learning methods as an approach deemed capable of producing more accurate and realistic correction results.

1.1 Background

Color is a visual aspect that plays a crucial role in human life. Through the ability to distinguish colors, people can recognize objects, interpret visual information, and perform various activities more effectively. However, some people worldwide experience color vision deficiency (CVD), a condition in which an individual has difficulty distinguishing certain colors, particularly within the red-green spectrum. This condition is generally genetic and hereditary, with most cases caused by a recessive gene mutation linked to the X chromosome, thereby affecting the photoreceptor pigments in the cone cells of the retina [1].

Color vision deficiency is generally classified into three main types: protanopia, which involves a reduced ability to perceive red; deuteranopia, characterized by diminished sensitivity to green; and tritanopia, which affects the perception of blue [2]. This condition can limit a person's color perception, leading to difficulties in daily activities, such as distinguishing text colors against certain backgrounds. To date, there is no effective treatment for Color Vision Deficiency (CVD) [3].

Various methods have been developed to detect these CVD disorders. The Ishihara test is the most commonly used tool for rapid screening of red-green color blindness, while the Farnsworth D 15 and Hardy Rand Rittler (HRR) tests are used to determine the severity of the condition and detect other color vision disorders. In addition, the Cambridge Colour Test (CCT) and the computer-based Colour Assessment and Diagnosis (CAD) allow for more accurate measurement of color discrimination thresholds [4].

In Indonesia, a study by Rifdah et al., which examined elementary school-aged children on Gili Ketapang Island, Probolinggo Regency, East Java, used the

Ishihara test to screen students aged 8 to 12 years from several elementary schools in the region. The results showed that the prevalence of color blindness reached 3.14%, with a higher proportion of male patients compared to females, consistent with the X-linked genetic inheritance pattern. Most of the cases of color vision deficiency (CVD) identified were classified as red-green color blindness (protanopia and deuteranopia) [5]. The findings of this study underscore the importance of conducting early screenings using the Ishihara test in elementary schools to detect color vision disorders from a young age. With earlier detection, students with CVD can receive appropriate intervention and learning support, particularly in activities that require the ability to accurately distinguish colors. Given these findings, color correction of images is necessary so that individuals with CVD can perceive visuals that are easier to distinguish and better suited to their visual needs.

Color vision correction is a critical factor for the well-being of individuals with CVD, as the inability to accurately distinguish colors can interfere with daily activities [3]. Therefore, research on color correction methods needs to continue to be developed to provide more effective visual support for people with CVD. Although various deep learning-based approaches have been implemented, the resulting color corrections often still face limitations in maintaining naturalness and color accuracy. Thus, improvements to color correction methods remain necessary to help individuals with CVD distinguish between similar colors, especially in areas with low contrast [6]. Previous studies have also sought to develop color correction techniques and improve visual perception for individuals with CVD. Various deep learning approaches have been applied to improve color accuracy and color discrimination capabilities in images. However, each existing method still has its own limitations, necessitating the development of a more optimal, adaptive color correction approach capable of producing visuals that remain natural for both CVD users and those with normal vision.

According to the study by Adyani et al., the color correction method developed combines image transformation into the LMS color space with saliency detection, thereby focusing the correction process on the important parts of the image. The procedure includes converting the image to the LMS color space, simulating CVD vision conditions, identifying the most prominent areas (salient regions), and applying color correction selectively to those areas [7]. Meanwhile, Dimitrovski et al. utilized a U-Net architecture with a symmetric encoder-decoder structure, where the encoder extracts key features from the image, while the decoder reconstructs spatial details to produce pixel-level precise segmentation [8]. In addition, according to Eason Lin, Pix2Pix is a conditional GAN model designed for image-to-image translation tasks, in which the model learns to map an input image directly to a target image [9].

Based on previous research, this study aims to develop a deep learning-based image color correction pipeline by integrating U-Net as the primary model to perform color correction on image areas with perceptual distortion, and Pix2Pix as the reconstruction model to restore the corrected results to their original color space. This integrated approach is designed to improve correction quality, enhance color representation, and provide more optimal performance in helping CVD patients distinguish colors that are difficult to identify. Additionally, the developed model will be integrated into a Graphical User Interface (GUI) so that users can easily upload images, view correction results, and compare the before-and-after views interactively and more intuitively. Through the development of this system, it is hoped that an effective, accurate, and user-friendly color correction method can be achieved, thereby improving visual accessibility for CVD patients.

1.2 Problem Statement

Based on the background description, the research questions in this study are:

1. How can a deep learning-based image color correction pipeline be designed by integrating U-Net and Pix2Pix to improve color perception for individuals with Color Vision Deficiency (CVD)?
2. How can the application of U-Net improve the accuracy of color correction in image areas experiencing color perception distortion due to color blindness?
3. To what extent can the combination of U-Net and Pix2Pix improve the quality of color-blind simulation images compared to conventional methods?

4. How can a graphical user interface (GUI) be designed to facilitate the image upload process, display correction results, and allow for easy and efficient comparison between pre- and post-correction images?

1.3 Purpose

Based on the research questions formulated, the objectives of this study are as follows:

1. To develop a deep learning-based image color correction pipeline integrating U-Net and Pix2Pix to help individuals with CVD distinguish colors more accurately.
2. To implement U-Net as the primary model for performing color correction on image areas experiencing perceptual distortion.
3. Implement the Pix2Pix reconstruction model to improve the visual quality and color of images corrected by U-Net.
4. Design and build a graphical user interface (GUI) that allows users to upload images, display correction results, and compare images before and after correction in a practical and interactive manner.

1.4 Benefits

This research is expected to provide the following contributions and benefits:

1. Expand research in the fields of image enhancement and assistive vision technology by introducing U-Net and Pix2Pix pipelines for color correction in color-blind simulation images.
2. Provide a reference for future research focused on assistive vision technology to assist individuals with color perception disorders.
3. The developed pipeline can serve as a foundation for further research in the field of computer vision, including color restoration, image quality enhancement, and visual adaptation for users with other color perception disorders.
4. Producing a GUI prototype that facilitates users in understanding and evaluating color correction results, thereby supporting the implementation of this technology in practical applications.

1.5 Scope of The Study

To maintain the research focus and limit the scope of the discussion, the problem boundaries for this study are defined as follows:

1. This study focuses on individuals with partial color blindness—specifically protanopia, deuteranopia, and tritanopia—with one type of color blindness per individual.
2. The dataset used consists of color-blind simulation images from Kaggle's "Color Blindness Simulation & Correction" dataset.
3. The deep learning models used are limited to U-Net for color correction and Pix2Pix for image reconstruction.
4. Model performance evaluation relies solely on quantitative image metrics—namely PSNR, SSIM, and Delta E—and includes subjective perception testing or direct validation by 15 individuals with color vision deficiency (CVD).
5. This study only developed a simple GUI that functions to upload images, display correction results, and perform visual comparisons before and after correction, without including advanced features such as video processing, real-time processing, or mobile platform integration.