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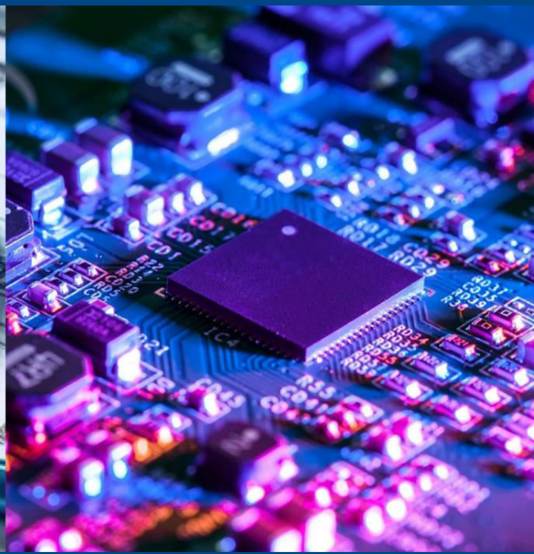

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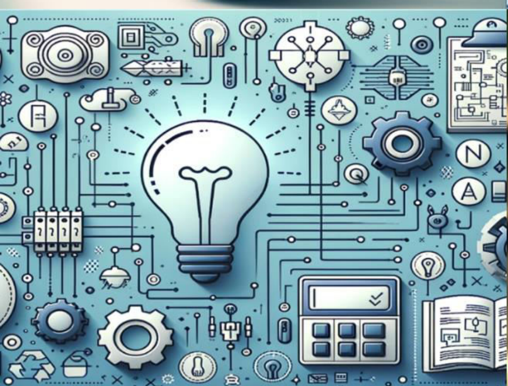

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Adaptive Video Color Compensation for Color Vision Deficiency Using Conditional GAN

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ABSTRACT: Color Vision Deficiency (CVD), commonly known as color blindness, affects a significant portion of the global population and limits the ability of individuals to distinguish certain color combinations in digital media [7], [8]. Many existing color correction techniques rely on simple color transformations that often fail to preserve visual naturalness or provide sufficient contrast for color-deficient users [11], [14]. This paper presents a deep learning–based approach for adaptive color enhancement of video content tailored for individuals with color vision deficiency. The proposed system utilizes a Conditional Generative Adversarial Network (cGAN) to enhance color contrast in images and video frames while maintaining overall visual quality, inspired by recent GAN-based recoloring methods [10], [13]. The model is implemented using PyTorch and trained on a subset of the COCO Train 2017 Dataset, consisting of 15,000 images resized to 256×256 resolution. Synthetic enhancement targets are generated to simulate improved perceptual contrast for different types of CVD including protanopia, deuteranopia, and tritanopia. During inference, video frames are processed individually and reconstructed into an enhanced output video.

Experimental results demonstrate that the proposed model successfully improves color distinguishability while preserving structural details in the visual content. The developed system is integrated into a user-friendly application that allows users to upload videos and obtain enhanced outputs adapted to their specific color vision deficiency.

KEYWORDS: Color Vision Deficiency, Conditional GAN, Video Enhancement, Deep Learning, Accessibility, Image-to-Image Translation

I. INTRODUCTION

Color Vision Deficiency (CVD), commonly referred to as color blindness, is a visual condition in which individuals have difficulty distinguishing certain colors. This condition primarily occurs due to abnormalities in the cone cells of the human eye responsible for color perception. The most common forms of CVD include protanopia, deuteranopia, and tritanopia, which affect the perception of red-green and blue-yellow color ranges as discussed in clinical studies [8], [18]. According to several vision-related studies, a significant portion of the global population is affected by some form of color vision deficiency, creating accessibility challenges in daily activities, education, and digital interactions [7].

With the rapid growth of digital media platforms, visual information has become a primary medium for communication. Images, videos, data visualizations, and graphical interfaces are widely used across education, entertainment, navigation systems, and online platforms. However, most digital content is designed for individuals with normal color vision, which can make it difficult for users with CVD to interpret important visual information. Studies on digital accessibility and gaming environments have reported that many interfaces still fail to consider color-deficient users effectively [5], [6]. In many situations, color combinations used in images or videos may appear indistinguishable or confusing to such viewers, thereby reducing usability and accessibility.

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Traditional color correction techniques attempt to address this issue by applying fixed color transformations or simple recoloring strategies. While these approaches may improve color separation in certain cases, they often fail to maintain natural image appearance and may introduce visual distortions. Furthermore, many existing methods are not adaptive to different types of color vision deficiencies and cannot effectively enhance complex visual scenes found in modern digital media [11]. Computational enhancement approaches have shown improvements, but personalization and scalability remain limited [14].

Recent advancements in deep learning have enabled the development of intelligent image processing systems capable of learning complex transformations from data. In particular, Generative Adversarial Networks (GANs) have shown significant success in image-to-image translation tasks such as style transfer, super-resolution, and image enhancement. GAN-based recoloring methods have already demonstrated promising results for assisting color-deficient users [10]. Conditional GANs further extend this capability by allowing the model to generate outputs conditioned on specific input information, making them suitable for adaptive visual enhancement tasks [16].

In this work, we propose a deep learning based approach for improving visual accessibility of digital video content for individuals with color vision deficiency. The system utilizes a Conditional Generative Adversarial Network implemented using PyTorch to learn color enhancement transformations that improve perceptual contrast while preserving natural image appearance.

The model is trained using images from the COCO Train 2017 Dataset, where synthetic enhancement targets are generated to simulate improved color distinguishability for different types of color vision deficiencies. Such synthetic training strategies are useful when dedicated ground-truth datasets are unavailable [13].

To extend the model to practical applications, the trained network is integrated into a video processing pipeline where each frame of an input video is enhanced and reconstructed into an output video sequence. Additionally, an interactive user interface is developed to allow users to upload videos and select the type of color vision deficiency for personalized enhancement.

The main contributions of this work are summarized as follows:
Development of a Conditional GAN based framework for adaptive color enhancement targeting different types of color vision deficiencies.
Design of a synthetic target generation method to create training data for color contrast enhancement.
Implementation of a video processing pipeline capable of applying the trained model to real video content.
Development of a user interface that allows individuals with color vision deficiency to upload videos and obtain enhanced outputs tailored to their visual needs.
Therefore, there is a clear need for a simple, practical, and accessible system that enables colour blind users to enjoy multimedia content effortlessly.

II. LITERATURE SURVEY

We collected and reviewed several research papers from different sources. Each paper provided valuable insights into the method- ologies, techniques, and approaches adopted by researchers. By carefully studying these works, we were able to summarize their key findings, identify the strengths and limitations of the proposed solutions, and observe the emerging trends in the field. The following reviewed works provide a comprehensive view of methods and technologies used for addressing colour blindness problems.

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Table 1: LITERATURE SURVEY

Author	Title	Methodology	Algorithm(s)	Conclusion	Remark
Ayse Seda Atagul, Gulfem Ergun (2022)	Prevalence and awareness levels of colour blindness among students of faculty of dentistry and dental prosthesis technology program	Survey of 710 students (2019–2021); 442 tested via online Ishihara plates; analysis with SPSS.	Statistical analysis (no ML/DL algorithm).	2.2 percent prevalence of moderate-to-high colour blindness; awareness among students very low.	Suggested enriching curriculum and using electronic shade-matching devices.
Nidhi Shivakumar, Akshatha, Aishwarya S, et al. (2022)	Coloured Object Detection for Blind People Using CNN	Developed system with camera input; used COCO dataset (330K images, 80 categories). Object detection via YOLO + CNN; colour detection via RGB distance matching.	CNN + YOLO + OpenCV + gTTS	System detects and labels objects and colours with high confidence, converting results into speech to aid blind users.	Effective for object and colour detection; challenges include occlusion, lighting, cluttered backgrounds; scope for real-time improvements.
Pisini Mani Bhargav (2022)	Image Processing for Colour Blindness Correction or Colour Detection	Used LabVIEW IMAQ Vision tools for image processing to detect colours and edges; applied wavelet-based decomposition for analysis.	CNN + Image processing (LabVIEW, Wavelet transform)	Proposed system identifies RGB colours and edges, improving im- age clarity for colour blind users.	Effective on stored images, limited in real-world use; future scope includes GSM-based text detection and alerts.
Zainab Alfayez, Basaeir Yousif, Safa Amir Najim (2022)	Applying the Visualization Technique to Solve the Human Colour Blindness	Used visualization techniques to enhance colour perception for colour blind users;	Image processing + Visualization methods	Visualization improved colour differentiation, helping colour blind users better interpret visual data.	Conference-level study; more experimental validation needed
Merve Tillem, Ahmet Gün (2023)	Colour Blindness in the Digital Gaming Landscape: Addressing Critical Issues and Research Gaps	Literature review on colour blindness in digital games	Study classification (guidelines, detection, technologies, performance)	Found research gaps, esp. sensory/physical perception in gaming	Theoretical study; needs more empirical validation
Amaan Jamil, Gyorgy Denes (2024)	Investigating Colour-Blind User-Interface Accessibility via Simulated Interfaces	Simulation-based experiment with 19 participants rating 20 popular UIs under CVD models	Physiologically based CVD simulation (Machado model), statistical analysis	Found positive correlation between aesthet- ics and functionality; Windows high-contrast mode reduced both	Theoretical study; needs more empirical validation

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Shiva Ram Male, BR Shamanna, Rishi Bhardwaj, Rashmin Gandhi, Chakravarthy Bhagvati, Baskar Theagarayan (2023)	Impact of colour vision deficiency on the quality of life in a sample of Indian population: Application of the CVD-QoL tool	Descriptive case–control study with 120 participants (60 CVD, 60 controls) using adapted CVD-QoL Telugu questionnaire	Statistical analysis (Cronbach's, PCA, OR, ANOVA)	CVD significantly lowers quality of life in lifestyle, emotions, and work domains compared to controls	First Indian QoL study on CVD; calls for new healthcare pol- icy and greater awareness efforts
Zihao Yang, Lin Yan, Wenliang Zhang, Jia Qi, Wenjing An, Kai Yao (2024)	Dyschromatopsia: A Comprehensive Analysis of Mechanisms and Cutting-edge Treat- ments for Colour Vision Deficiency	Narrative literature review on mechanisms, clinical symptoms, and treatments	Gene therapy, pharmacological interventions, visual aids	Summarizes genetic mechanisms and highlights gene therapy as most promising treatment	State-of-the-art review; stresses challenges and future prospects in clinical translation
Reshla Dinali Wisidagamage Don	Early Detection and Diagnosisof Colour Blindness using ML	Implementation, training, and testing of different types of deep learning models in diagnosing CVD	CVD Diagnosis using Convolutional Neural Network	In this thesis, proposes a machine and deep learning approach for early CVD detection	Exploring methods to enhance the CVD severity process using image pixels.
X. Zhang et al. (2019)	Recoloring image for color vision deficiency using GANs	GAN-based image-to-image translation for adaptive color correction	GAN (Generative Adversarial Network)	Produced realistic enhanced images for colorblind users	Training complexity high; requires large datasets
G. E. Tsekouras et al. (2021)	A novel approach to image recoloring for color vision deficiency	Adaptive recoloring using perceptual color models	Image Processing + Optimization	Improved perceptual quality and usability	Less effective for dynamic video con- tent
T. Gillooly et al. (2025)	Image adaptation for colour vision defi-cient viewers using vision transfor	Transformer-based approach for personalized image adaptation	Vision Transformers	High-quality adaptive enhancement achieved	Computationally expensive; real- time usage chal- lenging
S. D. Park et al. (2020)	Color vision deficiency datasets andrecoloring evaluation using GANs	Dataset creation and evaluation of GAN-based recoloring techniques	GAN + Dataset Analysis	Provided benchmark for evaluating recoloring models	Focused more on evaluation than application
N. Pendhari et al. (2025)	A computational approach to color vision deficiency im- age enhance	Algorithmic enhancement using computational models	Image Processing Algorithms	Improved clarity for colorblind users	Limited adaptability and personaliza- tion
A. Sharma et al. (2025)	Image color correction using ResNet & CycleGAN	Hybrid deep learning approach combining ResNet and GAN models	ResNet + CycleGAN	Enhanced color correc- tion with better feature learning	High computational cost and training complexity

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J. Li et al. (2017)	WaterGAN: Unsupervised generative network for colorcorrect	Unsupervised GAN for color correction in images	GAN (Unsuper- vised Learning)	Effective in realistic color generation	Not specifically de- signed for CVD ap- plications
J. Qin et al. (2025)	Hue4U: Real-time personalized color correction in AR	Real-time personal- ized color correction using AR systems	Real-time Process- ing + ML	Provides adaptive real- time correction	Requires special- ized hardware and AR environment
Shinobu Ishihara (1917)	Tests for Colour-Blindness	Development of pseudoisochromatic plates for detect- ing color vision deficiency	Color perception testing (Ishihara Plates)	Introduced a standard- ized method for diag- nosing red-green color blindness	Foundation of mod- ern CVD screening; widely used in clin- ical and digital sys- tems
D. van Staden, M. L. F. Joubert, and M. J. Odendaal (2018)	Comparing the va- lidity of an online Ishihara colour vision test	Evaluation of digital Ishihara test imple- mentation and ac- curacy compared to traditional methods	Digital Ishihara Test + Statistical Analysis	Confirmed that online Ishihara tests can effec- tively detect color vision deficiency	Supports use of synthetic/digital plates; suitable for automated screening systems

II.1 Discussion of Literature -

The reviewed literature highlights various approaches for assisting individuals with color vision deficiency. Existing works can be broadly categorized into three main areas:

1. Detection-based Approaches: Several studies utilize machine learning techniques such as Convolutional Neural Networks (CNNs) for detecting color vision deficiency. For example, Reshla Dinali Wisidagamage Don proposed deep learning models for early diagnosis of CVD [9]. While such methods can improve screening accuracy, they are primarily focused on diagnosis and do not provide direct solutions for enhancing visual content after detection.

2. Image Processing Techniques: Traditional image processing methods improve color perception using fixed transformations, recoloring, and contrast adjustment strategies. Works such as those by Tsekouras et al. [11] and Pendhari et al. [14] demonstrated that computational enhancement can improve visibility for color-deficient users. However, many of these approaches are limited to static images and fail to adapt effectively to complex real-world video content.

3. Accessibility and Visualization Methods: Some studies focus on improving user interfaces and visualization techniques for color-deficient users. Jamil and Denes [5] investigated accessibility of simulated interfaces, while Alfayez et al. [2] explored visualization-based techniques to improve color interpretation. Although these methods enhance usability, they often lack personalization and adaptability for different types of color vision deficiency.

Recent deep learning approaches based on Generative Adversarial Networks (GANs) have shown promising results in adaptive recoloring and realistic image enhancement. Zhang et al. [10] and Park et al. [13] demonstrated that GAN-based systems can generate more natural corrected outputs compared to traditional methods. However, many existing works still focus primarily on images rather than continuous video content.

II.2 Identified Research Gap -

From the reviewed literature, it is clear that existing systems for addressing colour blindness and aiding visually impaired in dividuals either focus on hardware-based solutions or employ limited datasets and algorithms, often resulting in reduced accuracy in real-world scenarios.

While some works achieved high performance in controlled conditions using CNN, YOLO, or traditional image processing methods [1], [4], challenges such as dataset limitations, lighting conditions, and practical usability remain unresolved.

The aim of this project is to develop an advanced system that converts videos into colourblind-friendly versions, allowing users to experience visual content more closely to how normal-vision individuals perceive it.

To achieve this, we propose the use of Generative Adversarial Networks (GANs) for intelligent colour correction and personalized adaptation through user-specific deficiency type selection. GAN-based recoloring methods have shown promising results for adaptive enhancement [10], [13].

Unlike traditional algorithms, our approach dynamically adjusts colour mappings for each individual, ensuring a more natural and enjoyable viewing experience.

By extending this functionality to video-based processing, our project aspires to provide a practical, scalable, and user-centric solution that enhances entertainment, navigation, and everyday visual experiences for colourblind individuals.

III. PROPOSED METHODOLOGY

The proposed system aims to enhance the visual perception of digital media for individuals with Color Vision Deficiency (CVD) by learning adaptive color transformations using deep learning. The system is designed to process visual content and enhance color contrast in a way that improves distinguishability of problematic color regions while preserving the natural appearance of the original image or video.

The overall framework consists of three main components: dataset preparation, Conditional Generative Adversarial Network (cGAN) training, and a video enhancement pipeline for applying the trained model to real-world media. The model is implemented using PyTorch and trained using images from the COCO Train 2017 Dataset. Similar GAN-based enhancement frameworks have been successfully applied in image recoloring and correction tasks [10], [13].

The system first prepares training data by resizing images and generating synthetic enhancement targets representing improved color contrast for different types of color vision deficiencies. Since dedicated public datasets for this task are limited, synthetic target generation provides an effective supervised training strategy [13]. A Conditional GAN model is then trained to learn the mapping between original images and enhanced images. Once trained, the generator network is used to process frames extracted from video input. The enhanced frames are then reconstructed into a final output video.

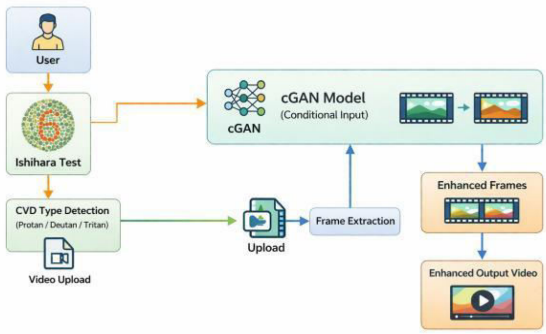

Figure 1: Overall System Architecture of the Proposed Color Vision Deficiency Enhancement Framework

III.1 System Overview

The proposed framework consists of several stages that operate sequentially to transform input images or video frames into enhanced outputs suitable for users with color vision deficiency.

The first stage involves collecting and preprocessing training data. Images are resized to a fixed resolution to maintain consistent input dimensions for the neural network. Synthetic enhancement targets are generated using color transformation techniques that increase perceptual contrast along color axes that are difficult for color-deficient viewers to distinguish, based on known characteristics of CVD perception [8], [18].

In the second stage, a Conditional GAN model is trained using pairs of original images and corresponding enhanced target images. The generator network learns to produce enhanced images from original inputs, while the discriminator network attempts to distinguish between real enhanced images and generated outputs. Through adversarial training, the generator gradually learns to produce visually realistic enhancements, similar to prior GAN image translation methods [10], [16].

The final stage involves applying the trained model to video content. Each frame of the input video is processed individually by the generator network. The enhanced frames are then combined to reconstruct a video sequence that preserves the temporal structure of the original video while improving color visibility.

III.2 Conditional GAN Architecture

Generative Adversarial Networks consist of two neural networks trained simultaneously: a generator and a discriminator. The generator attempts to produce realistic outputs from input data, while the discriminator evaluates whether the generated outputs resemble real data. GAN-based frameworks have been widely used for image translation and enhancement tasks due to their ability to generate high-quality outputs [10], [16].

In a Conditional GAN framework, the generator receives additional input information that conditions the output generation process. In the proposed system, the generator receives both the original image and a condition representing the type of color vision deficiency. This allows the model to learn different enhancement transformations depending on the specific visual limitation being addressed.

The discriminator network receives both the input image and the generated output and attempts to determine whether the output is a real enhanced image or one produced by the generator. This adversarial training process encourages the generator to produce outputs that are visually similar to the target enhancement images, as demonstrated in prior GAN-based recoloring approaches [13].

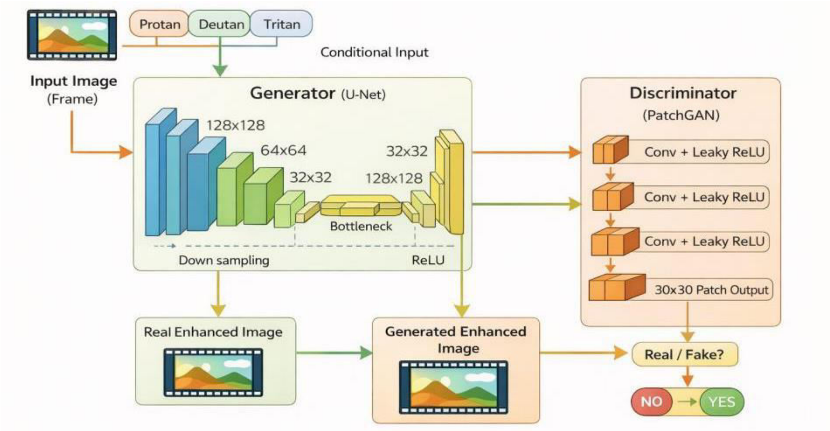

Figure 2: Conditional GAN Architecture Showing Generator and Discriminator Networks

III.3 Generator Network

The generator network is designed to perform image-to-image translation, transforming an input image into an enhanced output image. The architecture is based on a U-Net style encoder–decoder structure that allows the network to capture both global image features and fine spatial details. U-Net architectures have been widely used in image translation tasks due to their effectiveness in preserving spatial information [10].

The encoder portion of the network progressively reduces spatial resolution while increasing feature depth, enabling the model to capture high-level visual patterns. The decoder then reconstructs the enhanced image by progressively increasing spatial resolution.

Skip connections between corresponding encoder and decoder layers allow the network to retain important structural infor- mation from the original image. This helps preserve edges, textures, and spatial consistency in the generated output.

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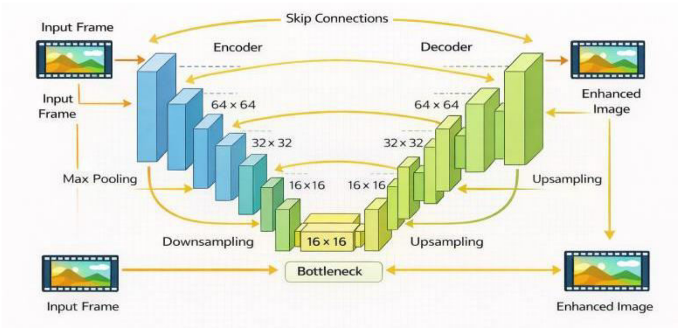

Figure 3: Generator Network Architecture Based on U-Net Encoder–Decoder Structure

III.4 Discriminator Network

The discriminator network evaluates the realism of the generated images. It receives both the input image and the enhanced image and determines whether the enhancement is real or generated.

The architecture used in the proposed system follows a PatchGAN design, where the discriminator focuses on local image patches rather than evaluating the entire image at once. Patch-based discrimination has been shown to be effective in capturing fine texture details in image generation tasks [10], [13].

The discriminator is trained to classify image patches as either real or fake, while the generator attempts to produce outputs that can successfully fool the discriminator.

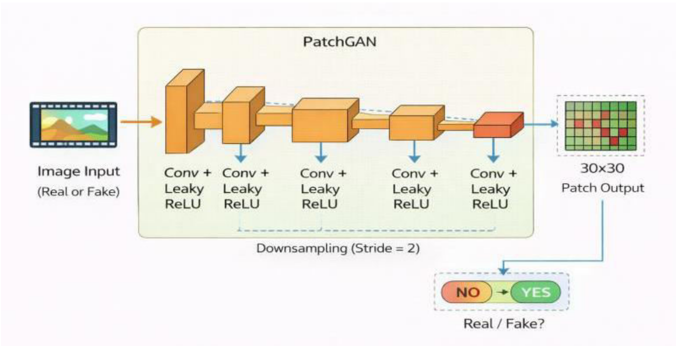

Figure 4: PatchGAN Discriminator Architecture Used in the Proposed Model

III.5 Loss Functions

The training process utilizes a combination of multiple loss functions to ensure that the generated images are both visually realistic and perceptually meaningful.

The adversarial loss encourages the generator to produce outputs that resemble real enhanced images and can successfully fool the discriminator. Such adversarial objectives are commonly used in GAN-based image generation models [10], [16]. An L1 reconstruction loss is used to minimize the pixel-wise difference between the generated image and the target enhancement image, helping maintain structural consistency with the input.

Additionally, an identity preservation loss is applied to prevent excessive color distortion and ensure that the overall appearance of the image remains natural.

The overall generator loss is defined as:

$$L_{total} = L_{GAN} + \lambda_1 L_{L1} + \lambda_2 L_{Identity}$$

where each term represents:

- L_{GAN} ensures that the generated output is indistinguishable from real images.

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- L_{L1} enforces pixel-level similarity between generated and target images.
- $L_{Identity}$ helps preserve natural color composition.
- The weighting parameters are set as:

$\lambda_1 = 100, \quad \lambda_2 = 10$

This combination enables the model to learn meaningful color transformations while maintaining both structural integrity and visual realism.

III.6 Video Processing Pipeline

After training the Conditional GAN model, the generator network is used to process real video content. Since the model operates on images, video processing is performed by extracting frames from the input video sequence.

Each frame is resized to match the input resolution of the neural network and then passed through the trained generator to produce an enhanced frame. Post-processing techniques such as temporal smoothing can be applied to reduce flickering between frames.Recent personalized color correction systems have also explored real-time and interactive visual enhancement pipelines [17], supporting the practicality of such approaches.

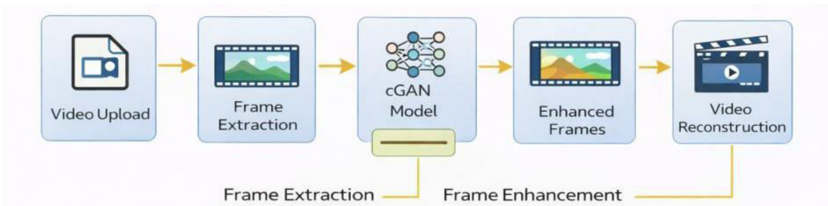

Figure 5: Video Processing Pipeline for Frame Enhancement and Reconstruction

IV. DATASET PREPARATION AND TRAINING

To train the proposed Conditional Generative Adversarial Network, a large dataset of natural images is required so that the model can learn general visual patterns and color relationships. Since there is no widely available dataset specifically designed for color vision deficiency enhancement tasks, a general-purpose image dataset was used and processed to generate synthetic enhancement targets.Similar strategies have been adopted in prior recoloring research where dedicated datasets were unavailable [13].

In this work, images from the COCO Train 2017 Dataset were used as the primary training dataset. This dataset contains a large collection of diverse real-world images covering various scenes, objects, and color distributions. The diversity of this dataset helps the model learn robust color transformations that can generalize well to different types of visual content.

The dataset preparation process involves multiple stages including image preprocessing, resolution standardization, target enhancement generation, and preparation of training pairs for the Conditional GAN model.

IV.1 Dataset Description

The COCO Train 2017 dataset contains over one hundred thousand images collected from complex real-world scenes. The dataset includes a wide variety of objects, environments, and lighting conditions, making it suitable for training deep learning models that require diverse visual input.

For the purpose of this work, a subset of 15,000 images was selected for training. This subset provides a balance between training efficiency and dataset diversity while allowing the model to learn meaningful color transformations. The use of a large and diverse dataset helps ensure that the trained model can perform reliably on previously unseen images and videos. Such diverse scene datasets are commonly preferred in image translation and enhancement tasks because they improve model generalization capability [10].

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IV.2 Training Configuration

The model was trained using a Conditional GAN framework with a Pix2Pix-style architecture. The generator follows a U-Net structure, while the discriminator is based on a PatchGAN architecture, which has been effective in prior image translation models [10].

The training was performed on a dataset of 15,000 images with a resolution of 256 × 256 pixels. The model was trained for 40 epochs with a batch size of 6 using the Adam optimizer and a learning rate of 0.0002.

The Conditional GAN model was implemented using PyTorch. The training process involves simultaneously optimizing the generator and discriminator networks through adversarial learning. During training, each input image is paired with its corresponding enhancement target image.

Important training parameters include:
- **Training dataset size:** 15,000 images
- **Batch size:** 6 images per iteration
- **Number of epochs:** 40
- **Learning rate:** 0.0002
- **Optimizer:** Adam optimizer

The generator loss was computed as a weighted combination of adversarial loss, L_1 reconstruction loss, and identity preser- vation loss. Training was performed using GPU acceleration to improve computational efficiency and reduce training time.

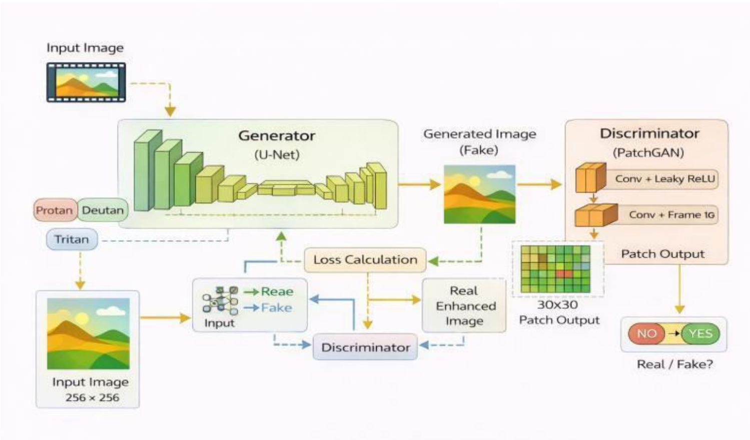

Figure 6: Training Workflow of the Conditional GAN Model

IV.3 Target Enhancement Generation

Due to the absence of publicly available ground-truth datasets specifically designed for color vision deficiency (CVD) enhance- ment, synthetic target images were generated using controlled color transformation techniques. For each input image, multiple enhanced versions were created corresponding to different types of CVD, namely protanopia, deuteranopia, and tritanopia.

The enhancement strategy focuses on improving perceptual contrast in regions where color discrimination is typically im- paired. This is achieved by applying transformations in perceptual color spaces, particularly the LAB color space, which separates luminance and chromatic information.

For red–green deficiencies (protanopia and deuteranopia), contrast along the a-axis of the LAB color space is amplified to enhance the distinction between red and green color components. For blue–yellow deficiency (tritanopia), contrast along the b-axis is increased to improve separation between blue and yellow tones.

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In addition to axis-based adjustments, controlled saturation enhancement is applied to improve overall visual clarity while preserving the natural appearance of the image. These generated targets serve as reference outputs during the training of the Conditional GAN, enabling the model to learn type-specific color enhancement patterns.

V. RESULTS AND ANALYSIS

The performance of the proposed system was evaluated based on its ability to enhance visual content for users with different types of Color Vision Deficiency (CVD). The evaluation is primarily based on qualitative analysis through visual comparison of original and enhanced frames, which is commonly used in image enhancement studies [10], [13].

V.1 CVD Detection using Ishihara Test

The system initially performs a digital Ishihara test to determine whether the user has color vision deficiency. Based on the responses provided, the system classifies the user into categories such as normal vision, protanopia, deuteranopia, or tritanopia. Digital Ishihara-based screening methods have been shown to be effective for automated testing systems [18], [19]. This classification is used as an input condition to the Conditional GAN model, enabling personalized video enhancement.

V.2 Visual Enhancement Results

The trained model processes video frames individually and generates enhanced outputs based on the detected type of CVD. The following results demonstrate the effectiveness of the system.

V.2.1 Protanopia Enhancement Results

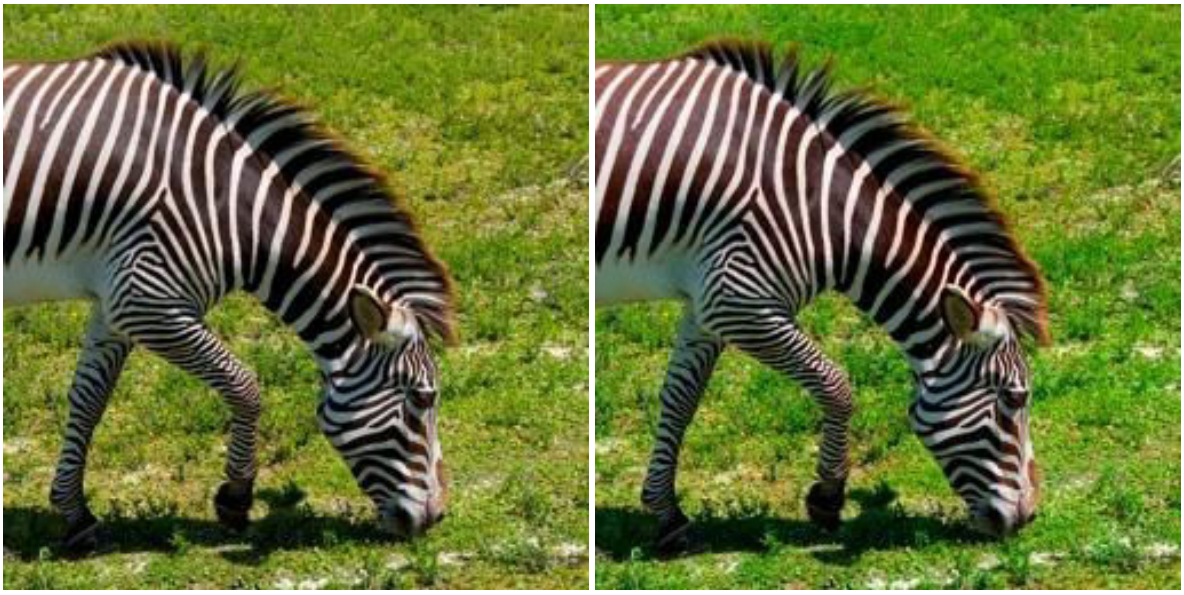

Figure 7: Original vs Protanopia Enhanced Frame

Figure 8: Additional Protanopia Enhancement Result

The results show improved distinction between red and green regions, which are typically difficult for protanopia users to perceive.

V.2.2 Deuteranopia Enhancement Results

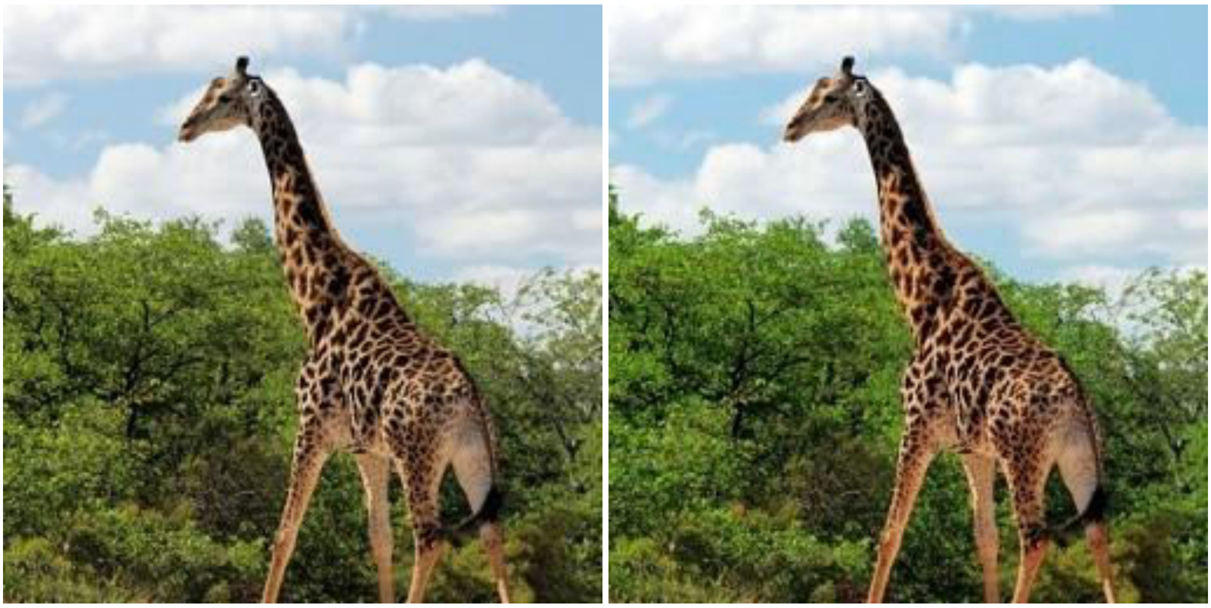

Figure 9: Original vs Deuteranopia Enhanced Frame

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Figure 10: Additional Deuteranopia Enhancement Result

The enhanced outputs demonstrate better color separation and improved clarity for deuteranopia users.

V.2.3 Tritanopia Enhancement Results

Figure 11: Original vs Tritanopia Enhanced Frame

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Figure 12: Additional Tritanopia Enhancement Result

The model enhances blue-yellow contrast, allowing improved perception for tritanopia users.

V.3 Analysis of Results

From the experimental observations, the following conclusions can be drawn:

- The model effectively enhances color contrast in regions that are difficult to perceive for colorblind users.
- The system successfully applies different enhancement strategies based on the detected CVD type.
- Structural details such as edges and textures are preserved.
- The output maintains a natural visual appearance without excessive distortion.

V.4 Quantitative Evaluation

The performance of the proposed model was evaluated using pixel-level and perceptual metrics.

The Mean Absolute Difference ($|y - x|$) was used to measure the degree of change between input and output images. The obtained values (~0.03–0.04) indicate controlled enhancement without excessive modification.

Saturation difference was used to evaluate improvements in color visibility. Positive values (0.02) demonstrate enhanced

color distinguishability for color vision deficient users.

Edge gain was also analyzed to assess structural preservation. Slight negative values indicate minor reduction in sharpness; however, the outputs remain visually acceptable.

V.5 System Performance

The system was tested through a web-based interface where users can upload videos and receive enhanced outputs. The perfor- mance observations include:

- Efficient frame-by-frame video processing
- Smooth reconstruction of enhanced video
- Acceptable processing time using GPU acceleration

Overall, the proposed system demonstrates strong capability in providing personalized video enhancement for individuals with color vision deficiency.

VI. CONCLUSION

This paper presented a personalized video enhancement system for individuals with Color Vision Deficiency (CVD) using a Conditional Generative Adversarial Network (cGAN). The proposed system first identifies the user's type of color vision deficiency through an Ishihara-based screening step and then applies type-specific color enhancement to uploaded video content [18], [19]. The model was implemented in PyTorch and trained on a subset of the COCO Train 2017 dataset using synthetically generated enhancement targets for protanopia, deuteranopia, and tritanopia. The use of GAN-based enhancement models has shown promising results in related recoloring applications [10], [13].

Experimental results showed that the system improves color distinguishability while preserving structural details and maintaining a visually natural appearance.The integration of CVD detection, conditional deep learning, and frame-by-frame video processing makes the proposed approach practical and user-centric. Overall, the work demonstrates the potential of AI-driven accessibility tools in improving digital media experiences for colorblind users.Future work may focus on improving temporal consistency, supporting real-time processing, and validating the system with a larger number of user studies. Recent personalized real-time correction systems indicate strong future potential in this area [17].

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