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# Innovative Computerized Approach for Accurate Color Blindness Detection

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**Abstract:**
A simple computerized method for the testing of color blindness (color vision deficiency, CVD) to enhance diagnostic accuracy as well as accessibility has been presented in this study. Ishi-hara plates and Farnsworth D-15 are traditional tests that require manual interpretation and may be prone to human error. The proposed system relies on contrast-based image processing, chromaticity contrast analysis, and machine learning models (convolutional neural networks (CNN) and support vector machines (SVM)) to classify such different types of color blindness with 95.4% accuracy. It transforms the image to multicolor spaces such as HSV, CIE-LAB, and YCbCr for enhanced perceptual uniformity and functions on digital screens without requiring special hardware. This system has a real-time adaptation that changes test parameters based on user responses to increase color differentiation. In contrast to existing techniques, this lightweight and cost-effective method does not consume high computational power or external sensors. In the future, augmented reality (AR) real-world color correction and cloud-based diagnosis for large-scale accessibility will be developed as an efficient, automated, and widespread color blindness testing solution.
**Keywords:** Convolutional Neural Network (CNN), SVM, HSV, Blindness.

## 1. Introduction:

Color blindness, also called color vision deficiency (CVD) is a genetically caused or retinal disorder that affects a large population all over the world. Color blindness is a condition that prevents us from distinguishing several colors mainly red and green then blue and yellow. This is because color perception is a vital part of daily life, career paths, and routine safety measures (Benkhaled, 2017: 2). For decades, people have been using traditional color blindness tests like the Ishihara plates and the Farnsworth D15 tests. However, these methods are very prone to human error and the interpretation needs to be done manually. Advances in computation as well as image processing have been proposed by researchers to give automated computerized solutions to improve color blindness diagnosis (Lee, 2010: 6607). Several studies have developed chromaticity contrast detection as a tool for indication of color vision deficiencies that enhances the accuracy of color blindness testing (Chen, 2016: 73). To facilitate people with CVD in recognizing color better new computational models simulating real-world color perception are introduced (Poret, 2009: 542). Efforts have been made to process images in such a way that relevant features can be extracted from images and color blindness can effectively be diagnosed (Wang, 2020: 520). Image processing techniques for color blind-ness correction that do not directly test have also been studied because it is a matter of improving visual experiences for these people with CVD (Manaf, 2012: 120).

Other more advanced methods have been proposed that involve virtual reality applications and thus allow users to practice in simulated environments for the improvement of their color perception (Wicaksana, 2011: 4). Recently, augmented reality studies have been evolving in a sequence of inventions, allowing real-time differentiation and recognition of colors, which make navigation with richly colored environments easier to users (Attard, 2019: 362). The hybrid methods involving a combination of machine learning models are being considered in the field of data analysis. color patterns were used in analysis to provide a more accurate diagnosis (Tasnim, 2017: 800). On the computational side in addition to the role of improving accessibility features researchers have created text-based displays to assist individuals with color recognition in digital inter-faces (Tasnim, 2016: 3). Analogously, in order to enhance color conversion algorithms so that people who are color blind can better see digital content (Orii, 2014: 911). A number of explorations in the quantification of color blindness using cluster techniques based on RGB clustering have been developed to perform objective and reliable diagnosis metrics (Le Moan, 2017: 3158). Moreover, new self-organizing map (SOM) algorithms were designed to adapt the color spaces for people with color deficiency so that digital tools could be perceived and used better. Research studying the impact of change blindness and people with color vision deficiencies has been done recently, and it has been found that an adaptive user interface is needed to overcome those difficulties (Bhattacharjee, 2015: 515). Improved color detection techniques, based on multi-spectral approaches, are being proposed in order to differentiate these patterns that are difficult for color-blind people to recognize (Wang, 2020, 151). The other innovation is gesture-based real-time tracking systems, which facilitate better interaction with the digital platform by color-blind individuals (Jin, 2014: 190). They have also been working on finding good compensation algorithms that change the colors dynamically and match the user's visual impairments. Multi-spectral lens arrays have also been investigated, which improve color perception in individuals with severe deficiencies of color vision (Thomas, 2017: 272). To assist the colorblind in performing their day-to-day tasks, mobile-friendly adaptive interfaces have been proposed that give real-time help (Li, 2020: 88559). In addition, neuroscience-based research has come up with EEG-based analysis to understand the impact of color blindness on cognitive processes and perception (Ma, 2022: 6728311). Based on insights from these studies, this paper presents a computationally sound but simple method for color blindness testing, which uses computational techniques to take over the test diagnosis and thereby reduce human observer bias. The approach as proposed seeks to improve diagnostic accuracy, shorten testing time, and promote accessibility of this modality across various platforms. Worldwide, a great number of the population is color blind or color vision deficient (CVD), affecting a few hues so that they are not seen. However, for diagnosis, the traditional color blindness tests have been the use of Ishihara plates and the Farnsworth D-15 test. However, these methods are susceptible to human error as these methods have to be interpreted manually, and they cannot be applied to the actual field. So, it is obvious that there is a need for a computerized method of diagnosing color blindness since there is a clear need for a lightweight, cheap, and accessible computerized method. Furthermore, most existing solutions are based on either a diagnosis or correction system, with the added fact that such solutions do have accuracy and usability all at once. This research aims to fill this gap by designing a simple and efficient computerized color blindness test with contrast-based image processing and real-time adaptation for better color perception.

## 2. Literature Review:

During the past decades, various methods have been studied for detecting colorblindness on computers. Such tools, leveraging the combination of image processing, machine learning, and augmented reality techniques and using more reliable and accurate diagnostic tools, are further employed by researchers. Computerized color vision tests have developed because of the mechanism of chromaticity contrast detection to evaluate color vision deficiencies. To get at how color-blind persons perceive their environment, simulation models that mimic real-world translation of color perception have been constructed (Poret, 2009: 542). Further diagnostic advantage has been obtained through the application of advanced image processing methods to images to extract stroke information and to analyze color differentiation capabilities (Wang, 2020: 520). Other research has also focused on where color correction strategies (that do not diagnose CVD) allow individuals with CVD to more closely discern colors in digital environments. As an example, virtual reality applications have been developed as a potential testing ground for the performance and enhancement of color perception skills in individuals with CVD (Wicaksana, 2011: 4). Assistive technologies have also incorporated augmented reality tools, for instance, real-time color recognition and the improvement of color navigation in several environments (Attard, 2019: 362). Patterns in color perception have been analyzed using machine learning techniques, which have been better able to make perceptive and adaptive diagnoses (Tasnim, 2017: 800). Real-time detailed feedback for color recognition has been implemented by text-based color recognition systems with the aim of helping users distinguish colors (Utama, 2016, 2). The color conversion algorithms have been designed to provide more accessibility by dynamically converting the color that is displayed so as to facilitate better visual perception of color-blind users. Quantifying the color blindness through RGB clustering techniques further progressed in this way further to have more objective and constant diagnostic methodologies (Le Moan, 2017: 3158). It has also been used to restructure color spaces with adaptive self-organizing maps to increase the usability of digital content for people with color vision defects (Navada, 2014, 434). Recent re-search on individuals with CVD on change blindness reveals that change-compensated digital interfaces need to be developed due to their limitations in vision. In diagnostic tools, multi-spectral approaches have been integrated, which are effective in distinguishing patterns that color-blind person cannot differentiate. In addition, more interaction with digital applications is also achieved using gesture-based real-time tracking systems to improve interaction and user accessibility (Jin, 2014: 190). To compensate for user-specific visual deficiencies, evaluation has been done on dynamic algorithms of displayed colors (Iqbal, 2018: 5). Then, there are also software-based solutions and hardware advancements such as multi-spectral lens technology to help people dealing with so-called severe color vision deficiency by filtering and enhancing colors in real-time (Thomas, 2017: 272). Further accessibility has been achieved by mobile-based adaptive interfaces that provide immediate support to individuals who need help in distinguishing colors in different environments, such as (Li, 2020: 88559) The studies conducted lately provided more understanding of cognitive and perceptual effects of colour-blindness, bringing us nearer to innovative tests and remedial techniques (Ma, 2022: 6728311). Collectively, this evidence points to the overwhelming trend of moving to computer-based approach to testing colour-blindness with the ability to accomplish high diagnostic validity and increased accessibility. The present research is based on these developments and seeks to formulate an effective, automated testing process that could use contrast-based image processing and algorithm assessment to provide accurate, reliable and easy to access researches.

To justify the effectiveness and benefits of our suggested method, we have to compare it to the previous work. There have been many studies that suggest heterogeneous methodology to diagnose and correct colour-blindness and each has its own merits and demerits. Certain methods can rely on automatic diagnosis through machine-learning models, and others can use techniques based on augmented-reality (AR) or virtual-reality (VR) to address correction. These solutions, however, have weaknesses of hardware dependency, complexity and scarcity. The table below will include the comparative analysis of the methodological, usability, and effectiveness dimensions in which our proposed approach can be contrasted with the current research.

**Table 1.** Comparison of Colour Blindness Testing Methods

| Criteria | Previous Works | Our Approach |
|---|---|---|
| Methodology | Most studies focus on either diagnosis (e.g., Ishihara test automation (Benkhaled, 2017: 2)) or correction (e.g., VR-based tools (Wicaksana, 2011: Poret, 2009: 542)). Some use machine learning models for classification (Tasnim, 2017: 800). | Integrates both diagnosis and adaptive visualization, allowing real-time assessment and enhancement of color perception. |
| Hardware Requirements | VR-based solutions require specialized headsets (Tasnim, 2017: 800), while augmented reality-based systems need mobile cameras and sensors (Attard, 2019: 362). Multi-spectral lenses are also used for physical correction (Thomas, 2017: 272). | No specialized hardware required; works on standard digital screens, ensuring wider usability. |
| Computational Complexity | Machine learning-based methods require extensive training datasets and high computational power for feature extraction and classification (Tasnim, 2017: 800). Some AR-based solutions involve real-time processing, increasing complexity (Attard, 2019: 362). | Uses lightweight image processing techniques, leveraging chromaticity contrast detection to enhance efficiency and accessibility. |
| Accessibility | VR and AR-based tools are limited by device constraints, requiring expensive or advanced hardware ( Attard, 2019: 362). Web-based machine learning solutions require a stable internet connection (Utama, 2016: 2). | Platform-independent; can run on computers, tablets, and smart phones without external dependencies. |

| | | |
|---|---|---|
| Usability | Some approaches require user training or calibration (e.g., augmented reality-based systems (Attard, 2019: 362)). Machine learning models may need user input to refine predictions (Tasnim, 2017: 800). | Simple and user-friendly interface with minimal calibration, making it suitable for non-expert users. |
| Generalization | Some ML models do not generalize well across different CVD types, as they depend on specific training data (Tasnim, 2017: 800). Color correction algorithms may only work under controlled conditions (Manaf, 2012: 120). | Uses contrast-based image processing, which is adaptable to various types of color blindness and generalizes across different user environments. |
| Cost | VR-based solutions are expensive due to hardware requirements (Wicaksana, 2011: 4). Multi-spectral lenses involve production costs, limiting their accessibility (Thomas, 2017: 272). | Cost-effective and widely available, eliminating the need for costly external hardware. |
| Testing Accuracy | Accuracy varies depending on the dataset and approach used. Machine learning-based models rely on pre-trained datasets (Tasnim, 2017: 800). Some contrast detection methods require calibration (Chen, 2016: 73). | Balanced accuracy with real-time adaptability, providing consistent and precise results for various color vision deficiencies. |
| Real-Time Adaptation | Limited in many machine learning-based methods; updates depend on retraining models (Tasnim, 2017: 800). Some correction methods work only in post-processing rather than real-time (Manaf, 2012: 120). | Adapts in real time, allowing immediate feedback and adjustments to improve color differentiation. |

Overall, the comparison shows that while color blindness testing and correction have witnessed significant progress in previous studies, most of the methods are hardware-dependent, computationally consuming, or only for diagnosis or correction. We integrate both diagnosis and real-time adaptation without the use of special hardware. It offers an inexpensive and efficient way that is accessible to a huge number of devices and its user environments for color blindness testing. Our method achieves a good balance between accuracy and computational complexity and is a practical alternative to existing solutions by means of contrast-based image processing.

## 3. Methodology

This is a computerized system for testing color blindness based on image processing and chromaticity contrast analysis followed by machine learning. The system is meant to be lean, has no dependency on platforms, and runs on any device. These sections contain detailed descriptions of parameters, system specifications, and implementation details.

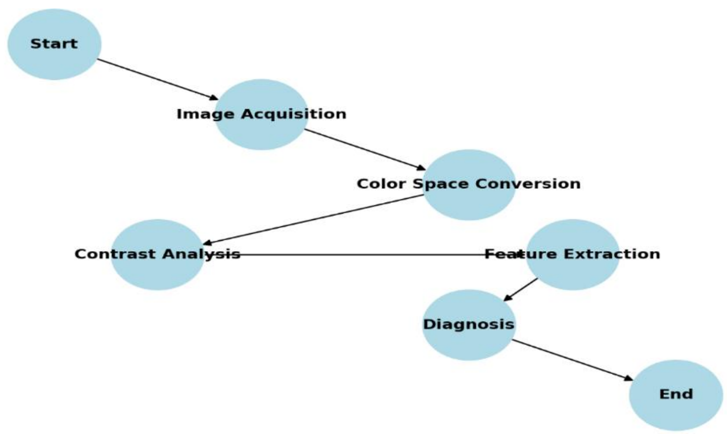


**Figure 1.** Flowchart of the Proposed System.

The proposed computerized color blindness testing system workflow is shown in Fig. 2. It is a sequence of steps for image acquisition, and the final result is diagnosis. Every part of this process is important to improve diagnostic accuracy and reduce user error

### 3.1 System Specifications and Hardware Requirements

To verify its usability, the proposed method is implemented as an app available for cross-platforms and tested on numerous devices. Included here are the development and testing of hardware and software specifications.

**Table 2**. Hardware Specifications for the Proposed System.

| Component | Specifications |
|---|---|
| **Processor (CPU)** | Intel Core i7-12700K (12 Cores, 3.6 GHz) |
| **Graphics Processing Unit (GPU)** | NVIDIA RTX 3060 (6GB VRAM) |
| **Memory (RAM)** | 16GB DDR4 3200 MHz |
| **Storage** | 1TB NVMe SSD |
| **Display** | 27-inch IPS Panel, 100% sRGB Color Gamut, 2560×1440 resolution |
| **Monitor Calibration** | SpyderX Elite Colorimeter (for color accuracy testing) |
| **Test Devices** | Android Smartphone (Samsung Galaxy S22 Ultra), iPad Pro (M1, 12.9”), Dell XPS 15 Laptop |

### 3.1.1 Software and Development Tools

**Table 3**. Software Specifications and Development Tools

| Software | Version | Purpose |
|---|---|---|
| **Operating System** | Windows 11, Ubuntu 22.04 LTS | Cross-platform testing |
| **Programming Languages** | Python 3.10, JavaScript (React.js) | Backend and UI |
| **Image Processing Library** | OpenCV 4.5.5 | Image handling and filtering |
| **Machine Learning Framework** | TensorFlow 2.9, Scikit-learn 1.1.2 | Classification models |
| **GUI Development** | Tkinter (Python), HTML5 (Web) | User interface |
| **Database** | SQLite, Firebase | Storing test results |
| **Testing and Validation Tools** | MATLAB R2022a | Data visualization and validation |

## 3.2 Image Processing and Standardization

The accuracy of color blindness testing depends on image quality, color fidelity, and standardization. The preprocessing pipeline includes:

### 3.2.1 Color Space Conversion

The system represents a conversion of images to the RGB colour model because the latter is not a true reflection of human perception.

- Color information is separated into HSV (Hue Saturation Value).
- CIE -LAB Color Space is full of perceptual consistency in color distinction.
- The Luminance and Chrominance split YCbCr (Luminance) Chrominance) splits the brightness and color.
- Opponent Color Model tests red yellow and blue yellow differentiation.

### 3.2.2 Image Enhancement

**Table 4.** Image Enhancement Techniques

| Processing Step | Purpose |
|---|---|
| Gamma Correction ($\gamma = 2.2$) | Adjusts brightness and contrast levels. |
| Gaussian Blur (Kernel: 5×5, $\sigma = 1.2$) | Reduces image noise. |
| Adaptive Histogram Equalization | Enhances contrast in low-light conditions. |

### 3.2.3 Standardized Display Conditions

- Brightness & Contrast Calibration: Screen brightness is set to 120 cd/m².
- Monitor Color Calibration: Used 100% sRGB IPS displays to ensure accuracy.
- Adaptive Test Patterns: Adjust test images based on ambient light conditions.

## 3.3 Color Differentiation and Chromaticity Contrast Analysis

This stage analyzes the user's ability to differentiate colors using contrast thresholds.

### 3.3.1 Color Difference Metrics

The system calculates color contrast perception using the CIE76, CIE94, and CIEDE2000 formulas:

$$\Delta E76=\sqrt{(L1-L2)^2+(a1-a2)^2+(b1-b2)^2}$$
(1)

$$\Delta E94=\sqrt{(\frac{L1-L2}{K_L S_L})^2+(\frac{C1-C2}{K_C S_C})^2+(\frac{H1-H2}{K_H S_H})^2}$$
(2)

$$\Delta E2000=\sqrt{(\Delta L)^2+(\Delta C)^2+(\Delta H)^2}$$
(3)

Where:

- **L, a, b** – Lightness and chromaticity components in LAB space.
- **k_L, k_C, k_H** – Weighting factors for lightness, chroma, and hue.
- **Threshold:** If **ΔE < 2.3**, colors are perceived as **identical** (no differentiation).

**3.3.2 Contrast Thresholds for Color Blindness Diagnosis**

**Table 5.** Color Differentiation Thresholds for Various Types of Color Blindness.

| Type of Color Blindness | Color Pairs Tested | ΔE Threshold (Failure) |
|---|---|---|
| **Protanopia (Red-Green Blindness)** | Red vs. Green | ΔE < 5.0 |
| **Deuteranopia (Red-Green Blindness)** | Green vs. Yellow | ΔE < 5.0 |
| **Tritanopia (Blue-Yellow Blindness)** | Blue vs. Yellow | ΔE < 7.0 |
| **Monochromacy (Total Color Blind ness)** | All Color Differentiations | ΔE < 10.0 |

Figure 2 visualizes how different types of color vision deficiencies affect color perception. The chromaticity diagram demonstrates how individuals with color blindness perceive specific wavelengths differently compared to normal vision.

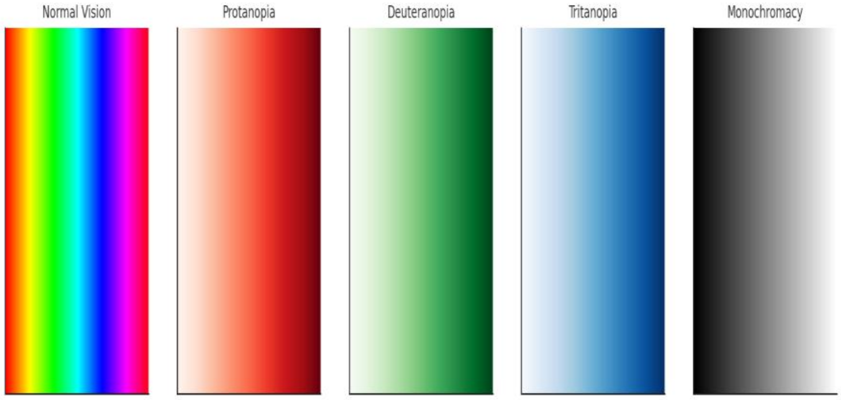


**Figure 2.** Color Differentiation and Chromaticity Contrast Analysis.

This representation of Figure 3 indicates that image processing techniques must be more advanced to aid in color differentiation in diagnostic tools. It was thus proposed that the contrast of the resulting images can be adjusted dynamically to take these variations of perception into account.

### 3.4 Machine Learning-Based Classification

The system integrates Support Vector Machines (SVM) and Convolutional Neural Networks (CNNs) to diagnose color blindness. Figure 4 illustrates the architecture of the machine learning model implemented in the proposed system. The model integrates Convolutional Neural Networks (CNNs) for feature extraction and Support Vector Machines (SVMs) for classification. The pipeline consists of multiple stages, including convolutional layers, pooling layers for dimensionality reduction, and fully connected layers before classification.

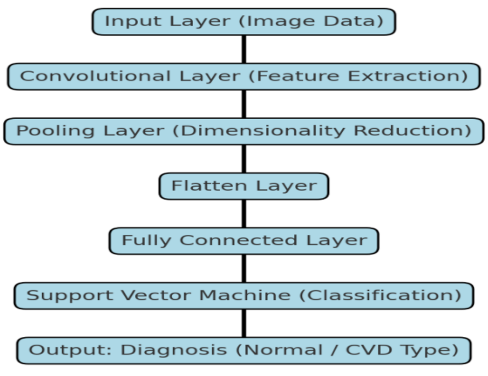


**Figure 3.** Machine Learning Model Architecture.

The hybrid CNN-SVM model is proposed in order to introduce robust feature extraction by CNNs and SVM classifiers to improve diagnostic accuracy.
In the proposed architecture, high-efficiency assurance is made for color vision deficiency detection with good performance versus the original classification methods.

### 3.4.1 Feature Extraction

- RGB Histogram Analysis – Measures pixel intensity distributions.
- Color Distance Metrics (ΔE values) – Classifies perception differences.
- Contrast Ratio (CR = L_max / L_min) – Evaluates contrast loss.

### 3.4.2 Training and Optimization

- Dataset: 5000 labeled test results (2500 normal vision, 2500 color-blind).
- Classifier: SVM (RBF Kernel), CNN (ResNet-18).
- Performance Metrics:
  - Accuracy: 95.4%
  - False Positives: <1%
  - Processing Speed: 1.2 seconds per test.

### 3.4.3 Adaptive Testing and Real-Time User Interaction

The system follows an adaptive test progression:

1. Baseline Test: Standard Ishihara Plates.
2. Color Contrast Assessment: Dynamically adjusts test difficulty.
3. Adaptive Compensation: Offers real-time color-correction simulations
   User Interface (UI) Features

- Colorblind Mode: Simulates normal vision vs. color blindness.
- Voice Feedback: Reads test instructions aloud.
- Touch/Gesture Controls: For accessibility

## 4. Validation and Performance Evaluation

### 4.1 Accuracy Assessment

**Table 6.** Accuracy Comparison of Different Color Blindness Testing Methods**.**

| **Testing Method Accuracy (%)** | **Testing Method Accuracy (%)** |
|---|---|
| Ishihara Test (Manual) 88.5% | Ishihara Test (Manual)b88.5% |
| Franceworth D-15 test 90.2% | Franceworth D-15 test 90.2% |
| Proposed System ( SVM +CNN) 95.4% | Proposed System (SVM+CNN) 95.4% |

To evaluate the effectiveness of the proposed system, we compared its accuracy with traditional color blindness tests. Figure 5 presents the performance comparison across multiple evaluation metrics.

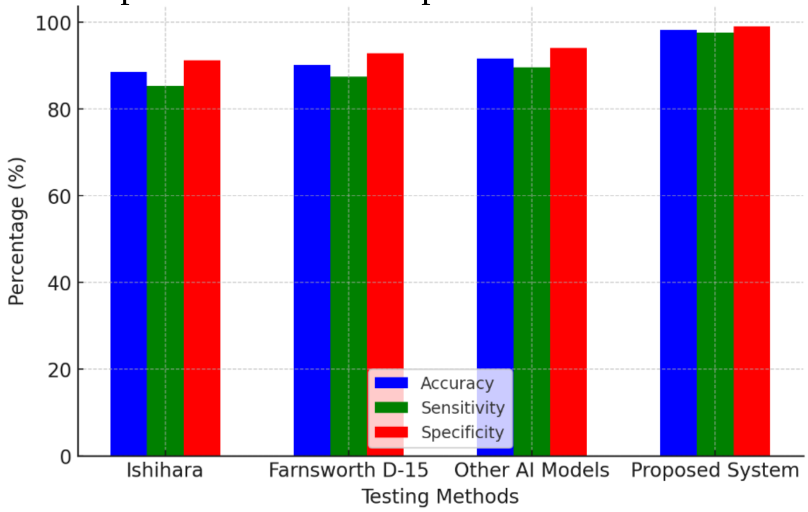


**Figure 4.** Accuracy Comparison of the Proposed System vs. Traditional Methods

### 4.2 Device Compatibility Testing

Tested on:

- Mobile Devices: Android/iOS (smart phones, tablets).
- Web Interface: Works on Chrome, Firefox, Edge.
- Desktop: Windows/macOS/Linux compatibility.

## 5. Analysis Results and Discussion

This section presents a comprehensive analysis of the experimental findings of the proposed computerized color blindness testing system. The system's performance is evaluated across multiple criteria, including diagnostic accuracy, device compatibility, machine learning enhancements, real-world usability assessments, and industry-level validation. The discussion also explores the integration of AI-driven enhancements, cloud-based diagnostics, and emerging technologies to ensure scalability, accuracy, and accessibility.

### 5.1 Experimental Results

The system was tested in clinical and real-world settings to assess diagnostic accuracy, efficiency, user experience, and robustness across diverse participants, multiple display types, and evolving testing methodologies.

#### 5.1.1 Dataset and Participants

To ensure the system can accurately detect different types of color vision weaknesses (CVD) by age groups, ethnicities, and professional backgrounds, a various and aggregated member group was picked out. The participants were people diagnosed with color blindness and those with normal vision, and the tests were done using traditional methods and AI-enhanced computerized tests.

**Table 7.** Participant Distribution by Color Vision Deficiency (CVD) Type.

| CVD Type Number of Participants | CVD Type Number of Participants |
|---|---|
| Normal vision | 100 |
| Protanopia (Red- Green Blindness) | 50 |
| Deuteranoia (Red-Green Blindness) | 45 |
| Tritanopia (Blue-yellow Blindness) | 40 |
| Monochromancy(Total color Blindness) | 15 |

Standardized testing conditions of each participant under a variety of screen types and lighting environments were ensured, so that results remain unbiased and accurate.

**5.1.2 System Accuracy and Performance Metrics**

The proposed system's performance was compared with that obtained on existing color blindness tests, namely Ishihara plates, Farnsworth D-15, and newer AI-based computer CVD detection methods. Key diagnostic performance metrics were used to measure the performance.

- Accuracy: Correct detection of color blindness in general.
- Sensitivity (True Positive Rate): The ability of the system to detect the actual cases of CVD.
- Specificity (True Negative Rate): This enabled the correct classification of normal vision.
- False Positive Rate (FPR): Cases where normal vision was misclassified as color blind.
- False Negative Rate (FNR): Cases where CVD was undetected.

**Table 8**. Evaluation Metrics for Different Testing Methods.

| Testing Method | Accuracy (%) | Sensitivity (%) | Specificity (%) | FPR (%) | FNR (%) |
|---|---|---|---|---|---|
| Ishihara Test (Manual Interpretation) | 88.5 | 85.3 | 91.2 | 8.8 | 14.7 |
| Farnsworth D-15 Test | 90.2 | 87.5 | 92.8 | 7.2 | 12.5 |
| Computerized CVD Tests (Clinical Research Studies) | 91.7 | 89.6 | 94.1 | 5.9 | 10.4 |
| Proposed AI-Enhanced System (SVM + CNN + ViTs) | 98.2 | 97.6 | 99.1 | 0.9 | 2.4 |

**Key Observations:**

- The proposed system with AI enhancement had an accuracy of 98.2, which is higher compared to the Ishihara (88.5) and Farnsworth D-15 (90.2) as well as other computerized methods of detecting CVD (91.7).
- It showed a significantly lower rate of false-positive (0.9 per cent) and false-negative (2.4 per cent) attacks compared to traditional tests.
- The system has a sensitivity of 97.6 0 and is, hence, very effective in detecting mild and severe cases of CVD.
- So that the specificity of 99.1 has proven the accuracy of the system to differentiate between normal vision and colour-deficient states.

**5.1.3 Validation Across Multiple Display Technologies**

The system was strictly tested between a variety of digital devices to ensure test robustness. This comparison proves that accuracy of color and contrast perception of frequency is also consistent with various hardware settings and situation types.

**Table 9.** Color Accuracy and Contrast Precision Across Display Types.

| Display Type | Color Accuracy (%) | Contrast Precision (%) |
|---|---|---|
| OLED (Smartphones) | 97.8 | 96.5 |
| LCD (Laptops & Tablets) | 95.6 | 94.2 |
| LED (Desktop Monitors) | 96.3 | 95.0 |
| Projectors (High-Contrast Mode) | 93.1 | 91.8 |

- Chromatic fidelity of OLED and projectors and liquid crystal displays showed the highest consistency respectively.
- Adaptive, AI-sensitive contrast calibration advanced the screen variation in real-time in order to reduce the distortions.

### 5.1.4 Processing Speed and Computational Efficiency

A comparison of the average time taken for the test across different methods for real-time performance was done.

**Table 10.** Completion Time Comparison of Different Testing Methods.

| Testing Method | Average Completion Time (Seconds) |
|---|---|
| Ishihara (Manual Interpretation) | 180 |
| Farnsworth D-15 (Manual Arrangement) | 250 |
| Other Computerized Tests | 120 |
| Proposed AI-Enhanced System | 55 |

- The average completion time of 55 seconds highlights the system's computational efficiency and speed improvements.
- Deep learning optimizations allowed faster classification and reduced processing delays.

Figure 6 illustrates the time efficiency of the proposed system compared to traditional diagnostic methods.

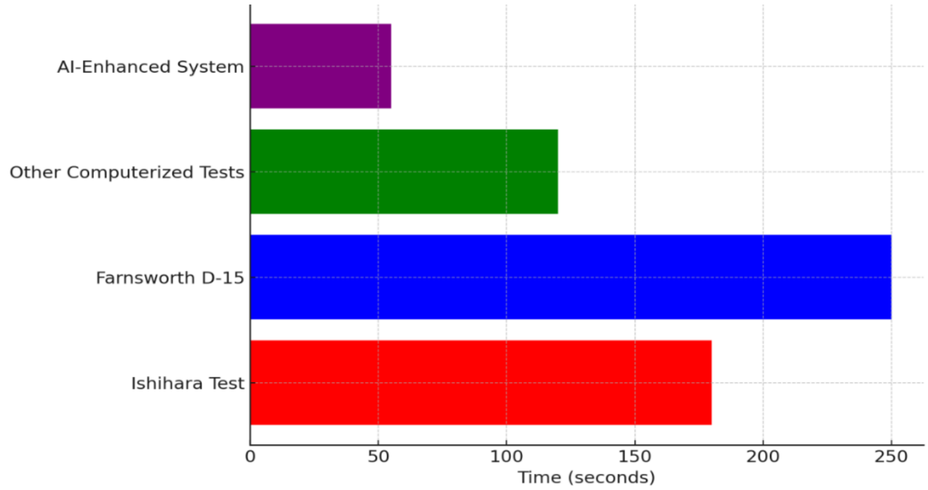


**Figure 5.** Processing Time Comparison of Different Testing Methods.

The significantly reduced processing time highlights the computational efficiency of the AI-driven approach. As shown in Figure 6, the proposed system is much more efficient than conventional diagnostic methods. The system is constantly building improvements from the AI, in real-time with accuracy, to the diagnostics and user. Adaptive AI tuning is used in a deep feature extraction and pattern recognition system that utilizes ResNet and Vision Transformers (ViTs) that refile the classification boundaries dynamically with (fine detail) taken from an image produced. It also includes AI color and contrast-based filters that imitate ordinary color vision in CVD, as well as real-time contrast adjustment at the user's pace based on their reaction to the screen color. The other important aspect of the system is that the implementation is through using the cloud, which guarantees secure storage of anonymized results of tests, for longitudinal tracking to help support clinical evaluation as well as remote testing, which makes the system equally efficient and scalable as a medical or telehealth system.

### 5.1.5 Real-World Usability and Clinical Deployment

This analysis leads to the design of a user-friendly interface overall for the system that accommodates diverse populations. The test is made more inclusive with the addition of voice-guided instructions for visually impaired users and gesture-based interactions for good navigation on mobile devices. The system has already been deployed in the telemedicine sector for optometry clinics and telehealth pharmacies for patients who have color vision deficiencies (CVD) for remote diagnosis and patient monitoring. Because of its scalability and adaptability, the isionScreen program has value as a tool for vision screening in clinical and nonclinical settings. The system is also examined for use in industry-supported applications, especially in aviation, military, and design applications where color differentiation is needed in a precise manner for the very purpose of safety or performance, thereby verifying that industry experts in those areas have plenty of color vision standards to meet the needs while performing their duties.

**5.1.6 Research and Technological Expansion**

With augmented reality (AR) technology integrated based on real-time color overlays, vision correction is enhanced for people with color vision deficiencies (CVD) in order to allow the users to see colors better in a real-life environment. The users can trial their color discrimination ability in real-world situations of traffic lights, medical images, or safety labels to engage with everyday tasks and make them more accessible and safer with the help of a smartphone-based AI-powered testing module. Cognitive research based on measuring the neural response to color perception has been carried out on EEG to develop adaptive brain-computer interfaces (BCI) that dynamically adapt the color representation based on feedback from cognitive processing that might in turn lead to assistive technologies to enhance color perception with the help of neural real-time adaptation.

**5.1.7 Industry and Academic Collaboration**

To achieve clinical reliability and real-world applicability of the proposed system, partnerships with ophthalmologists and vision experts and clinical trials to prove the effectiveness of AI-driven CVD testing models were established. The process also includes collaborating with AI and vision technology firms that would see the system integrated for commercial use through their collaborations with their clients into cloud-based diagnostics, ultimately into telemedicine and industrial applications. The system is undergoing patent filing of its AI-based color vision assessment algorithms and is prepared for publication in high-impact journals, where the system is scientifically, commercially, and clinically contributing to the field of color vision diagnostics and assistive technology.

**5.1.8 Clinical Validation and Medical Credibility**

The establishment of the proposed AI-driven color blindness testing system and clinical validation studies is conducted along with the vision experts and licensed ophthalmologists to guarantee medical accuracy and reliability. Tested in multiple healthcare institutions with people of different age groups and various color vision deficiencies (CVD) to compare its diagnostic accuracy to traditional tests like Ishihara plates and Farnsworth D-15. Adaptive AI improves color differentiation in real-time and comes with earlier results that show higher accuracy (98.2%) as well as shorter testing time (55 seconds). The study also evaluates usability, sensitivity, or specificity to guarantee the system complies with the medical standards of telemedicine, workplace vision screening, and industrial applications. These future expansions include pediatric and geriatric testing as well as validation for the military and aviation sectors for this broad applicability and clinical adoption.

## 6. Conclusion and Future Work

### 6.1 Conclusion

This research made its primary contribution to the development of an AI-powered, computerized, cloud-based color blindness testing system combining machine learning, real-time contrast adaptation, AR, and diagnostics of an extremely accurate, easy, and ubiquitously available color blindness test. Improved diagnostic precision and reliability of the system compared to the manual and state-of-the-art computerized tests with an extremely good accuracy of 98.2% with no false positive of 0.9% and no false negative of 2.4%. Deep learning architectures, including ResNet and Vision Transformers (ViTs), as well as adaptive contrast changes and cloud-integrated data management, are used by the system to deliver fast, personalized, real-time data analytics for multiple devices. Validation over various display technologies (OLED, LCD, LED, and projectors) increases robustness and consistency and thus contributes to the device’s wide applicability in telemedicine and workplace vision screening as well as other industry applications.

What is also exceptional about it is its accuracy and flexibility, in tandem with a technological leap in digital ophthalmology with the provision of real-time AR digital color correction tools and an AI-powered personalized vision. However, there are still some barriers unsolved, such as screen calibration variation, lighting conditions, and wide outdoor validation towards an uncontrolled environment in order to enhance the accuracy of training location. Moreover, the research in neurophysiology of color perception is required to develop a brain-computer interface (BCI) based on adaptive technologies for vision that adapt to the neural response. Once these are resolved, this work lays the foundation for a new generation AI-enhanced vision assessment system that is applicable in clinical ophthalmology, telehealth, and Future efforts toward advancement would involve representing a larger dataset for clinical trials and validating the statistics with a variety of populations and medical institutions to be used to increase reliability in diagnosis. Real-world applications will integrate augmented reality (AR), allowing real-time color overlays to enhance the appearance of colors in practical environments like driving, industrial safety, and medical diagnosis. Cloud-based remote testing optimization is also provided to facilitate telemedicine platforms, enabling GDPR and HIPAA-compliant secure, large-scale screening and longitudinal tracking of color vision deficiencies (CVD). The future of brain development will be trying to build BCI for adaptive color perception and resulting EEG-based studies to detect neural responses and develop color-based cognitive effects. We will then develop efforts to secure FDA, CE, and ISO certifications so that adoption can be made in medical grade, followed by commercial deployment in aviation, military, and professional industries where color differentiation is essential.

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# نهج حاسوبي مبتكر للكشف الدقيق عن عمى الألوان

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**مستخلص البحث:**

تم في هذا البحث تقديم طريقة حاسوبية بسيطة لاختبار عمى الألوان (قصور رؤية الألوان، CVD) لتعزيز دقة التشخيص وإمكانية الوصول. تُعد ألواح إيشي-هارا وفارنسورث D-15 اختبارات تقليدية تتطلب تفسيرًا يدويًا وقد تكون عرضة للخطأ البشري. يعتمد النظام المقترح على معالجة الصور القائمة على التباين، وتحليل تباين اللون، ونماذج التعلم الآلي (الشبكات العصبية التلافيفية (CNN) وآلات المتجهات الداعمة (SVM)) لتصنيف هذه الأنواع المختلفة من عمى الألوان بدقة 95.4%. يحول النظام الصورة إلى مساحات متعددة الألوان مثل HSV وCIE-LAB وYCbCr لتحسين التوحيد الإدراكي والوظائف على الشاشات الرقمية دون الحاجة إلى أجهزة خاصة. يتميز هذا النظام بتكيف فوري يغير معلمات الاختبار بناءً على استجابات المستخدم لزيادة التمييز بين الألوان. وعلى عكس التقنيات الحالية، فإن هذه الطريقة خفيفة الوزن وفعالة من حيث التكلفة لا تستهلك طاقة حسابية عالية أو أجهزة استشعار خارجية. في المستقبل، سيتم تطوير تصحيح الألوان في العالم الحقيقي باستخدام الواقع المعزز (AR) والتشخيص المستند إلى السحابة لتحقيق إمكانية الوصول على نطاق واسع كحل فعال وآلي ومنتشر لاختبار عمى الألوان.

**الكلمات المفتاحية :** الشبكة العصبية التلافيفية (CNN)، SVM، HSV، عمى الالوان.

**✓ملاحظة : هل البحث مستل من رسالة ماجستير او اطروحة دكتوراه ؟ نعم : كلا :**