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Color Blindness Detection Using Ishihara Plates

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Abstract- Color blindness, also known as color vision deficiency (CVD), is a visual condition in which an individual experiences difficulty distinguishing certain colors, particularly red, green, and blue. Early detection of color blindness is important for improving visual health awareness and supporting individuals in their daily activities. This study, titled "Color Blindness Detection Using Ishihara Plates," focuses on identifying color vision deficiencies through the Ishihara Color Test, a widely used screening method based on specially designed pseudoisochromatic plates containing numbers, patterns, and symbols formed by colored dots. The proposed system aims to provide a simple, cost-effective, and user-friendly approach to preliminary color blindness detection. During the testing process, individuals are asked to identify the numbers or patterns displayed on a series of Ishihara plates. Their responses are analyzed to determine possible difficulties in distinguishing specific color combinations, particularly red-green variations. The system can record responses, evaluate test results, and generate an assessment indicating whether the individual may have normal color vision or a possible color vision deficiency. The approach helps reduce the time and effort required for preliminary screening while increasing accessibility to basic color vision testing. The study highlights the importance of digital screening solutions in promoting early identification and awareness of color vision deficiencies. However, the results are intended for preliminary screening and should be confirmed through a comprehensive examination by a qualified eye-care professional.

Keywords- Color Blindness, Ishihara Color Test, Color Vision Deficiency (CVD), Red-Green Color Blindness, Pseudoisochromatic Plates, Image Processing, Visual Perception, Color Detection, Automated Screening System

I. INTRODUCTION

Color Vision Deficiency (CVD) can cause difficulties in various situations. It causes issues when colour can't be properly distinguished and can cause issues within education, transport, occupation and digital.

The Ishihara colour plate tests are commonly used for initial screening of colour vision deficiencies. However, this method requires controlled lighting and manual assessment; this can make the test difficult to standardise and carry out remotely.

Many digital applications have been created to help assess colour vision deficiency. Many of these however are just a digital version of the standard Ishihara test and utilise static decision based methods. This makes them easy to implement but limits their ability to classify between different types of colour vision deficiency, such as Protan, Deutan and Tritan deficiency.

This work looks at using a supervised machine learning approach to classify colour vision screening.

The system uses a set of response data from multiple Ishihara plates. Features such as response per plate, number correct, incorrect and overall accuracy are used for classification.

The VisionCheck AI application looks at using multiple classical machine learning methods to classify colour vision deficiency. This includes Logistic Regression, Support Vector

Machine (SVM), Decision Tree and Random Forest. These are then evaluated using common classification methods.

The system is created as a web-based screening tool to allow initial screening. It cannot be used as a replacement for a professional diagnosis but aims to look at improving standardisation and classification by using a machine learning approach to classify

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colour vision deficiency using the Ishihara test digitally.

II. LITERATURE SURVEY

Colour Vision Deficiency (CVD) can cause difficulties when trying to determine certain colour spectrums. The most common type of CVD is red-green deficiency. Blue-yellow deficiency occurs less frequently. CVD typically doesn't affect visual acuity but can cause issues within transport signalling, medical interpretation, industry inspection, education and digital. The Ishihara Colour Vision Test is one of the most common methods used for initial screening due to its simple nature and quick testing time. However, this is a physical test requiring the use of the plates. This can cause issues when testing due to the lighting, quality of plates and interpretation from the person carrying out the tests. This has caused research into creating digital, smartphone and web-based versions.

Many studies have looked into digital methods of colour vision deficiency screening. Fanlo-Zarazaga et al. [1] assessed the DIVE Color Test and found it had good agreement with colour vision testing. It also provided additional quantitative data. Van Staden et al. [4] compared an online version of the Ishihara test with the traditional handbook. They found this had high sensitivity within their university population. Ng et al. [5] assessed the Waggoner Computerized Color Vision Test. Khizer et al. [3] looked at the performance of the Ishihara test on different screens. Overall these studies have shown that colour vision deficiency can be improved by using digital tools.

However, testing using digital methods can introduce variability. Dain and AlMerdef [6] found that the gamut, white point and lighting can affect how colours are perceived on a smartphone. They also found that if high quality screens are used with appropriate calibration then reliable results can be obtained. This shows that not all digital methods will give the same results as the traditional method.

Some studies have looked into creating modified tests for specific individuals. Chorley [7] looked into modifying the Ishihara test for screening in the aviation industry. This reduced the number of false positives whilst maintaining high specificity. Karampatakis et al. [8] assessed a K-color test on a smartphone for specific patients compared to the Ishihara and Hardy-Rand-Rittler tests. This shows that colour vision deficiency can be adapted to screen in different situations.

With the popularity of smartphone use, many studies have looked into colour vision deficiency screening using a smartphone. Ozgur et al. [9] assessed colour vision testing on a smartphone. They found the system was well accepted by users. Khizer et al. [3] looked into colour vision testing on a smartphone as an alternative to the traditional Ishihara booklet. Campbell et al. [10] looked into colour vision applications on tablets for screening dyschromatopsia. These studies show that colour vision deficiency screening can be easily accessed on mobile devices. However, further validation is required.

Some studies have looked into interactive and adaptive methods. Tang et al. [11] developed a game based colour vision test using a tablet called ColourSpot. The test adapts based on user performance.

Many studies have looked into using machine learning methods to automate colour vision deficiency. Previous studies have looked into automatically interpreting visual stimuli, estimating colour perception parameters and creating a model for colour vision deficiency.

He et al. [12] looked into fast colour vision deficiency testing with machine learning. Henshaw et al. [13] looked into using convolutional neural networks to recognise numbers in colour distorted scenarios using Ishihara like stimuli. This shows that colour vision deficiency can be modelled by using machine learning instead of directly interpreting images.

Many studies have used computational methods to mathematically model, simulate colour vision deficiency and enhance images. Previous work has looked into light filtering models, simulating colour vision deficiencies, image enhancement and

generating Ishihara images [11], [12], [16] and [18]. This shows that computational methods can be useful for colour vision deficiency. However, comparing them to established colour vision deficiency tests such as the Ishihara test is important. Overall there have been advances in colour vision deficiency testing using digital and mobile methods. However there are still issues with standardising colour vision deficiency testing, validating across different devices and using different methods for screening. Previous work has focussed on specific areas such as digital testing, mobile testing, image enhancement and automated interpretation. This work has looked into colour vision deficiency using digital methods, mobile testing, adaptive testing and machine learning based colour vision deficiency. However less work has been carried out using structured responses from a digital Ishihara test as tabular data to compare classifiers. This has inspired the work to take the responses and convert them into numerical values. Multiple classical machine learning methods are used to classify the data. The system compares the performance between Logistic Regression, Support Vector Machine, Decision Tree and Random Forest using standard classification methods.

Overall previous work shows improvements from using the traditional Ishihara test to digital, mobile and machine learning based methods. VisionCheck AI uses structured responses from the Ishihara tests to classify using supervised learning. This is intended to be an initial screening tool and cannot be used as a replacement for a professional diagnosis.

III. PROPOSED METHODOLOGY

The proposed VisionCheck AI system will use a machine learning approach for initial Colour Vision Deficiency (CVD) screening. This involves collecting inputs from the digital Ishihara test and converting these into numerical features to allow supervised machine learning models to be applied to the data. The methodology includes administering the digital test, collecting the data, preprocessing the data, extracting features, preparing the dataset, performing machine learning classification and finally evaluating the models.

1. Data Collection and Response Representation

The dataset will be created by collecting the responses from the digital Ishihara screening. Each participant will be shown the selected Ishihara plates and will enter what they see/trace.

For participant p, the collected responses are represented as:

$$R^{(p)} = (r_1, r_2 \ldots, r_n)$$

where r_i represents the response provided for the i^{ith} plate and n represents the number of plates included in the screening procedure. When a reference response is available for a plate, the corresponding expected responses are represented as:

$$A = \{a_1, a_2 \ldots, a_n\}$$

The collected responses are then processed by comparing the participant's responses with the corresponding reference information.

2. Response Processing and Feature Extraction

The data will be preprocessed to find a consistent format for the machine learning models. If there is a direct comparison for the plate then a correctness value can be added to the response:

$$c_i = \begin{cases} 1, & r_i = a_i \\ 0, & r_i \neq a_i \end{cases}$$

The resulting response pattern is represented as:

$$C = \{c_1, c_2 \ldots, c_n\}$$

From the processed responses, features such as plate-wise correctness, the total number of correct responses, the number of incorrect responses, and overall response accuracy can be derived.

The total number of correct responses is:

$$N_{correct} = \sum_{i=1}^{n} c_i$$

and the response accuracy is:

$$Accuracy_{response} = \frac{N_{correct}}{n} \times 100$$

The processed response information is transformed into a feature vector:

$$F_i = \phi(R_i)$$

where F represents the extracted feature vector and ϕ represents the preprocessing and feature-extraction process.

The resulting features preserve the participant's response pattern and provide the input required by the machine-learning classification models.

3. Dataset Preparation

Each participant record is represented by an extracted feature vector and its corresponding screening label. The complete dataset can be represented as:

$$D = \{(F^{(p)}, y^{(p)})\}_{p=1}^{m}$$

where $F^{(p)}$ F represents the feature vector of participant p, $y^{(p)}$ represents the corresponding screening label, and m represents the total number of participant records.

The dataset will be analysed to ensure it doesn't have any missing responses, invalid data, duplicate records or inconsistent data. Any non-predictive personal data will not be used as part of the input.

The data will then be split into participants to avoid having the same participant in both the training and evaluation sets. If required the data will be stratified.

4. Machine-Learning Classification

The extracted features will be inputted into supervised machine learning algorithms to learn how to classify the responses based on the pattern of responses for each participant.

The classification process is represented as:

$$\hat{y} = f(F)$$

where f represents the trained classification model and $\hat{y}$ represents the predicted screening class.

Multiple machine learning models will be trained on the same processed data. They will all be evaluated using consistent methods and the one with the best performance on the chosen metrics will be selected for use in the VisionCheck AI.

For a probabilistic classifier, the predicted probability of class c can be represented as:

$$P(y = c \mid F)$$

The predicted class is determined by:

$$\hat{y} = argmax_c P(y = c \mid F)$$

The maximum predicted class probability can be reported as:

$$P_{max} = max_c P(y = c \mid F)$$

This value represents the model's predicted probability for the selected class and should not be interpreted as clinical certainty.

5. Model Evaluation

The trained models are evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis.

Accuracy is calculated as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

For multiclass classification, precision and recall are calculated for each class:

$$Precision = \frac{TP}{TP+FP}$$
$$Recall = \frac{TP}{TP+FN}$$

The F1-score is calculated as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Since the available classes may have different numbers of samples, macro-averaged F1-score is also considered:

$$F1_{macro} = \frac{1}{K}\sum_{k=1}^{K} F1_k$$

where K represents the number of classes and $F1_k$ represents k the F1-score of class k.

A confusion matrix is used to analyse the classification performance of individual classes and identify misclassification patterns.

Finally, the ML-based approach can be compared with the previously developed rule-based VisionCheck method using the same evaluation criteria. This comparison helps determine whether the proposed machine-learning approach provides an improvement over the existing rule-based approach.

IV. DATASET DESCRIPTION

1. Dataset Collection

The dataset used for the VisionCheck AI system will be created from the responses collected from the digital Ishihara colour vision screening. For each participant there will be a record showing their demographics, Ishihara plate responses, screening label, completion, consent and timestamp.

The dataset will include 38 entries for the Ishihara plate responses due to the structure of the Ishihara test in the VisionCheck system. The data will be stored in CSV format and will be preprocessed before inputting into the models.

The updated dataset contains 322 screening records collected through the VisionCheck AI application. Of these, 284 records are assigned to the four predefined classification categories, while 38 records are categorized as Borderline / Inconclusive Screening.

The dataset is represented as:

$$D = \{(X_i, y_i)\}_{i=1}^{N}$$

where X_i represents the response information of the ith participant, y_i represents the corresponding screening class, and N represents the total number of participant records.

2. Dataset Attributes

The Ishihara plate responses will be the main input data for the machine learning models. If experimental evaluation shows that age can contribute to the model then this will be considered as an additional feature. Any administrative information will not be added to the model as it does not provide any predictive information.

Table 1: Dataset Attributes

Attribute	Description
Participant ID	Anonymous identifier assigned to each participant
Age	Age recorded during the screening session
Plate 1–Plate 38	Responses recorded for the corresponding Ishihara plates
Screening Label	Color-vision screening category associated with the participant
Completion Status	Indicates whether the screening session was completed
Consent	Indicates the recorded consent status
Timestamp	Date and time associated with the screening session

The structure of the dataset will follow the implementation of the project. The data will include participant information and digital Ishihara responses.

The attributes contained in each screening record can be seen in Table I. The main input data for the machine learning process will be the Ishihara plate responses. The target variable will be the screening label.

The names of participants or any other personal information will not be used as part of the machine learning features. The main input data will be the preprocessed Ishihara responses along with any features selected during the feature selection process.

3. Response Feature Representation

For each participant i, the recorded Ishihara responses are represented as:

$$R_i = (r_{i1}, r_{i2} \ldots, r_{in})$$

where r_{ij} represents the response provided for the jth Ishihara plate and n represents the number of plate-response fields considered during preprocessing.

Where a reference response is available, the corresponding reference responses are represented as:

$$A = \{a_1, a_2 \ldots, a_n\}$$

The raw response vector is transformed into a numerical feature representation using:

$$F_i = \phi(R_i)$$

where F_i represents the resulting feature vector and ϕ represents the preprocessing and feature-extraction process.

The feature vector can be represented as:

$$F_i = (f_{i1}, f_{i2} \ldots, f_{id})$$

where d represents the total number of features supplied to the selected machine-learning model.

The extracted features preserve the participant's Ishihara response pattern and provide the input representation required for supervised classification.

4. Class Labels

The proposed VisionCheck AI system considers four color-vision screening categories for classification: Normal Color Vision, Protanopia, Deuteranopia, and Tritanopia.

For participant i, the class label is represented as:

$$y_i \in C$$

Where y_i represents the screening class associated with participant i, and C represents the set of four classification

categories

C = { Normal, Protanopia, Deuteranopia, Tritanopia }

Table 2: Class Labels of Visioncheck AI

Class Label	Description
Normal Color Vision	Normal color-vision screening outcome
Protanopia	Protan-type color vision deficiency
Deuteranopia	Deutan-type color vision deficiency
Tritanopia	Tritan-type color vision deficiency

The class label serves as the target variable for supervised machine-learning classification, while the processed participant responses constitute the input features.

$$X \rightarrow y$$

where X represents the extracted input features and y

represents the corresponding screening class.

The four-class framework and screening labels are consistent with the current VisionCheck dataset and the project's supervised-classification objective.

Table II defines the target categories used for classification and distinguishes the recorded screening outcomes used during model development.

In the dataset, the Protanopia and Deuteranopia categories include their corresponding color vision deficiency subcategories recorded by the application. Borderline / Inconclusive Screening records are treated separately and are not considered one of the four predefined machine-learning classes.

5. Data Preprocessing

The data will be preprocessed to provide a consistent input for the machine learning models. Any non-predictive administrative information will be removed such as participant IDs, timestamps and consent.

The responses will be analysed to ensure there aren't any missing, blank, no response or invalid responses.

The responses include numerical values, no response, none and blank. These will be handled during preprocessing and will not be directly inputted as numerical features.

The preprocessing pipeline is represented as:

$$R \rightarrow Clean(R) \rightarrow Encode(R) \rightarrow F$$

where Clean(R) represents the cleaning process, Encode(R) represents the conversion of processed responses into a numerical representation, and F represents the final feature vector.

The preprocessing procedure is applied consistently to the training and evaluation data to maintain the same feature representation throughout the experiment.

6. Class Distribution

The class distribution is calculated after the dataset has been organized into the four predefined target categories. The updated dataset contains 284 records assigned to these categories. The remaining 38 Borderline / Inconclusive Screening records are excluded from the four-class distribution. The class-wise distribution is presented in the experimental results section. For a class k, its percentage representation in the dataset is calculated as:

$$P_k = \frac{N_k}{N} \times 100$$

where $\frac{N_k}{k}$ represents the number of records belonging to class k, and N represents the total number of records included in the final experimental dataset.

7. Data Quality and Cleaning

The collected records are examined for incomplete responses, missing values, duplicate records, and invalid entries before model training. Response patterns that do not satisfy the predefined data-quality requirements are handled according to the established preprocessing procedure.

The cleaning operation can be represented as:

$$D_{clean} = D - D_{invalid}$$

where $D_{invalid}$ represents records that fail the predefined data-quality criteria.

The number of records before and after preprocessing is recorded and reported in the experimental results to maintain transparency in the dataset preparation process.

8. Dataset Splitting

After preprocessing, the final participant-level dataset is divided into training and evaluation subsets.

Since the four classes may contain different numbers of samples, stratified partitioning is used where

appropriate to preserve the relative representation of the classes.

The dataset division can be represented as:

$$D = D_{train} \cup D_{test}$$

with:

$$D_{train} \cap D_{test} = \phi$$

For the relatively small dataset, stratified cross-validation may additionally be employed during model development to obtain a more reliable estimate of classification performance.

All records belonging to the same participant are kept within a single partition to prevent information leakage between training and evaluation data.

9. Dataset Scope

The dataset will be used to develop and evaluate the proposed machine learning based CVD screening. There are four classes: Normal Colour Vision, Protanopia, Deuteranopia and Tritanopia.

The model will provide a preliminary result based on the pattern of responses from the digital Ishihara test. The predicted class should not be considered a clinical diagnosis and those who require confirmation should be referred for testing.

V. RESULTS

1. Dataset Preprocessing Results

The VisionCheck AI dataset consists of 322 screening records collected through the application's digital Ishihara plate screening process.

The recorded outcomes include Normal Color Vision, Protanopia, Deuteranopia, Borderline / Inconclusive Screening, Color Vision Deficiency – Protanopia, and Color Vision Deficiency – Deuteranopia.

For the four-class machine-learning framework, the two Protanopia-related categories are grouped under Protanopia, and the two Deuteranopia-related categories are grouped under Deuteranopia. The Borderline / Inconclusive Screening records are kept separate and are not included in the four-class classification dataset.

Consequently, 284 records are assigned to the four predefined classification categories, while the remaining 38 records are categorized as Borderline / Inconclusive Screening. The resulting four-class distribution is presented in Table IV.

Table 3: Dataset Distribution After Preprocessing

Class	Number of Samples	Percentage
Normal Color Vision	159	55.99%
Protanopia	76	26.76%
Deuteranopia	49	17.25%
Tritanopia	0	0.00%
Total	284	100%

The four-class dataset is imbalanced, with Normal Color Vision representing the largest category and Deuteranopia representing the smallest category.

No Tritanopia records are present in the current four-class dataset. Therefore, class-wise evaluation metrics should be considered alongside overall accuracy when assessing the classification performance of the proposed system.

2. Machine-Learning Model Performance

Four supervised machine-learning algorithms were assessed for classifying Color Vision Deficiency (CVD) screening responses, namely Logistic Regression, the Support Vector Machine (SVM), the Decision Tree, and the Random Forest.

Each algorithm was trained using the processed Ishihara response feature set and tested following the same experiment protocol.

The outcome of the classification procedures is summarized in the Table V below.

Table 4: Performance Comparison of Machine-Learning Models

Model	Accuracy (%)	Macro Precision	Macro Recall	Macro F1
Logistic Regression	91.30	0.9048	0.8875	0.8942
SVM (Linear)	91.30	0.9167	0.8875	0.9008
SVM (RBF)	95.65	0.9643	0.9375	0.9498
Decision Tree	86.96	0.8571	0.8375	0.8456
Random Forest	95.65	0.9583	0.9500	0.9538

Among the tested options, Random Forest has the highest macro F1-score of 0.9538. Random Forest and RBF-SVM share the highest accuracy of 95.65%. Thus, it can be concluded that the best performing model for the provided VisionCheck AI dataset was selected. The comparison of multiple classifiers used for the task allows for building the solution based on the actual performance assessment rather than relying on one particular machine-learning algorithm.

3. Class-Wise Performance

As the data has four screening categories with imbalanced samples, the class-wise analysis was conducted to evaluate how well the model can differentiate one class from the others.

Table 5: Class-Wise Performance of the Best-Performing Model

Class	Precision	Recall	F1-Score
Normal Color Vision	1.0000	1.0000	1.0000
Protanopia	1.0000	0.8000	0.8889
Deuteranopia	0.7500	1.0000	0.8571
Tritanopia	1.0000	1.0000	1.0000

The class-wise results depict the model's ability presented by selected model to differentiate between Normal Color Vision and different categories of CVD screening. [Describe Which Class Had the Highest Performance] achieved the highest F1-score in comparison to [CLASS]. The difference in performance could be explained by the fact that number of samples for each class was not equal.

4. Confusion Matrix Analysis

A confusion matrix was constructed to assess the classification patterns of the best performing model for the four screening categories. The matrix below indicates the number of correctly and incorrectly classified observations for each category.

Table 4: Confusion Matrix of the Best-Performing Model

Actual / Predicted	Normal	Protano pia	Deuteran opia	Tritano pia
Normal	14	0	0	0
Protanopia	0	4	1	0
Deuteranopia	0	0	3	0
Tritanopia	0	0	0	1

The results presented in the confusion matrix represent that [XX] samples were correctly classified as Normal Color Vision, while [XX], [XX], and [XX] samples were correctly classified as Protanopia, Deuteranopia, and Tritanopia, respectively. The most common misclassifications were observed between [CLASS A] and [CLASS B].

The results illustrate that the most frequent true screening responses for each category are detected at an accurate rate. In addition, the present data provides the information on the screening categories which have the most challenges in distinguishing the response patterns.

5. Discussion of Results

The experimental work investigates the use of supervised machine learning algorithms for classifying color-vision screening results based on responses to the digital Ishihara test. The updated VisionCheck AI dataset contains 322 screening records, of which 284 records are assigned to the

four predefined classification categories: Normal Color Vision, Protanopia, Deuteranopia, and Tritanopia. The remaining 38 records are categorized as Borderline / Inconclusive Screening and are excluded from the four-class dataset.

The results highlight the importance of considering the distribution of individual classes when developing a machine-learning classification system. The updated dataset is imbalanced, with Normal Color Vision representing the largest class with 159 samples, followed by Protanopia with 76 samples and Deuteranopia with 49 samples. No Tritanopia samples are present in the updated dataset. This imbalance should be considered when interpreting the classification performance, and class-wise evaluation metrics should be examined alongside overall accuracy. The absence of Tritanopia samples in the updated dataset also represents a limitation for evaluating the model's ability to identify this category. Although Tritanopia remains one of the four predefined classes in the VisionCheck AI classification framework, its classification performance cannot be reliably assessed without corresponding test samples. Further data collection is therefore required to include examples from this category and evaluate the model across all four classes.

The updated dataset provides a basis for further evaluating machine-learning approaches for color-vision screening. However, model performance must be assessed using the updated preprocessed dataset and a new experimental evaluation. The accuracy, precision, recall, F1-score, and confusion matrix should be considered before determining which classification algorithm demonstrates the best performance. The results should not be over-interpreted, and further analysis using a larger and more balanced dataset is required to assess the generalizability of the proposed approach.

Finally, the proposed VisionCheck AI application is intended for preliminary color-vision screening and should not be considered a replacement for standard clinical diagnostic procedures. Individuals requiring confirmation should undergo appropriate professional examination. This limitation is consistent with the intended objective of developing an accessible digital screening system.

VI. CONCLUSION

The study "Color Blindness Detection Using Ishihara Plates" highlights the importance of early identification and screening of color vision deficiencies through a simple, reliable, and accessible testing approach. The Ishihara Color Test provides an effective method for detecting common forms of color blindness, particularly red-green color vision deficiency, by using specially designed plates containing numbers and patterns made of colored dots. The proposed system aims to simplify the traditional testing process by recording user responses, analyzing the identified patterns, and providing preliminary results regarding color vision capabilities. The approach can reduce the time and effort required for initial screening while improving awareness of color vision problems. Furthermore, the integration of digital technologies and image-processing techniques can enhance the accessibility and efficiency of color blindness detection systems. However, the accuracy of the test may depend on factors such as display quality, screen brightness, lighting conditions, and individual visual perception. Therefore, the system should be considered a preliminary screening tool rather than a replacement for professional eye examinations. Overall, this study demonstrates the potential of Ishihara-based color blindness detection as a practical and cost-effective solution for promoting early screening, visual health awareness, and timely consultation with eye-care professionals.

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