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Color Identification System Based on Single Board Computer for Color Blind Individuals Using HSV and CLAHE

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***Abstract*— Color vision deficiency (CVD) affects approximately 8% of males and 0.5% of females globally, causing difficulties in distinguishing certain colors in daily activities. This condition often leads to social misunderstandings and psychological impacts, including embarrassment when identifying colors incorrectly. This research aims to design and implement a portable wearable system capable of automatically detecting and identifying colors to assist CVD individuals. The system utilizes computer vision technology with HSV (Hue, Saturation, Value) color space analysis combined with adaptive CLAHE (Contrast Limited Adaptive Histogram Equalization) and gamma correction preprocessing, implemented on a Raspberry Pi 4 Model B integrated into a jacket. A JETE W7 USB webcam captures images, and color detection results are conveyed through pre-recorded audio feedback via earphones. The system employs a 4-stage multi-stage detection algorithm with weighted scoring to handle HSV range overlapping among 12 target colors. Testing was conducted using color palettes and real-world objects under three lighting conditions: bright (1000-1100 lux), normal (90-100 lux), and dim (33-35 lux). Results demonstrate that the system achieved an overall accuracy of 86.39%, with 91.11% accuracy on color palettes and 81.67% on real objects. The system operates stably on Raspberry Pi 4 with average CPU usage of 35.7% and maintains thermal stability at 43.2°C. User testing with color-blind participants confirmed that the system effectively assists in color identification and increases user confidence in social situations.**

***Keywords*— Color detection; computer vision; HSV;CLAHE; color blindness.**

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I. INTRODUCTION

Color vision deficiency (CVD), commonly known as color blindness, is a condition that impairs the ability to distinguish certain colors. This condition is generally congenital due to genetic mutations inherited from generation to generation. Globally, CVD affects approximately 8% of males and 0.5% of females worldwide[1]. Besides genetic factors, color vision deficiency can also be triggered by eye injuries, chemical exposure, or drug side effects[2]. The severity depends on the type and number of dysfunctional cone cells in the retina, so the impact varies among individuals.

In the Indonesian context, the 2007 Basic Health Research (Riskesdas) conducted by the Ministry of Health of the Republic of Indonesia reported a prevalence of color blindness of 0.7% in the population (based on respondents' reports). Several provinces were recorded to have prevalence rates above the national figure, including Nanggroe Aceh Darussalam, West Sumatra, South Sumatra, Bangka Belitung, DKI Jakarta, and West Nusa Tenggara [3]. Although this data is quite old, it can serve as a general picture of the fact that color blindness also occurs in Indonesian society and warrants attention.

In daily life, CVD individuals face various challenges, especially in activities that require color identification, such as reading maps, choosing clothes, understanding color codes in documents or designs, and interpreting traffic signals. These difficulties not only affect their social lives but can also impact their professional careers. Professions that heavily depend on color perception, such as graphic design, electrical engineering, and medical fields (especially pathology or surgery), can pose challenges for individuals with color vision deficiency [4].

From a psychological perspective, CVD individuals often experience feelings of inferiority and lack of confidence, especially when facing social environments that do not understand their condition. Social stigma is also a challenge, where sufferers are often considered "careless" or "unable to recognize colors properly." This can make them reluctant to acknowledge their condition and even lead to discrimination in education and employment. According to a study from Psyence (2024), CVD individuals face psychological challenges in adapting to environments that rely on color as a form of visual communication. They often feel marginalized when having to depend on others' help to understand color-based information. This can increase stress and anxiety levels, especially in situations that require quick decision-making based on color perception [5].

According to an integrative review in "The Impacts of Abnormal Color Vision on People's Life," the impact of color blindness extends to social and economic aspects. Many sufferers face limitations in career choices, especially in fields that heavily depend on color perception, such as graphic design, medicine, electrical engineering, and jobs in creative industries. Some countries even have regulations that restrict individuals with color blindness from certain professions. As a result, many sufferers must seek alternative careers or develop compensation strategies to overcome their limitations [6].

Various solutions have been developed to help CVD individuals recognize and distinguish colors. One of the most well-known solutions is color blind glasses, such as EnChroma Glasses. These glasses are designed to improve color perception for red-green color blind individuals by filtering certain wavelengths so colors appear clearer. However, this solution has limitations: it is only effective for red-green color blindness and does not help blue-yellow color blindness or monochromats. Additionally, EnChroma glasses are relatively expensive, making them inaccessible to all sufferers [7].

Several studies have also been conducted to develop assistive devices for individuals with CVD. One of them is the research "Design and Build Color Detection Aid for Color Blind Sufferers with Voice Output Based on Internet of Things (IoT)," which developed a color detection device using the TCS3200 color sensor and NodeMCU ESP-8266 microcontroller. The TCS3200 sensor converts the intensity of incident light into frequency signals, which the microcontroller then processes to determine the color of the detected object. However, this solution remains limited, as it provides only basic color information without accounting for environmental factors that can affect color perception [8].

Artificial intelligence-based technology has also begun to be applied in color detection. One approach is to use Convolutional Neural Network (CNN) methods, such as YOLO (You Only Look Once), to recognize colors under various lighting conditions. This technology has been used in the research paper "Papaya Ripeness Detection Using YOLO Algorithm Based on Android," which demonstrates the potential of CNNs for object classification based on color [9]. However, deep learning approaches require powerful hardware and higher implementation costs.

Based on the identified problems and needs, this research aims to design and implement a solution that helps CVD individuals better recognize and understand colors in daily activities, without causing embarrassment or discomfort in social interactions. The developed solution is expected to accurately detect colors, provide intuitive, easy-to-understand feedback, and be designed with comfort, aesthetics, and visual conspicuousness in mind.

II. METHOD

This research addresses the need for an accessible and automated tool for early detection of color identification for color vision deficiency individuals. The purpose of this study is to design, build, and evaluate a portable detection system based on a Single-Board Computer (SBC) running computer vision algorithms. The system aims to automatically identify and classify 12 target colors from images captured in front of the user, providing immediate audio feedback.

A. System Design

The system architecture integrates a wearable jacket equipped with a camera for image capture, a central processing unit for color analysis, and audio output for conveying detection results. Figure1 illustrates the general system design where the jacket captures images from the environment, processes them to identify dominant colors, and delivers audio feedback to the user through earphones.

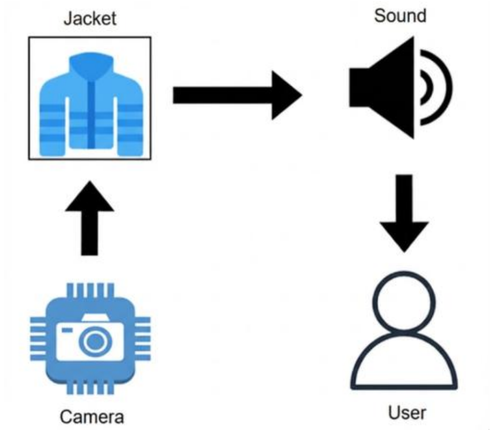

Figure 1. General system design

The hardware configuration (Figure 2) consists of a Raspberry Pi 4 Model B (4GB RAM variant) serving as the central processing unit. For image capture, a JETE W7 USB Webcam was selected after initial testing with the Waveshare Raspberry Pi Camera revealed color distortion, with purple dominance. The webcam provides accurate color capture without distortion and offers a flexible USB connection. A Baseus H17 wired headset with a 3.5mm jack provides audio output, and a Baseus Bipow Series 20000mAh powerbank supplies portable power with 5V/3A output to meet Raspberry Pi 4 requirements.

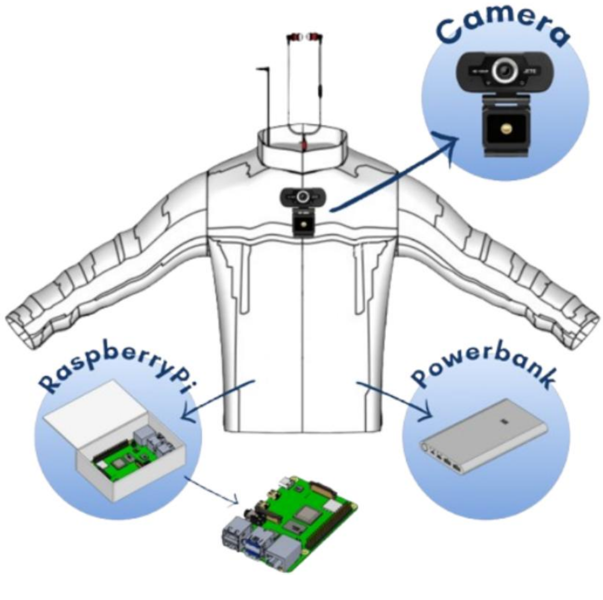

Figure. 2. Overall system design

Table I presents the system specifications designed to meet the functional requirements of the color identification system.

TABLE I
SYSTEM SPECIFICATIONS

Requirement	Specification
Image Capture	Minimum 720p camera, effective distance 30cm - 1m
Color Recognition	12 target colors (Red, Green, Blue, Teal, Brown, Purple, Pink, Orange, Yellow, Lime Green, Maroon, Olive Green), Accuracy ≥ 85%
Audio Output	TTS via 3.5mm jack to wired earphone (60-85 dB), delay < 2 seconds
Portable Power	Rechargeable power ≥ 10000mAh supporting 15W consumption for 6-8 hours

The software underwent several development iterations before reaching the final version. The initial implementation used a simple HSV-based approach without additional preprocessing. However, analysis of the color range definitions revealed fundamental weaknesses in the threshold logic, leading to significant overlap between colors and detection conflicts.

The final implementation integrates three main components: Adaptive CLAHE for contrast normalization, Gamma Correction for brightness normalization, and Multi-Stage Detection with weighted scoring to handle color overlap. Figure 3 shows the overall system flowchart.

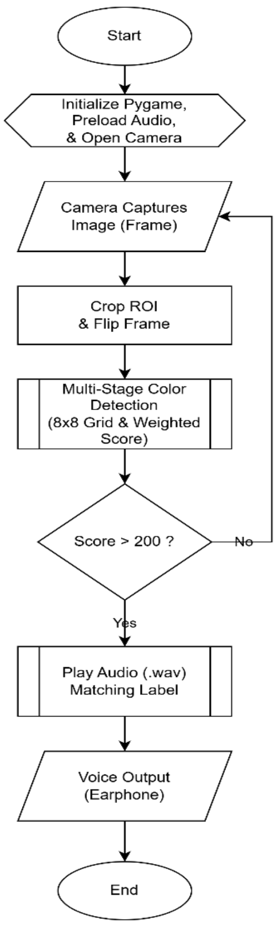

Figure 3. System flowchart

B. CLAHE and Gamma Correction Preprocessing

CLAHE (Contrast Limited Adaptive Histogram Equalization) is a contrast adjustment technique that works adaptively on small areas (tiles) of the image. Unlike standard histogram equalization that applies global transformation, CLAHE divides the image into small tiles and performs equalization locally on each tile. The clip limit parameter is used to limit contrast amplification so noise is not amplified, as in Figure 4.

The CLAHE implementation in this system is performed on the Luminance (L) channel of the LAB color space. The reason for choosing LAB over direct BGR or HSV is because the L channel represents brightness independently from color information (channels a and b). Thus, contrast adjustment does not change Hue and Saturation characteristics that are critical for color detection.

Gamma correction is applied as an advanced stage after CLAHE to normalize overall brightness. The gamma value is determined adaptively based on the mean brightness of CLAHE results: gamma < 1.0 to dim images that are too bright, and gamma > 1.0 to brighten images that are too dark. The gamma transformation follows the formula: output = input^(1/gamma) × 255.

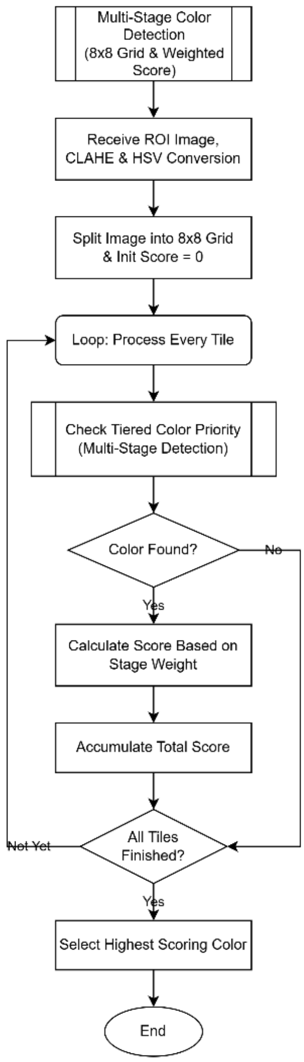

Figure 4. Color Detection Sub-process

C. HSV Color Space and Multi-Stage Detection

The HSV (Hue, Saturation, Value) color space was chosen for color detection because it separates color information (Hue) from intensity information (Value). This makes detection more robust to lighting variations compared to RGB color space. In OpenCV, Hue has a range of 0-180 (half of the standard 360°), Saturation 0-255, and Value 0-255.

HSV ranges for each color were calibrated using the JETE W7 camera. The calibration process was performed by taking HSV sample values from color palette references printed on Canon PRO-541, then determining lower and upper bounds with margins to accommodate variations. Table II shows the HSV configuration for 12 target colors.

Colors are grouped into four categories using OrderedDict from the collections module to ensure consistent checking order. This strategy addresses the overlap problem by ensuring more specific colors (subsets) are checked first before more general colors (supersets), as in Table III.

TABLE II
HSV CONFIGURATION FOR 12 TARGET COLORS

Color	Hue	Saturation	Value	Stage
Lime Green	40-56	50-160	140-255	1 (Special)
Brown	0-15	80-180	60-140	1 (Special)
Green	56-85	50-255	50-255	2 (Priority)
Red	0-8, 170-180	150-255	140-255	2 (Priority)
Yellow	20-35	100-255	100-255	2 (Priority)
Orange	15-22	120-255	140-255	2 (Priority)
Blue	100-130	100-255	50-255	3 (Secondary)
Teal	85-100	100-255	80-255	3 (Secondary)
Purple	130-160	50-255	50-255	3 (Secondary)
Maroon	0-10, 170-180	80-200	20-60	3 (Secondary)
Olive Green	35-50	40-150	40-140	3 (Secondary)
Pink	160-175	30-150	150-255	0/3 (LowSat)

TABLE III
THE CATEGORIES OF COLORS

Stage	Category	Weight	Reason
0	Low Saturation	1.2×	Bonus for special detection
1	Special Colors	2.5×	Strict threshold, more reliable
2	Priority Colors	1.5×	Common colors, medium threshold
3	Secondary Colors	1.0×	Fallback, needs many tiles

D. Region of Interest and Grid Analysis

Camera frames are cropped to a Region of Interest (ROI) of 60% of the center area. This cropping produces an analysis area of 384×288 pixels which is then divided into an 8×8 grid, producing 64 tiles with each tile size of 48×36 pixels. Each tile is analyzed independently using the detect color() function that implements multi-stage detection.

E. Audio Feedback Implementation

The audio feedback system was implemented using the Pygame library for playing preloaded WAV files at startup. This approach was chosen to replace Festival TTS used in the initial implementation because it produces more consistent sound quality. Audio files are stored in a specific folder with paths configured based on platform. Each color has one WAV file with lowercase naming convention without spaces.

To prevent annoying audio spam, the system implements a dual delay mechanism based on color change: 1.5 seconds delay for new colors (different from previous), and 4.5 seconds delay (3× longer) for the same color to avoid disturbing repetition. Only detections with scores ≥200 produce audio, filtering noise and unconfident detections.

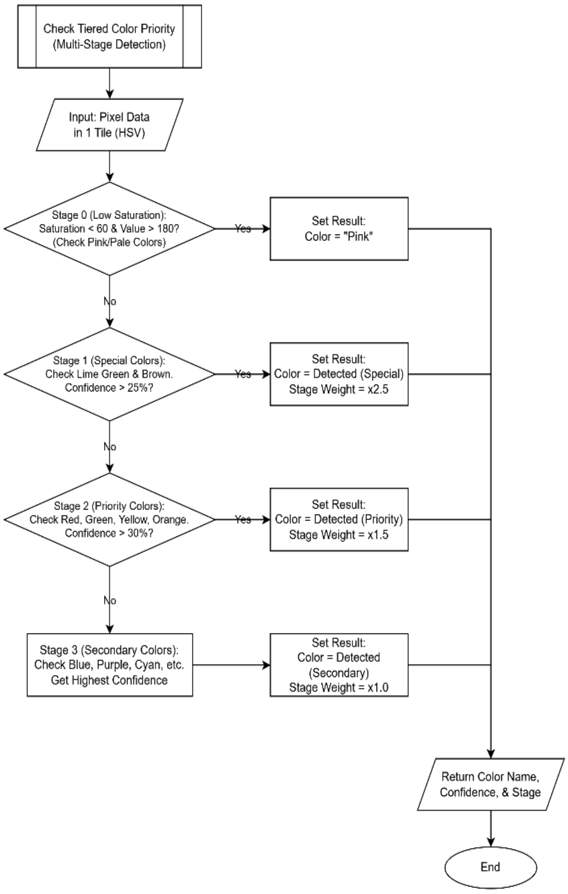

Figure 5. Multi-stage detection flowchart

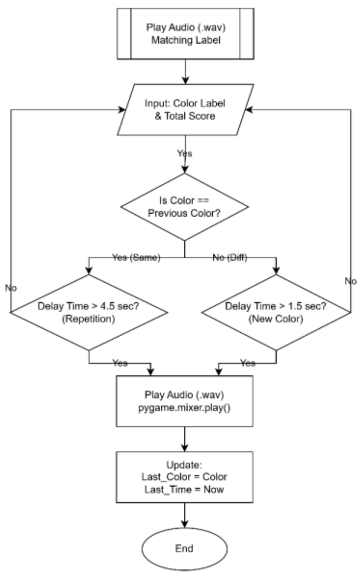

Figure 6. Audio playback logic flowchart

III. RESULT AND DISCUSSION

A. Hardware Implementation

The Raspberry Pi 4 is placed in the right inner pocket of the jacket, functioning as the core processing unit responsible for real-time image processing, color identification using HSV + CLAHE, and generating audio output based on detection results. The webcam is positioned at the center of the chest below the chin to capture images of the environment in front of the user. The powerbank is placed in the left inner pocket, providing stable power for the Raspberry Pi 4, as in Figure 7.

Figure 7. Hardware implementation

B. Image Capture Testing

This test aims to verify that the JETE W7 USB Webcam can capture clear object images at the specified distance. The camera must be able to produce images sharp and clean enough for the subsequent color detection process. Table IV presents the image capture test results.

TABLE IV
IMAGE CAPTURE TEST RESULTS

No	Object Size	Example	Distance	Result
1	Small (<10cm)	Eye drops box	30 cm	Object clearly visible
2	Small (<10cm)	Eye drops box	45 cm	Object visible but small
3	Small (<10cm)	Eye drops box	60 cm	Object visible but very small
4	Medium (10-20cm)	Tissue box	30 cm	Object very clearly visible
5	Medium (10-20cm)	Tissue box	45 cm	Object clearly visible
6	Medium (10-20cm)	Tissue box	60 cm	Object visible but slightly small
7	Large (>20cm)	Clothing	30 cm	Object very clearly visible
8	Large (>20cm)	Clothing	45 cm	Object clearly visible
9	Large (>20cm)	Clothing	60 cm	Object clearly visible

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Based on test results, the JETE W7 USB Webcam proved reliable in capturing object visuals at the effective distance range of 30-60 cm for small, medium, and large object categories. Analysis shows that large and medium dimensional objects have consistent visibility at all distance variations, while small objects (<10 cm) are most optimally detected at 30 cm distance to maintain visual detail.

C. Color Palette Testing

Color palette testing was conducted by placing a physical color palette containing 12 target colors in front of the camera at optimal distance. The physical color palette was chosen because it has consistent colors and can be used as a standard reference to measure detection accuracy. Testing was conducted under three different lighting conditions *Bright Lighting Condition (1000-1100 lux)*

TABLE V
COLOR PALETTE TEST RESULTS - BRIGHT CONDITION (1000-1100 LUX)

No	Color	Tests	Correct	Detection Error	Accuracy
1	Red	10	10	-	100%
2	Green	10	10	-	100%
3	Blue	10	10	-	100%
4	Teal	10	10	-	100%
5	Brown	10	10	-	100%
6	Purple	10	3	Detected as Pink (7)	30%
7	Pink	10	10	-	100%
8	Orange	10	10	-	100%
9	Yellow	10	10	-	100%
10	Lime Green	10	10	-	100%
11	Maroon	10	9	Detected as Purple (1)	90%
12	Olive Green	10	10	-	100%
Total Accuracy					**93.33%**

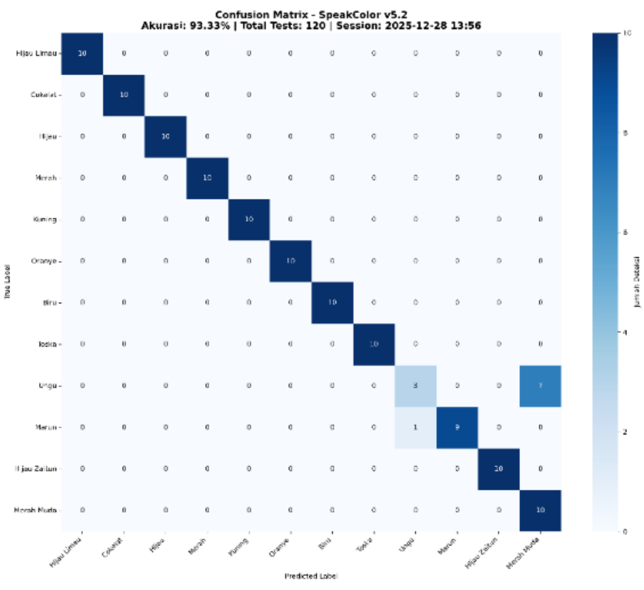

Figure 8. Confusion matrix - bright condition

Testing at high light intensity (1000-1100 lux) produced an overall accuracy of 93.33%, showing good system resilience to excessive light exposure. This stability is supported by the implementation of image preprocessing, including adaptive CLAHE and gamma correction, which maintains HSV value consistency. Significant detection errors occurred on Purple which was identified as Pink (7 cases), caused by Value parameter spikes due to bright light that forced Purple (wide Value range) to enter Pink's minimum Value threshold (150), this condition was exacerbated by the Hue range of both colors directly intersecting at value 160.

TABLE VI
COLOR PALETTE TEST RESULTS - NORMAL CONDITION (90-100 LUX)

No	Color	Tests	Correct	Detection Error	Accuracy
1	Red	10	10	-	100%
2	Green	10	10	-	100%
3	Blue	10	10	-	100%
4	Teal	10	10	-	100%
5	Brown	10	10	-	100%
6	Purple	10	10	-	100%
7	Pink	10	10	-	100%

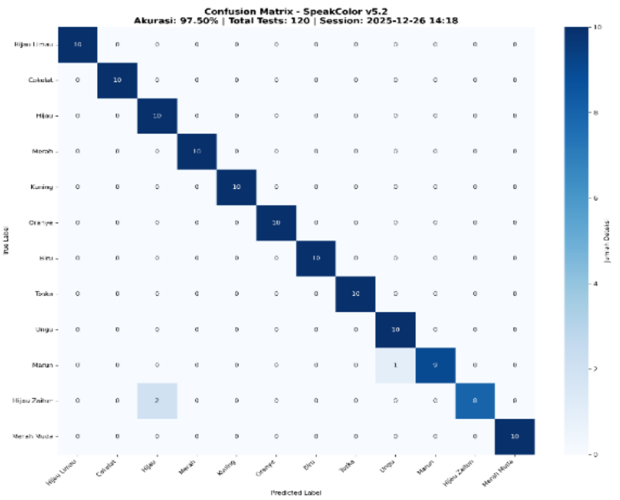

Figure 9. Confusion matrix - normal condition

Testing at 90-100 lux light intensity recorded the highest accuracy of 97.50%, (Table VI and Figure 9) confirming this condition as the most optimal operating environment for the system. The effectiveness of the 4-stage color detection algorithm proved significant, especially through weighting mechanisms at Stage 1 (2.5x) and Stage 2 (1.5x) which successfully differentiated colors with similar HSV characteristics.

TABLE 7
COLOR PALETTE TEST RESULT - DIM CONDITION (33-35)

No	Color	Tests	Correct	Detection Error	Accuracy
1	Red	10	10	-	100%
2	Green	10	10	-	100%
3	Blue	10	10	-	100%
4	Teal	10	10	-	100%
5	Brown	10	10	-	100%
6	Purple	10	10	-	100%
7	Pink	10	8	Detected as Purple (2)	80%
8	Orange	10	10	-	100%
9	Yellow	10	10	-	100%
10	Lime Green	10	0	Detected as Green (10)	0%
11	Maroon	10	3	Detected as Purple (7)	30%
12	Olive Green	10	8	Detected as Green (2)	80%
Total Accuracy					**82.50%**

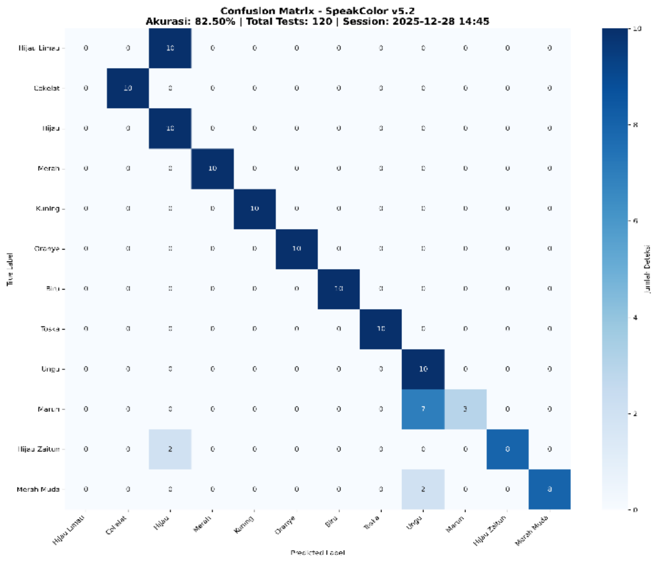

Figure 10. Confusion matrix - dim condition

Testing under dim lighting conditions (33-35 lux) produced an accuracy of 82.50%. This result still shows quite good system capability considering the heavy challenges in minimal light environments. This accuracy decrease is a normal phenomenon in computer vision systems, where low light intensity causes Value and Saturation values in HSV color space to decrease significantly, thus "masking" the unique characteristics of bright colors.

The confusion matrix analysis highlights very specific error patterns. The biggest error occurred on Lime Green color which was detected as Green in all experiments (100% error rate). This was caused by Lime Green characteristics that heavily depend on high Value (brightness) to be differentiated from its parent color. When lighting is dim, the object's Value drops below the Lime Green detection threshold, so the algorithm classifies it into Green which has a lower Value tolerance range.

D. Color Palette Test Summary

Based on recapitulation data from the three test scenarios, the system recorded detection performance with an overall average accuracy of 91.11%. This final value was obtained through arithmetic mean calculation of accuracy achievements in each lighting condition: (93.33% + 97.50% + 82.50%) / 3 = 91.11%. This aggregate figure significantly exceeds the minimum system specification target of 85%, validating that the developed color detection algorithm has high operational stability in various environmental conditions.

E. Real Object Testing

This test was conducted to validate the system's ability to detect colors on real objects that users will encounter in everyday life. Unlike physical color palettes that have solid and consistent colors, real objects have variations in texture, material, and color gradation that can affect detection results.

TABLE VIII
REAL OBJECT TEST RESULTS SUMMARY

Lighting Condition	Light Intensity	Accuracy	Major Errors
Bright	1000-1100 lux	83.33%	Orange→Red (100%)
Normal	90-100 lux	94.17%	Maroon→Purple (40%)
Dim	33-35 lux	67.50%	Orange→Brown (100%), Lime→Green (100%), Maroon→Purple (90%)
Average Accuracy		**81.67%**	

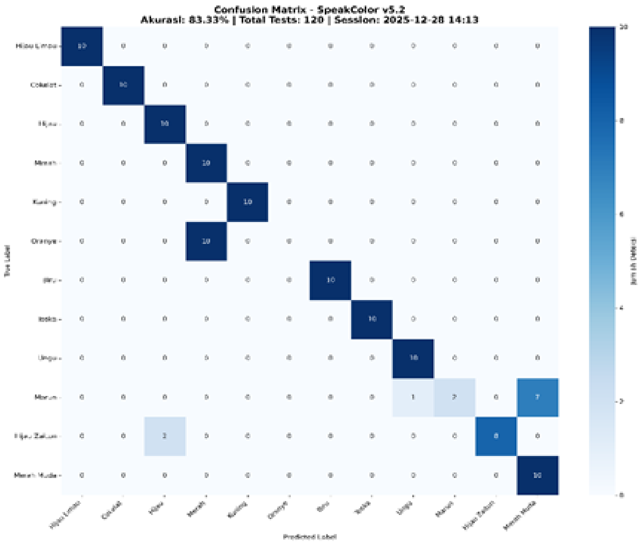

Figure 11. Confusion matrix real object - bright condition

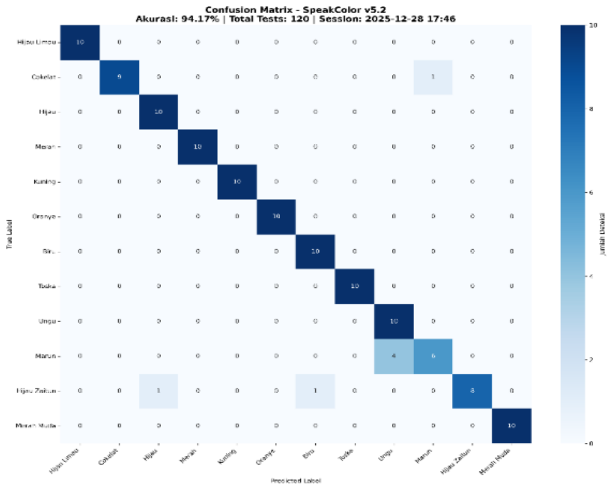

Figure 12. Confusion matrix real object - normal condition

This achievement shows a 9.44% performance decrease compared to physical palette testing (91.11%), indicating a significant impact of texture variation and reflectance of real object surfaces on system detection stability. Comparative analysis highlights that normal lighting is the most stable operating environment with only 3.33% accuracy decrease (to 94.17%). Conversely, bright lighting conditions experienced 10% degradation (to 83.33%) due to light reflection (glare) that shifted the orange spectrum to Red, while dim lighting conditions became the worst scenario with 15% decrease (to 67.50%) due to loss of color detail.

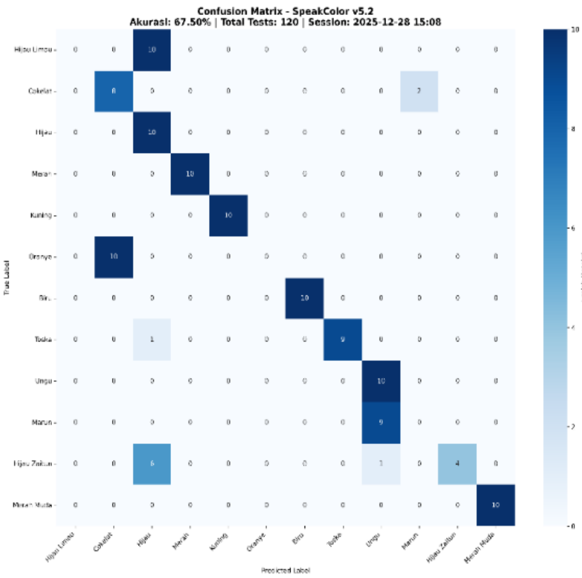

Figure 13. Confusion matrix real object - dim condition

F. Overall Color Detection Analysis

Testing was comprehensively conducted involving 720 experiments, evenly divided between physical color palette and real colored object methods across three lighting variations (bright, normal, dim). Based on aggregated data from both methods, the system achieved a total overall accuracy of 86.39%. This value was calculated based on the combined average performance: (91.11% + 81.67%) / 2 = 86.39%. This achievement indicates that the system successfully exceeded the minimum specification target (≥ 85%).

G. Audio Output Testing

This test aims to verify that the system can produce clear audio output through the headset. Testing includes sound loudness level and delay from when color is detected until sound is heard. Table IX presents the audio output test results.

TABLE IX
THE AUDIO OUTPUT TEST RESULTS

No	Color	Sound Level (dB)	Delay (seconds)	Clarity
1	Red	71	0.0251	Clear
2	Green	70	0.0233	Clear
3	Blue	72	0.0234	Clear
4	Teal	68	0.0242	Clear
5	Brown	71	0.0159	Clear
6	Purple	72	0.0182	Clear
7	Pink	70	0.0134	Clear
8	Orange	69	0.0217	Clear
9	Yellow	72	0.0209	Clear
10	Lime Green	73	0.0248	Clear
11	Maroon	69	0.0146	Clear
12	Olive Green	72	0.0286	Clear

H. Portable Power Testing

This test aims to verify that the Baseus Bipow Series 20000mAh powerbank can provide sufficient power to operate the system for a minimum of 6-8 hours of normal use. Table 10 presents the portable power test results.

TABLE X
REAL OBJECT TEST RESULTS SUMMARY

No	Parameter	Result	Description
1	Initial Powerbank Capacity	100%	Fully charged before testing
2	Start Time	13:54	System running
3	End Time	21:03	System turned off
4	Operation Duration	7 hours 9 minutes	More than 6 hours operation
5	Remaining Capacity	58%	Fifty-eight percent remaining
Test Status: [SUCCESS] Meets target ≥ 6 hours			

Based on test data, an estimate of additional operation duration can be made if the remaining 58% capacity is used until exhausted. With the same consumption pattern, where 42% capacity can operate the system for 7 hours 9 minutes, it can be calculated that each 1% powerbank capacity equals approximately 10.2 minutes of operation. Thus, the remaining 58% capacity is estimated to be able to operate the system for approximately 9 hours 55 minutes additional. Overall, if the powerbank is used from 100% condition until completely exhausted, the total system operation duration can reach approximately 17 hours 4 minutes. This figure far exceeds the minimum target of 6-8 hours set in the initial specifications.

I. System Performance

After the deployment stage was completed, system performance was monitored in real-time using an internal diagnostic module that utilized the psutil library and vcgencmd sensor. Operational monitoring results for 294 seconds showed that the system ran very stably with optimal resource efficiency. Average CPU usage was recorded at only 35.7% with a very safe working temperature of 43.2°C. In terms of responsiveness, the system was able to maintain a higher average frame rate of 16.1 FPS with constant RAM usage around 15.4% (approximately 600MB).

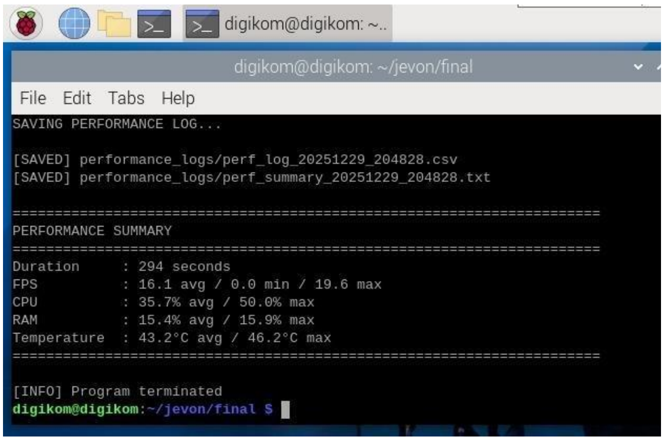

Figure 14. System performance monitoring

J. Direct User Testing with Color Blind Participants

This test aims to verify the effectiveness of the color identification system when used directly by target users. Testing involved participants who have been diagnosed with color vision deficiency, such as deuteranopia, protanopia, or tritanopia, to evaluate the extent to which the system can help them identify colors accurately.

TABLE XI
TEST PARTICIPANT DATA

No	Name/Initial	Age	Gender	CVD Type
1	Mahatir	21	Male	Red-Green
2	Sami	22	Male	Red-Green (Minor)
3	Rafi	22	Male	Red-Green (Minor)

Figure 15. Participant testing without system

Figure 16. Participant testing using system

TABLE XII
COLOR INDENTIFICATION TEST RESULTS SAMPLE

No	Participant (Initial)	Actual Color	Participant Answer	System Detection	Status
1	M	Maroon	Brown	Maroon	System Corrected
2	M	Teal	Pink	Teal	System Corrected
3	S	Teal	Gray	Teal	System Corrected
4	S	Yellow	Orange	Yellow	System Corrected
5	S	Maroon	Maroon	Purple	Lighting Issue
6	S	Pink	Pink	Purple	Lighting Issue

Based on data in Table XII, the system showed significant performance as a visual verifier in correcting participant color perception deficiency. For participant M, the system successfully corrected color perception on mixed spectrum, where Maroon objects that looked faded were perceived as "Brown", and Teal objects were incorrectly recognized as "Pink". In parallel, for participant Sami, the system also successfully corrected perception errors on bright and neutral colors, namely Teal objects that looked like "Gray" and Yellow objects that appeared as "Orange". In these four cases (samples 1-4), system intervention through audio feedback proved accurate in providing true color information.

However, result deviation was recorded in samples 5 and 6, where the system identified Maroon and Pink objects as Purple. Under lessthan optimal lighting conditions, the Value (brightness) on red-based objects (Maroon/Pink) experienced a drastic decrease that caused their spectrum characteristics to shift into the purple threshold range in HSV color space. This indicates that the system works very precisely following the mathematical color parameters received by the sensor, so physical light variations of the environment can affect real-time detection results

TABLE XIII
COLOR PAIR COMPARISON TEST RESULT

No	Participant (Initial)	Color Pair	Visual Perception	System Result	Conclusion
1	M	Teal vs Pink	Look Same/Similar	Detected Different	Helpful
2	S	Yellow vs Orange	Look Same	Detected Different	Helpful
3	S	Teal vs Pink	Look Different	Detected Different	Helpful

From the results of both tests (Identification and Pair Comparison), it can be analyzed that the system has a strategic dual role, namely as a corrective verifier on single color identification and as an ambiguity solver on color pair comparison. Test data from participants M and S confirm that the system can bridge the visual perception gap experienced by users. This is proven by the system's ability to provide accurate color labels on objects that visually appear wrong (like Brown that looks Red) or appear identical (like Teal and Pink) to participant vision.

K. User Feedback

Based on questionnaire results, participant responses showed positive correlation between device use and increased social courage. This was clearly seen in the answer to the psychological validation question: "Does this device make you more confident (not reluctant) to acknowledge your color blindness condition and use assistive devices in public?" All participants (100%) gave affirmative response "Yes, More Confident and Open". One participant, Sami (21 years), reinforced this with testimony that the device is very helpful because it changes his condition "from colors I don't know to knowing". This statement confirms that the device successfully provides certainty of information that has been a source of doubt and misunderstanding in communication.

Validation of solving shame problems was also supported by device ergonomic and aesthetic aspects. Participant M (22 years), who previously had very high level of doubt (scale 5) before using the device, gave positive reviews regarding the physical form of the system. He stated that the "jacket is quite comfortable and looks good as well as fits when worn". Although he noted that the device is slightly conspicuous, he explicitly affirmed that it "does not make me embarrassed". This data proves that the wearable design can be socially accepted and reduces stigma or user reluctance to wear assistive devices in public places.

IV. CONCLUSIONS

Based on the implementation and testing results conducted on the system, the following conclusions were obtained: The Grid Analysis and HSV Multi-Stage based color detection system has been proven capable of classifying colors well, with an overall average accuracy reaching 86.39%. This achievement has exceeded the established system specifications, namely minimum accuracy of greater than or equal to 85%. The total accuracy value was obtained from combining results of two test scenarios, consisting of 91.11% accuracy on Color Palette testing (ideal) and 81.67% on Real Object testing.

There is an accuracy difference between Color Palette and Real Object testing, where accuracy on real objects tends to be lower. This is caused by complexity factors of real object surfaces, material texture (fabric/plastic), presence of shadows due to wrinkles on clothing, as well as reflective material properties that cause Saturation and Value values in images to be non-uniform compared to flat surfaces on Color Palettes.

Direct testing results on partial colorblind participants showed significant impact on solving social problems (Complex Engineering Problem). All participants stated becoming more confident and open to acknowledge their condition in public, and felt their dependence on asking others was reduced after being assisted by audio feedback from the system.

System resource usage testing on Raspberry Pi 4 Model B showed that the system ran very stably with average CPU usage of 35.7% (Maximum 50.0%) and efficient memory (RAM) usage around 15.4%. The system was also able to maintain responsiveness with an average frame rate of 16.1 FPS, as well as maintaining operating temperature at an average of 43.2°C which is classified as very safe for long-term use on wearable devices.

For further development, it is realized that the main imperfection in the current computer vision-based color detection system lies in very high dependence on ambient light intensity. Although image preprocessing algorithms have been applied, optical physics limitations make system accuracy difficult to reach perfect point if lighting conditions are not ideal. Therefore, significant accuracy improvements in the future may be left to adoption of the latest camera sensor technology that has much higher High Dynamic Range (HDR) capabilities. In addition, transition of computation methods from Rule-Based (HSV) approach to Deep Learning can be considered so the system can understand object texture and shadow context more intelligently.

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