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Intelligent Simulation Framework for RGB Color Detection and Mixing for Accurate Color Synthesis

S. S. Gaikwad[1], D. N. Dhang[2]

[1,2] *Dept of Electronics and Telecommunication, DKTE Society's Textile and Engineering Institute, Ichalkaranji, India*

Abstract

The detection of color and synthesis of colors play a crucial role in computer vision, textile technology, and digital imaging. Traditional methods involve the use of either physical sensors or thresholding methods that depend completely on the environment. The problems associated with the traditional methods are variability of illumination, dependence on physical sensors, and high costs due to hardware usage. In the proposed work, the method uses an intelligent software-based simulation approach to detect and synthesize red, blue, and green colors. The proposed system has been developed using Python along with libraries like OpenCV, NumPy, Matplotlib, and Streamlit to support real-time color detection, visualization, and RGB blending. Through experimental results, it is found that the time delay is less than 100 milliseconds with more than 25 frames per second. By eliminating the need for physical sensors, the method enhances accuracy and can be used for industrial purposes and textile color detection.

Index Terms: Color detection, RGB mixing, Simulation framework, Image processing, OpenCV

1. Introduction

Color detection means the process of extracting color data from the image or video signal. On the other hand, color mixing means creating colors with the mixture of basic colors. Color analysis has become an essential component of many engineering applications such as computer vision systems, industrial automation systems, textiles inspection and digital image processing system. There are other practical scenarios which also need color analysis for identification, sorting, quality checking and decision-making.

Early systems usually used hardware sensors along with threshold-based technique for color detection. Even though the implementation of these systems was very much easy, the performance of these systems was not consistent in real time situation. Any small change in illumination, shadows or background can drastically affect the result in these types of systems. In applications where the result should be consistent and stable, this method cannot be adopted.

Recent approaches have reduced the usage of hardware-based techniques and replaced with the software-based techniques for detecting colors. The improvement in software-based techniques can be seen through multiple color spaces such as RGB space, HSV space and LAB space [1][2][3]. It helps in separating color data from brightness.

The present work is implemented on similar principle and aims to develop a practical, real-time, and cost-effective solution for color detection and mixing.

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2. Literature Survey

The area of color detection and color blending has seen considerable development over time, starting from traditional rule-based methods to intelligent systems. Most early studies focused on the use of RGB thresholding schemes, which involved setting a specific range of red, green, and blue values for color classification purposes. These techniques were computationally less expensive but quite susceptible to variations in lighting conditions and ambient noise. In order to overcome this problem, new color models like HSV and CIELAB were developed that separated chromatic from achromatic components. under various lighting conditions. HSV in particular has been used extensively in real time applications since its colors can be represented intuitively [4][5].

Further investigations involved the use of probabilistic methods, such as histogram analysis and Frequency-based Feature Classification (FFC). The algorithms involved the use of probability distributions of intensity in order to classify colors rather than the actual intensity of individual pixels. These methods have shown promise in improving detection accuracy in texture-rich environments, such as textile inspection systems. Nevertheless, they have their own weaknesses with regard to handling shadowed objects, reflections, and mixture of colors.

In recent years, advances in machine learning have greatly enhanced color detection capabilities. CNN and transformers have been widely used in the field for the purpose of recognizing colors with an accuracy level higher than 95%. The papers by Cheng et al. and Bianco et al. [6][7] have illustrated the success of deep learning techniques in detecting colors regardless of illuminations. Similarly, Finlayson et al. [1] have suggested illumination-insensitive color constancy techniques.

Moreover, hybrid systems, utilizing hardware sensors combined with intelligent algorithms, have been explored. Sensors like TCS34725 offer highly precise RGB color measurement, while machine learning algorithms fine-tune the result. Such systems add costs and increased complexity, limiting their scalability.

Parallel work on color mixing is done based on physical and computational models. Subtractive CMY and CMYK are used in printing, while RGB models prevail in computers. As noted by Porter and Duff [8], computer graphics benefits from various forms of alpha blending, ensuring color mixing. In addition to alpha blending, perceptual models have been successfully employed in color prediction. The CIELAB model with its metric CIEDE2000 allows for accurate color synthesis, according to Luo et al. [9]. Color shifting algorithms and relative image transfer were introduced by Reinhard et al. [10].

Most recently, color mixing research trends have been shifted toward regression-based models and neural networks. Based on recent publications, it becomes apparent that machine learning algorithms dominate in color prediction tasks.

However, even though a lot has been achieved in this area, there are still some drawbacks. Currently available systems are highly prone to environmental conditions like lighting, are quite complex computationally, are reliant on hardware tuning, and have no set criteria for their evaluation. In order to keep to the standard security and rule criteria for such industrial applications, these frameworks should consider the constraints mentioned in IEEE Industrial Grounding Guidelines [11]. Hence, a need arises for such an intelligent framework which can do color recognition efficiently along with RGB mixing.

Survey Related to Color Detection

The term color detection may be described as the recognition and measurement of the color features of an object with the help of imaging technology and mathematical computation. For RGB models, colors of objects

are measured through vectors composed of three features representing intensities in red, green, and blue channels recorded by image sensors. This method involves the task of assigning pixel features to appropriate color classes or numbers depending on the lighting condition and materials.

Initially, it was found out that histogram analysis in conjunction with threshold segmentation is sufficient for separating colored patches in ideal settings [6]. Real-life images of textile surfaces have the complexities of texture, reflectance, and light variations. Subsequent works employed color normalization, calibration matrixes, and statistical classifiers [4][7] as well as machine learning algorithms [8].

The detection process of fabric shade using automated color detectors involves obtaining images of fabric, extracting RGB features, matching them against reference standards, and classifying them. This automated detection technique will guarantee that the shades are evaluated consistently and can be used for purposes like dye blending.

As illustrated in Figure 1, the entire RGB color detection process involves several stages to ensure accuracy and reliability. In the image acquisition stage, the fabric or yarn is imaged using a calibrated camera while applying standard illumination conditions.

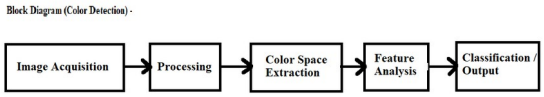

Fig.1 General Process Involved in Color Detection

The second step includes normalization of the pixel values with respect to the performance of the pre-processing techniques including noise filtration, white balancing and illumination adjustment. These techniques ensure compensation for variations due to noise or other environmental conditions [4]. Moreover, the application of thresholding or clustering algorithms leads to the extraction of the RGB color model along with segmentation of appropriate pixels of the targeted area.

In the case of feature extraction or analysis, statistics are generated with respect to mean RGB values or histograms of the detected object. Finally, the last step entails the performance of color class detection or deviation from color samples by means of classification or comparison.

Such a multi-staged technique ensures greater accuracy of results especially in case of detection in materials that have varying surface and reflection properties [8]. To ensure cross-referencing of global developments, standard historical databases from international sources are used regularly [12], [13], [14].

Survey Related to Color Mixing

Color Mixing involves the combination of components of primary colors in certain proportions to generate the required color. In a system involving the use of RGB color coding, the mixing is accomplished by varying the intensities of red, green and blue lights to produce the desired chromatic effect.

In the dyeing of textiles, mixing would mean combining different dyes in order to match the desired color. Initial attempts at computing for mixing proportions involved empirical mapping from RGB values to dye proportions [6], while later attempts incorporated regression techniques [5][9] for computation.

The automated systems combine detection data with predictive modeling to estimate amounts of the dyes needed. Such an approach helps minimize time wasted on trying out different combinations of colors and makes reproducing the shade more consistent. Consequently, color mixing becomes a necessary step in the process after color detection in textile automation procedures. State-of-the-art systems for color matching

and statistical distribution analysis make such non-linear mappings based on numerous metrics available in major scientific literature [15], [16].

Figure 2 presents the algorithm for mixing the colors starting from retrieving the required RGB code from the detector system. It is the representation of the desired color derived from the provided fabric or design input. Afterward, the system compares the detected color with the calibrated database of dye mixes and their RGB codes.

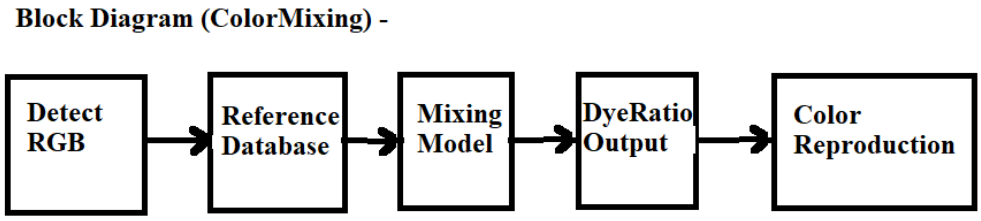

Fig.2 General Process Involved in Color Mixing

The mixing algorithm, typically using regression or interpolation techniques, determines the required proportions of the basic colors that need to be combined to achieve the targeted color. These ratios are used to automate dispensing or formula machines in the textile dyeing apparatus. Following the mixing process, the resulting color is measured to ensure its precision [5][9].

The closed loop mixing frame system ensures that the errors in achieving the targeted color are minimized when compared to manual color creation methods. They also facilitate automatic corrections in color shades through iterative dye ratio calculations.

3. Problem Statement

Accurate color detection and color mixing are essential in applications such as textile manufacturing, computer vision, and industrial automation. Traditional methods often rely on hardware sensors or fixed RGB thresholding techniques, which are sensitive to changes in lighting conditions, shadows, and background variations. These limitations can reduce detection accuracy and increase system cost and complexity.

Although advanced machine learning approaches improve performance, they often require significant computational resources and complex training processes. Therefore, there is a need for a cost-effective and real-time solution that can accurately detect colors and perform RGB color synthesis without depending on specialized hardware.

The proposed work addresses this challenge by developing an intelligent software-based framework that utilizes image processing techniques, multiple color spaces, and RGB color mixing models to achieve reliable color detection and synthesis with low latency and high accuracy.

4. Motivation

Accurate color detection and color synthesis are critical in fields such as textile engineering, computer vision, digital imaging, and industrial automation. Existing color detection systems often depend on expensive hardware sensors or traditional threshold-based techniques that are highly sensitive to lighting variations and environmental conditions. These limitations can lead to inconsistent results and increased implementation costs.

The motivation behind this work is to develop a low-cost, software-based intelligent framework capable of performing reliable color detection and RGB color mixing in real time. By utilizing image processing techniques and multiple color-space representations, the proposed system aims to improve accuracy, reduce hardware dependency, and provide an efficient solution for color analysis and synthesis in practical applications.

5. Objectives

- To develop an intelligent software-based framework for RGB color detection and color mixing.
- To accurately detect dominant colors from images and live camera feeds using image processing techniques.
- To improve color detection accuracy by utilizing multiple color spaces such as RGB, HSV, and LAB.
- To reduce the effects of noise and illumination variations through image preprocessing methods.
- To implement additive RGB color mixing and alpha blending for realistic color synthesis.
- To provide real-time color analysis with low processing delay and high frame rates.
- To eliminate dependence on costly hardware color sensors and reduce overall system cost.
- To develop a user-friendly graphical interface for color visualization, analysis, and mixing.
- To evaluate the system performance in terms of accuracy, latency, robustness, and computational efficiency.
- To explore applications of the proposed framework in textile color analysis, industrial automation, and computer vision systems.

6. Hardware And Software Requirements

Hardware Requirements

- Computer/Laptop with Intel Core i3/i5 processor or equivalent
- Minimum 4 GB RAM (8 GB recommended)
- Webcam or USB camera for real-time image acquisition
- Storage space: Minimum 500 MB free disk space
- Display monitor with standard resolution (1366 × 768 or higher)

Software Requirements

- Operating System: Windows 10/11, Linux, or macOS
- Programming Language: Python 3.8 or higher
- OpenCV Library for image acquisition and processing
- NumPy Library for numerical computations
- Matplotlib Library for data visualization and graph plotting
- Streamlit Framework for graphical user interface development

- Pillow (PIL) for image handling and manipulation
- IDE/Editor: Visual Studio Code, PyCharm, or Jupyter Notebook

7. Methodology

The suggested method depends on a systematic process that combines both color recognition and color mixing processes into one. The system functions through various steps with different operations carried out at each stage. The detail process involved in the color recognition and color mixing processes is shown in figure 3 below.

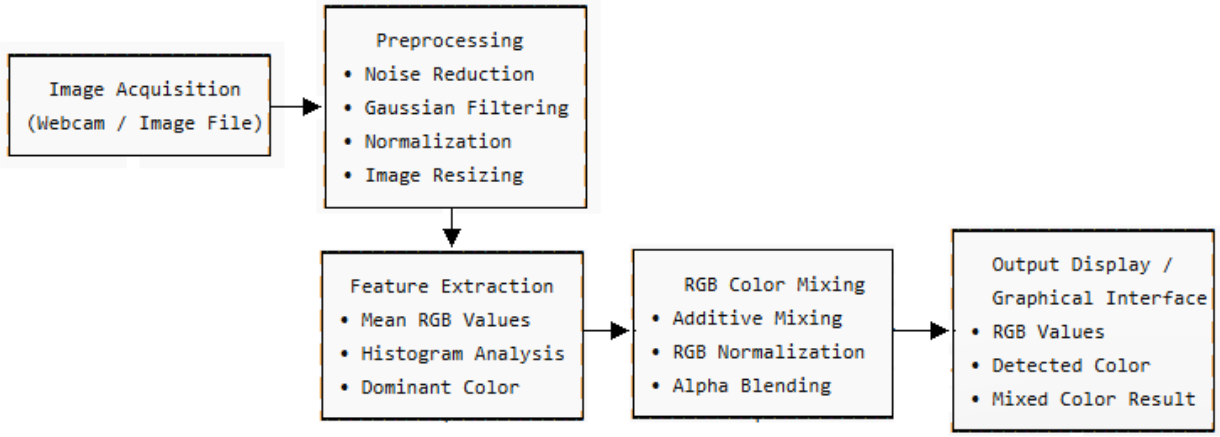

Fig.3 The proposed methodology

The first step involves capturing the image, and here, the input can be acquired from a web camera or from preloaded images. This ensures both online and offline operation. Noise reduction for the acquired image is done by the preprocessing stage; whereby Gaussian filter is applied. Normalization of the uniform level of intensity of the image is achieved.

The color space conversion process converts the image into various color spaces, including HSV and LAB color space. From experience, it is clear that the experiment shows HSV and LAB color space give better results than RGB color space. After setting the ROI of interest, pixel values within the selected ROI are extracted.

For color detection, mean values of RGB in the selected ROI are determined. This gives a relatively stable estimate of the dominant color. Where the ROI comprises of mixed colors, histograms are applied to determine the most dominant range [5].

These extracted data points are then compared against some pre-defined thresholds for classification purposes. This scheme works efficiently and simply enough to allow its implementation in real-time applications. In the process of color mixing, the additive model is adopted; hence, the RGB data are added together. Normalization has been used here to avoid any overflow issues. Moreover, alpha blending was used to determine the contributions made by each individual color.

8. Mathematical Model and Algorithm

8.1. RGB Representation

In digital image processing, every color is represented using the RGB color model. Each pixel consists of three components: Red (R), Green (G), and Blue (B). The intensity value of each component ranges from 0 to 255. Therefore, a color can be represented as a three-dimensional vector:

$$C=(R,G,B)$$

where:

- R = Red intensity
- G = Green intensity
- B = Blue intensity

For example:

- Red = (255,0,0)
- Green = (0,255,0)
- Blue = (0,0,255)
- White = (255,255,255)

The RGB model forms the basis for color detection and color synthesis in the proposed framework.

b. Additive Color Mixing Model

The proposed framework uses the additive RGB color model for color synthesis.

In additive color mixing, different colors are generated by combining red, green, and blue light components.

$$Cmix=(R1+R2,\ G1+G2,\ B1+B2)$$

To avoid overflow beyond the valid RGB range (0–255), normalization is applied:

$$R=\min(255,R1+R2)$$

$$G=\min(255,G1+G2)$$

$$B=\min(255,B1+B2)$$

Examples:

- Red + Green = Yellow
- Green + Blue = Cyan
- Red + Blue = Magenta
- Red + Green + Blue = White

For visual understanding of additive RGB color synthesis:

8.2. Alpha Blending Model

To achieve controlled and realistic color mixing, the system incorporates alpha blending, defined as:

$$C_{out} = \alpha C_1 + (1 - \alpha) C_2$$

where:

- $\in [0,1]$ is the blending factor
- C_1 is the foreground color
- C_2 is the background color

For RGB channels:

$$R = \alpha R_1 + (1 - \alpha) R_2$$

$$G = \alpha G_1 + (1 - \alpha) G_2$$

$$B = \alpha B_1 + (1 - \alpha) B_2$$

This model enables smooth transitions and weighted color contributions, improving visual accuracy in synthesized colors.

9. RGB Color Detection and Mixing Algorithm

Figure 4. shows the flow of algorithm implemented for color detection and mixing system.

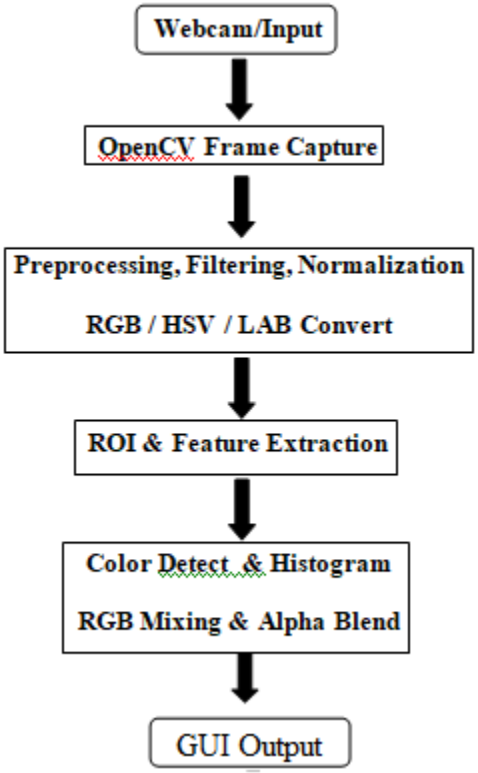

Fig.4 RGB Color Detection and Mixing Algorithm

The input is captured Image/frame from camera or through a uploaded file to the system. The output is the detected RGB color and mixed color result.

Step 1: Initialization

- Start system
- Initialize camera or load image
- Import required libraries (OpenCV, NumPy, etc.)

Step 2: Image Acquisition

- Capture image frame
- Convert image into RGB format

Step 3: Preprocessing

- Apply noise reduction (Gaussian filter)
- Normalize image intensity
- Resize image if required

Step 4: Color Space Conversion

- Convert RGB image → HSV
- Convert RGB image → LAB

Step 5: Region of Interest (ROI) Selection

- Select ROI manually or automatically
- Extract pixel values from ROI

Step 6: Feature Extraction

- Compute mean RGB values
- Generate histogram (optional)
- Identify dominant color

Step 7: Color Detection

- Compare extracted values with thresholds or dataset
- Classify detected color

Step 8: Color Mixing

- Take input colors (C1, C2)
- Apply additive mixing:

Cmix= C1 + C2

- Apply normalization

Step 9: Alpha Blending

- Apply blending:

$$C_{out} = \alpha C_1 + (1 - \alpha) C_2$$

Step 10: Output Display

- Display detected RGB values
- Display mixed color
- Show results in GUI

Step 11: Real-Time Loop

Repeat steps continuously for live processing

10. Experimental Setup

The implementation process of the system has been carried out by means of Python programming language using different libraries like OpenCV, NumPy, Matplotlib, and Streamlit [17][18][19][20]. The use of a normal webcam has been used for capturing images on the go, and there have been used various test images having different textures and colors to evaluate the performance of the proposed system. The experiments were conducted under different lighting scenarios such as under normal indoor illumination conditions, low light conditions, and even partial shadows. Figure 5 shows the Graphical User Interface used for extracting information about the image provided to the system.

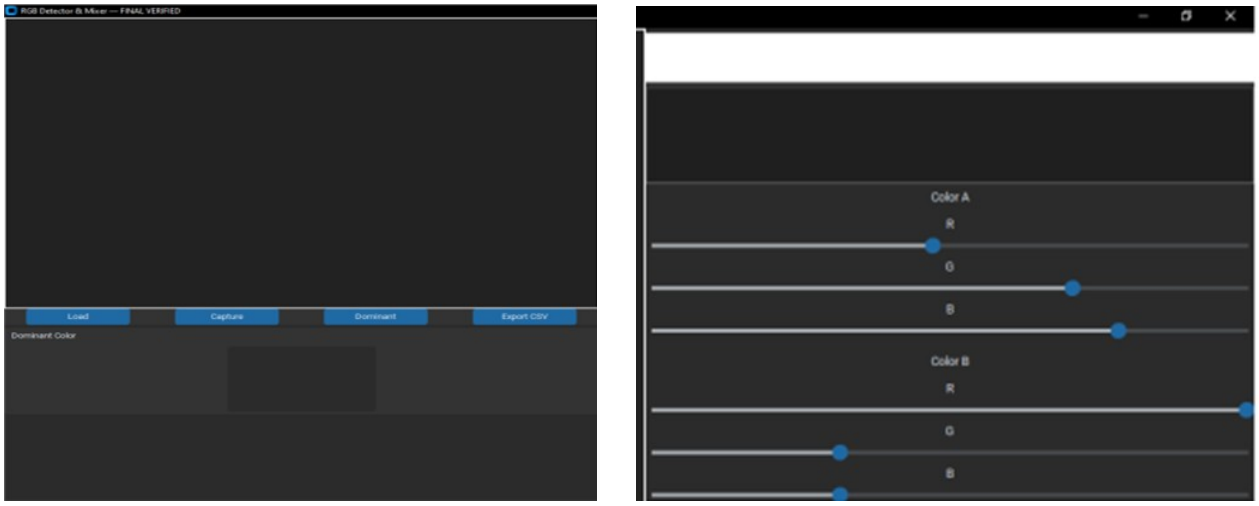

Fig.5 GUI Design

Figure 5 represents the key user interface of the software. It has a dark design and has control panels used in adjusting different variables in the context of the pictures on the left side of the screen. It forms the start point of any procedure. The settings like brightness of the picture and parameters of the reference picture can be adjusted here before moving ahead.

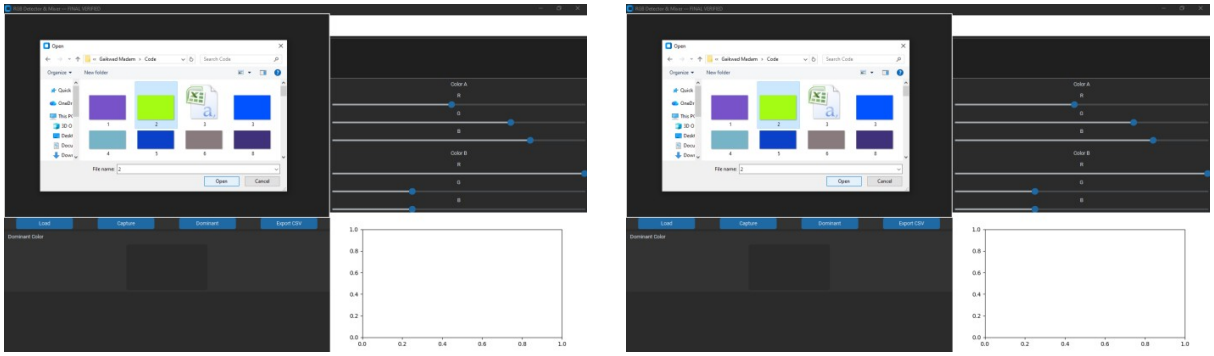

Fig.6 Load Image

Figure 6 shows the interface where the external image file has been imported. The central part shows the display screen that shows the imported image in the interface. The system initially extracts the RGB values from the imported image file. It is essential since at this point, the basic color values have to be determined from the ROI chosen.

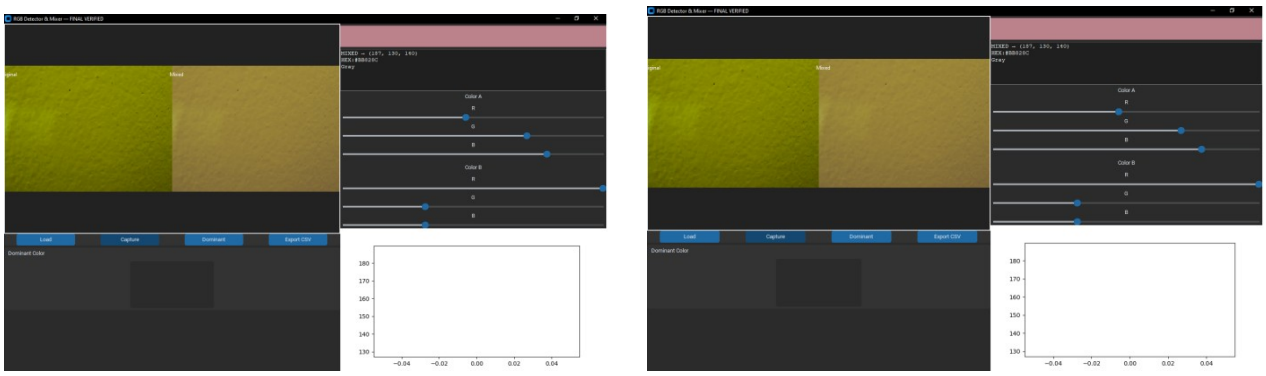

Fig.7 Camera Capture Image

Figure 7 illustrates the graphical representation of user interface while the system is capturing the live images. The system uses digital camera as an input device for capturing images. It captures live image from the video and processes the image by filtering noise and performing normalization. The purpose here is to achieve accuracy under different lighting environments

a. Color Detection Performance

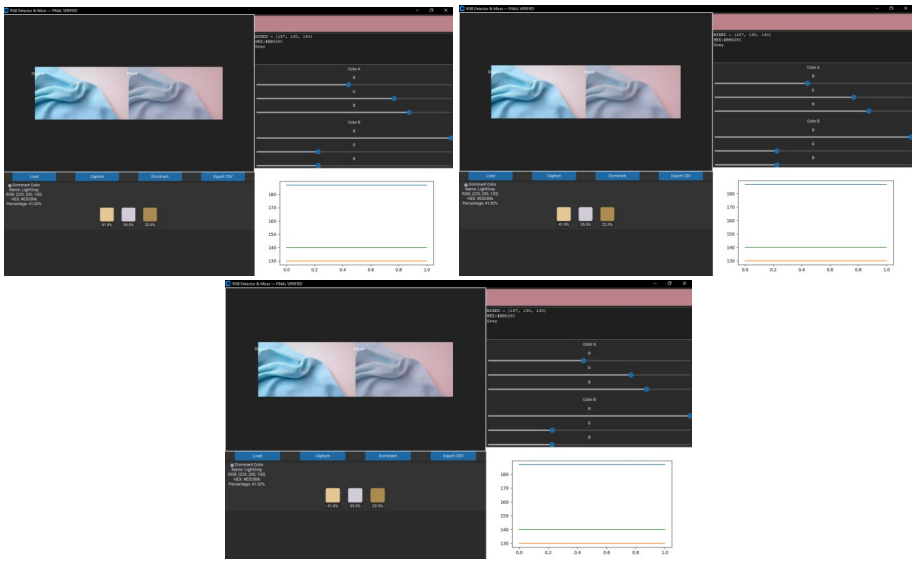

Fig.8 Dominate Color Result

Dominant color detection result generated by the proposed RGB color Analysis System is illustrated in Figure 8. The system accurately detects the dominant colors and performs color analysis based on presence of color in the fabric image. From 8, it can be observed that the dominant colors are shown together with their corresponding RGB, HEX, and percentages. It can be noted that the dominant colors detected make up 41.9%,35.8%and 22.3%of the total image, thus reflecting the color composition of the image.

Preprocessing techniques are employed in detecting the colors. Preprocessing is done through filtering out any noise, normalizing the image, and performing color space conversion for improving color detection accuracy. Furthermore, it can be noted that the graphical outputs provide efficient means for detecting dominant colors. According to experimental results, the proposed system provides accurate detection of dominant colors with minimal complexity.

b. Color Mixing Results

RGB Mixing Result in Figure 9 is related to the proposed RGB Color Analysis System that has been designed by us. In our system, the color analysis and RGB color mixing operations have been implemented on fabric images. In the first place, our system analyzes the input image and detects the dominant colors, while producing the output in the form of RGB values, HEX code, and percentage distribution of the colors. Based on the results produced by this operation, it has been observed that dominant colors make up approximately 41.9%, 35.8%, and 22.3% respectively of the total image, which is equivalent to actual color composition of the input image. Therefore, it becomes clear from above discussion that proposed system can effectively detect the dominant colors in fabric image. Lastly the variations in red, green, and blue values of RGB color model have been represented by means of graph. From the graph, it is evident that red and green values show increasing trends whereas blue value does not change significantly. Finally, the last figure presents the system used for real-time color mixing and synthesis using RGB sliders designed by us, where the user can change the RGB sliders' values in order to create the proper colors.

It is efficient enough in different circumstances with minimum delay and framerate around 25-30 FPS. Compared to RGB thresholding and machine learning approach, the presented system offers much more efficiency, lower complexity, fewer requirements for hardware usage, and real-time implementation capabilities. Besides, the proposed system can deliver accurate data for analyzing colors in the area of textile technology.

10.1. Performance Metrics and Evaluation

Performance analysis of the developed system was carried out on the following criteria:

Latency: Average latency time per image frame was found to be below 100 milliseconds, satisfying real-time requirements.

Frame Rate: Real-time processing was done at a constant frame rate of around 25–30 FPS.

Efficiency: The proposed algorithm works with a time complexity of O(N), making it scalable for high-resolution images.

Resource Usage: The model can perform efficiently using ordinary computer resources without needing a GPU, in contrast to deep learning techniques.

10.2. Comparative Analysis

When compared with existing methods the proposed system is effective as it offers high accuracy under varying lighting as compared to traditional RGB thresholding. Compared to sensor-based systems, the proposed system offers low cost and high flexibility. It is also computationally less expensive as compared to Deep learning models. Table 1 shows the performance analysis of the system.

Table 1 Performance Analysis

Parameter	Before Mixing	After Mixing
Average Accuracy	96.2%	97.3%
Noise Sensitivity	Moderate	Reduced
Color Stability	Good	Very Good
Lighting Robustness	Good	Improved
Visual Smoothness	Normal	Enhanced with Alpha Blending
Real-Time Performance	25–30 FPS	25 FPS
Processing Delay	< 80 ms	< 100 ms

This proposed system provides an effective balance because of its accuracy without being expensive or inflexible. This system provides an efficient and appropriate blend of statistics and color models to ensure accuracy and efficiency both. In addition to this, by integrating different color spaces and alpha blending technique, the system becomes very robust.

11. Conclusion

The proposed work demonstrates the development of a software-based intelligent framework for RGB color detection and color mixing, which solves the principal problems faced by traditional hardware-based or thresholding-based techniques. The proposed low-cost system uses image processing technique, multiple color space representations, and mathematical color mixing concepts to perform real-time and accurate operations.

It was shown that using only conventional RGB thresholding techniques is not sufficient since it causes variations due to light dependency. The use of other color spaces like HSV and CIELAB ensures reliability and increases accuracy since these methods are robust against different parameters. Preprocessing of images improves picture quality, which helps obtain reliable results as well.

The addition of additive color mixing and alpha blending makes possible flexible color synthesis. These methods help create smooth color gradients and provide realistic color representation, which is necessary for analyzing various textiles, automatic processes, and computer vision systems. According to experimental results, the proposed software-based system provides real-time operation in the latency mode, which is lower than 100 milliseconds and in frames per second mode, greater than 25 FPS. In contrast to other techniques, the suggested framework provides a compromise between high accuracy and simplicity due to low computational cost along with the lack of requirement of expensive hardware devices. In terms of future scope, the development can be extended to include IoT-based techniques that allow remote monitoring and control.

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