الجمهورية الجزائرية الديمقراطية الشعبية

People's Democratic Republic of Algeria

Ministry of Higher Education and Scientific Research

University of May 8 th , 1945 - Guelma -

Faculty of Mathematics, Computer Science and Material Sciences

Master's Thesis

Sector: IT

Option **:**SIQ

Theme

Towards an evolved color-light enhancement algorithm for low-light skin segmentation in a highly unstable lighting environment

presented by:

Khetatba Nardjis

N	Full Name	Quality
1	Ferkous Chokri	Chairman
2	Hallaci Samir	Supervisor
3	Kefali Abderrahmen	Examiner

Acknowledgment

Thank you, Allah, for providing me the capacity to think and write, the courage to hold into my convictions, and the perseverance to see my dreams through to completion.

I would like to express my profound gratitude to Dr. Samir Hallaci, my supervisor, for overseeing the completion of this task and for providing me with the best of his knowledge and assistance.

I also want to express my gratitude to the jury members for giving us the privilege of judging their work.

I want to express my gratitude to all of the IT department teachers especially Pr.Hamid Seridi and everyone else who helped to create this work.

Finally, I would like to thank my mother ,my father all my family, my friends, my colleagues from the university May 08, 1945 Guelma and the entire 2023 class of computing.

Dedication

To

My self

My family

My mother , my father, my sisters Benkirat Ines and my brothers, for their sacrifices, patience, love, and trust in me. They have done everything for my happiness and success. No dedication can express what I owe them; May God bless them with good health and a long life.

To

My friends

Abstract:

Detecting skin color and lights seems to be a very easy task that the brain can do with a very high level of accuracy and in the fundamental level of the vision system. In the opposite side, the machine is struggling to describe light and skin color and to find a compromise between the best color space reprentation and the optimum light enhancement method. So dealing with light have to be taken very seriously in the start of any vision system, since the most of confusion or misunderstanding are caused by ignoring light as the mean feature in color, shapes, textures and almost every object. Without light, we can't see, and incorrect description and/or treatment can lead to exponential degradation of results in detection, tracking, and recognition of objects. Several applications, such as face processing, computer-human interaction, human crowd surveillance, biometric, video surveillance, artificial intelligence and content-based image retrieval etc. All of these applications stated above, require skin detection, which is often simply considered as a preprocessing step, for obtaining the "object/face". In other words, many of the techniques are proposed for these applications assume that, the location of the skin is a simple task and pre-identified and available for the next step, but in the opposite skin tones are not easy to find especially in some complex conditions, one of the hardest problems to surpass is low-light Illumination because it's an important factor in determining the quality of images and also can have much effect on the evaluation. A wide variety of skin segmentatin methods have been proposed in recent years. However, most of them they don't take the low light problem seriously. And they assume that skin patches are readily available for treatment. We do not receive images with just skin or faces. We need a system, which can detect, locate and isolate them, so thzy can be given as input to deal with recognition systems, in real contexts with complex lighting environments and for a big variety of ethnic skin differences. we propose a new method for skin detection in a complex lighting environment, based on hybridaton of: first, Improved retinex light enhancement "Improved MultiSclae Retinex with Color Restoration (MSRCR-SCB), so the first is based on light compensation and the second is based on color amelioration", and second, multi-skin region detector based on the most famous color spaces (Ycbcr, RGB, HSV), and the choice is based on the robustness if each one in some situation. This enhancement or compensation of light consumes little computing time and conducts us to surpass a huge problem of chrominance and edges or even shapes that are deeply affected by the low light degradation, and the result is images to be used as an input in the recognition process, in order to improve the performance. This approach will be implemented and tested on a number of challenging low-light public databases (pratheepan/SFA/dark FACE/humanae/MASKcelebA...), and compared over several state-of-the-arts in terms of enhancement quality and efficiency and restore the natural colors into the images taken in real-world situations or darker lighting conditions.

Keywords: low-light enhancement, color restoration, MSRCR, skin detection, color space transformation.

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General Introduction

Skin detection is a vital component in numerous computer vision applications, including face detection, recognition, and tracking. However, accurately detecting skin in low light conditions presents a significant challenge due to limited contrast and color variations. In order to address this challenge, a two-stage system combining light enhancement using the Multi-Scale Retinex with Color Restoration (MSRCR) and Simplest Color Balance (SCB) algorithm, and a hybridization of color space segmentation has been proposed. This system aims to improve skin detection accuracy in low light environments.

The first stage of the system focuses on enhancing the low light images using the MSRCR algorithm. MSRCR is a widely used technique that enhances images by improving their contrast and SCB to deal with the color balance. By applying MSRCR-SCB, the system effectively improves the visibility of the skin regions in the input image, making them more distinguishable.

In the second stage, a hybridization approach is employed to segment the skin regions using multiple color spaces. To ensure accurate skin detection, the color space ranges are recalibrated using diverse datasets, such as the SFA and Pratheepane datasets. By recalculating the ranges on these datasets, the system aims to account for variations in skin color and lighting conditions, resulting in improved detection accuracy.

The hybridization process involves converting the enhanced image into different color spaces, such as RGB, YCbCr, and HSV. Thresholding techniques or range-based segmentation are then applied to each color space to identify potential skin regions. By incorporating recalibrated ranges, the system aims to better handle variations in skin appearance across different individuals and lighting conditions, leading to more accurate skin segmentation.

Furthermore, the system may employ additional post-processing techniques, such as morphological operations and noise removal, to refine the detected skin regions and minimize false positives or false negatives.

Through the refinement of color space ranges using recalibration on diverse datasets like SFA and Pratheepane, the proposed two-stage system aims to enhance the accuracy of skin detection in low light conditions. By improving the visibility of skin regions through MSRCR and incorporating recalibrated ranges, the system holds promise for a wide range of applications where accurate skin detection is crucial. These applications include biometrics, surveillance, and human-computer interaction.

In order to evaluate the effectiveness of our approach, we conducted experiments on three diverse datasets: CelebAHQ, DarkFace, and Humanae, in addition with the two first dataset SFA and Pratheepan. and an other Dataset LOL dataset was used to evaluate the light enhancement metrics.

During the evaluation process, we compare the performance of our approach against state-of-the-art skin detection methods, considering metrics such as accuracy, precision, and IoU. Additionally, we assess the computational efficiency of our method to ensure its practicality in real-world applications.

The results obtained from the evaluation on the SFA, Pratheepane, CelebAHQ, DarkFace, and Humanae datasets provide valuable insights into the effectiveness and robustness of our skin detection approach in low light conditions. By demonstrating superior performance compared to existing methods on these diverse datasets, our approach showcases its potential for various applications, including face analysis, image understanding, and human-computer interaction in challenging lighting environments. The thesis Organization: We chose to articulate our study in three main chapters:

- Chapter 01: skin detection and low light enhancement .
- Chapter 02: Conception .
- Chapter 03: Implementation and results .

we finished with a genreral conclusion.

Chapter 1

skin detection and low light enhancement.

1.1 introduction

skin detection in low light enhancement is a useful technique that can have many applications. In low light conditions, images can become grainy and lack detail, making it difficult to identify important features such as faces. By using skin detection, it becomes possible to enhance the skin tones in an image, thereby improving the overall quality of the image. Security systems can benefit from this technique by being able to better recognize faces in low light conditions, thereby improving their ability to detect and identify individuals. Medical imaging can also benefit from skin detection in low light enhancement by improving the accuracy of diagnoses for skin cancer .In digital photography, skin detection in low light enhancement can improve the quality of photos taken in low light conditions. By enhancing the skin tones, images can look brighter and more vibrant, with greater detail and clarity.

1.2 skin

1.2.1 Skin in biology[1]

skin is the largest organ of the body and is composed of multiple layers of tissue that cover and protect the underlying muscles, bones, and organs. The skin serves many functions, including protection against external physical, chemical, and biological hazards, regulation of

body temperature, and sensation of touch, pressure, and pain. The outermost layer of the skin, called the epidermis, is composed primarily of cells called keratinocytes, which produce a tough, protective protein called keratin. The epidermis also contains cells called melanocytes, which produce the pigment melanin that gives ***skin its color***.
In biology, as described in figure 1.1 the "skin tone" refers to the natural color or pigmentation of an individual's skin. It is determined by the amount and type of melanin. The distribution and quantity of melanin in the skin can vary among individuals due to genetic factors, environmental influences, and evolutionary adaptations.

Beneath the epidermis is the dermis, which contains blood vessels, nerves, hair follicles, and sweat glands. The dermis provides the skin with its elasticity and strength, and also affect somehow the skin tone color.

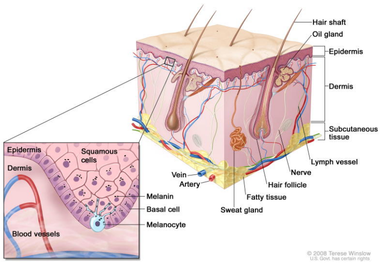


Figure 1.1: Anatomy of the Skin .

1.2.2 skin detection

Skin detection, is a computer vision or image processing technique used to identify and classify the skin tone or color in digital images or videos that correspond to human skin tones.

The relationship between skin in biology and skin tone detection lies in the fact that skin tone detection algorithms are designed to analyze and classify the variations in skin color observed in digital images or videos. These algorithms often rely on color analysis techniques and machine learning algorithms to determine the skin tone or color range present in an image.

Skin detection algorithms typically analyze the color and texture characteristics of a frame to identify areas that are likely to contain skin pixels. Skin detection has a wide range of applications, including in image and video processing, computer vision, and biometrics. It is commonly used in fields such as facial recognition, gesture recognition, and human-computer interaction, where accurate detection of skin regions is essential for identifying and tracking human features [3].

However, it is important to note that skin detection algorithms are not always accurate, and can be affected by factors such as lighting conditions, skin tone variability, and environmental factors. Therefore, it is important to carefully evaluate the performance and limitations of any skin detection algorithm before using it in a particular application.

1.2.3 Why skin detection ?

The majority of skin detection algorithms were designed for specific applications, and their evaluation is typically based on the total system efficiency rather than simply the skin detection component of the system. A crucial phase in the resolution of several picture problems is the detection of skin in an image, which is an important stage in many computer vision applications across many domains like [4]:

- detection of naked human bodies in an image.
- Face detection and recognition.
- skin cancer detection.
- tracking objects on image sequences while looking for hands or other visible organs.

The following applications make progress as a result of these issues being partially resolved:

- indexing images by content.
- searching for images on the web.
- web filtering, for example : report adult images.
- video segmentation.

1.2.4 Skin color detection difficulties

Human skin color can appear dramatically different in different image types and sources, which makes accurate skin detection difficult. The following elements contribute to the difficulties in skin detection[5]:

1. *Different ethnic groups (Race):* Because human racial groups differ physically, skin color appearance varies from person to person. For instance, the skin tones of Europeans (Caucasians), Africans, Asians, and others range from light to dark.

Figure 1.2: Ethnic diversity.

2. *Variations in lighting :*The most significant issue that significantly lowers segmentation performance in real-world situations is illumination variation. The distribution of the light sources or the level of illumination (indoor, outdoor, in highlights, shadows, or with non-white lights) can alter the color of the skin. The dark shadow on the face is typically caused by intense directional lighting that has partially blackened some facial areas. This is because the facial features are not plane-shaped. The reflection of bright lighting can occasionally cause a ”bright spot” on a face.

Figure 1.3: Lighting variations.

3. *Editing and reproduction of images :* The number of montage techniques for various image collections from the internet, movies, newspapers, and scanned images is typically limitless. Setting a new pigment concentration and using color transfer technology to alter the color of the skin image are two methods for recreating skin tones.

Figure 1.4: Montage and reproduction of images.

4. *Conditions of capturing images:* The skin′s appearance is influenced by things like camera characteristics (sensor response, lenses), which affect how the image is formed. Generally speaking, different color cameras don′t always produce the same color appearances for the same scene when imaging under the same conditions.

5. *Makeup:* Affects how skin tone appears.

Figure 1.5: makeup.

6. *Aging (Age):* Human skin ranges from cool elastic skin to rough dry skin with wrinkles.

Figure 1.6: Aging (Age).

7. *Background complexity:* Another issue is that many real-world objects have skin-like colors . The skin sensor detects false detections as a result of this.

1.3 Light

1.3.1 light definition[2]

From a physical standpoint, light can be described as waves of varying frequencies and wavelengths. It travels in straight lines at a constant speed in a vacuum, commonly referred to as the speed of light, which is approximately 299,792 kilometers per second (186,282 miles per second).

Light plays a crucial role in our perception of the world, as it allows us to see and interpret our surroundings. When light interacts with objects, it can be absorbed, transmitted, or reflected.

The reflection of light from objects is what enables us to see them. Different wavelengths of light give rise to the various colors we perceive.

When it comes to skin detection in computer vision or image processing, the effects of light can significantly impact the accuracy and reliability of the detection process. Here are some key considerations regarding the effects of light on skin detection:

1. ***Illumination Variations:*** Different lighting conditions, such as natural sunlight, indoor lighting, or low-light environments, can cause variations in the appearance of skin in images or video frames. The intensity, direction, and color temperature of light can influence the skin's perceived color and texture, which may affect the performance of skin detection algorithms.

2. ***Color Representation:*** Skin detection algorithms often rely on color information to identify and differentiate skin regions from the background or non-skin regions. However, variations in lighting can cause changes in the color representation of skin. For instance, under warm or cool lighting conditions, the skin's color may shift, making it challenging to establish consistent color thresholds or models for skin detection.

3. ***Shadows and Highlights:*** Lighting conditions can create shadows and highlights on the skin, altering its appearance. Shadows may darken certain areas of the skin, potentially leading to false negatives in skin detection. Similarly, highlights caused by strong light sources can brighten specific regions, potentially resulting in false positives or the miss classification of non-skin areas as skin.

4. ***Reflections and Specularities:*** When light reflects off the skin surface, it can produce specular highlights or reflections, particularly on oily or moist skin areas. These specularities can interfere with skin detection algorithms, as they may appear similar to skin regions or cause inconsistencies in the color and texture cues used for detection.

5. ***Image Noise:*** In low-light or high-contrast situations, the image quality may degrade, leading to increased noise levels or artifacts. Image noise can affect the accuracy of skin detection algorithms by introducing unwanted variations in color and texture, making it more challenging to distinguish between skin and non-skin regions.

1.3.2 Low light enhancement

Low light enhancement refers to techniques or processes aimed at improving the visibility and quality of images or videos captured in conditions with limited illumination. It involves enhancing the details, reducing noise, and overall improving the appearance of visual content captured in low light situations. The main goal of low-light enhancement is to mitigate the adverse effects of insufficient illumination, such as noise, reduced contrast, loss of details, and color distortion. By enhancing the visibility in low-light conditions, the details that are otherwise difficult to perceive can become more discernible, enabling better analysis, recognition, and interpretation of the visual content.

1.4 The relationship between lighting and skin detection

The relationship between lighting and skin detection is crucial, as lighting conditions can greatly impact the performance of skin detection algorithms. The accuracy of these algorithms can be influenced by factors such as the color and intensity of the lighting, shadows, and reflections .Under ideal lighting conditions, skin detection algorithms can perform quite well. For example, in a good environments with consistent lighting, skin can be easily distinguished from other objects based on its characteristic color. However, in real-world scenarios, lighting conditions can be far from ideal. Shadows, reflections, and variations in lighting intensity can make it difficult for skin detection algorithms to accurately identify skin regions. To address these challenges, skin detection algorithms often incorporate techniques such as color correction, histogram equalization, and skin color modeling. These techniques help to normalize the appearance of skin in images and improve the accuracy of skin detection algorithms. The relationship between light and skin detection is important, as lighting conditions can greatly impact the performance of skin detection algorithms[6].

1.5 Methods for detecting skin in an image

two are numerous strategies for utilizing characteristic qualities, owing to the enormous number of definable characteristics and detection approaches. We define two basic methods that we develop in the sections that follow:

- Detection based on the extraction of facial and/or hand characteristics.

- Detection based on color.

1.5.1 Detection based on the extraction of facial characteristics

In order to identify skin/persons, this approach is often utilized to segment skin patches on hands, faces, or both .Such segmentation frequently calls for the definition of models for the identifying characteristics of the desired model, and on rare occasions even a more or less accurate model of the human body.

Face detection

We commonly look for differentiating features like the eyes, outer contours, nose, and mouth, which we associate with configurations ("templates") that are known a priori or learned .According to the geometric constraints, the relative location of these identifying characteristics, as well as the presence or absence of a face, can be determined.[7]

1. edges-based Approaches :
   - The system proposed by Govindaraju and al [8]:
     The face is represented as a three-curve shape (top, right side and left side of the face).We can establish the position of the face by detecting these curves and grouping them based on their relative position.
   - Another contour-based strategy is to compare image contours to an ellipse that represents a face. The use of active contours, which allow adaptation to variations in the shape of the face, results in better face delineation. The most effective contour-based techniques are built on the use of active contours .Consider the work of Waite and al.[9], Craw and al. [10]], and Cootes and al. [11].
2. features-based approaches:
   There are numerous techniques that take advantage of distinguishing characteristics, largely as a result of the abundance of defined characteristics and detection methods. Eyes, brows, mouth, and nose are the facial features that are most frequently preserved and can have much finer detail. So the detection is based on the fact that the relative positions of the features on a face are fixed.
   - Kanade's method in 1973[12]: represents a first step in the development of face detection and recognition methods. based on the Principle:

(a) Image contours are extracted.

(b) The projection of contours along axes, both vertical and horizontal.

- Another method, which represents a generalized version of the first method, extracts face parameters using successive filters (Leung and al. [13], Graf and al. [14], Burl and al.[15]).
- In [15], Yow and Cipolla describe a face detection system where the three facial features—eyes, mouth, and nose—are extracted using phase quadrature filtering and grouped based on how likely they are to make up a face.

3. Comparison :
   Approaches based on facial feature extraction are more effective than approaches based on contours because they analyze local image structures along with geometric models of faces [16].

1.5.2 Color-based approaches

Color-based approaches are commonly used in skin detection algorithms to identify and distinguish skin regions from non-skin regions based on their color properties. These approaches leverage the fact that human skin tends to exhibit specific color characteristics within certain color ranges.

Color-based approaches have advantages such as simplicity, computational efficiency, and real-time processing capability. However, they can be sensitive to changes in lighting, complex backgrounds, or variations in skin tones. Therefore, they are often combined with other cues, such as texture or spatial information, to enhance the accuracy and reliability of skin detection algorithms.

It is important to note that color-based approaches may not be sufficient for skin detection in all scenarios, particularly when dealing with challenging lighting conditions, diverse skin tones, or complex backgrounds. Thus, combining multiple cues or employing more advanced techniques, such as machine learning or deep learning, can improve the performance of skin detection systems.

The most popular color spaces used in the field of skin detection are categorized as follows in table 1.1:

Spaces of color	Existing works
RGB	[17][18][19][20][21][22][23][24][25][25][26]
RGB-N	[27]
CIE-XYZ	[28]
HSI, HSV, HSL	[29][23][30][31][32]
YUV	[33][34]
TSL	[35]
YCbCr	[36][24]]
CIE-Lab, CIELuv	[37]
Hybridization	[32] [38][39][40][41] [42][43][44]

Table 1.1: Existing works of color spaces used in the field of skin detection.

1.Non-parametric methods

Without making any assumptions about the shapes of the distributions, non parametric methods only use the observations from the various samples of the classes to determine the distributions of the classes [4].
These techniques include normal correspondence tables, Bayesian networks, multilayer perceptron networks, self-organizing maps, and Bayesian classifiers coupled to histograms.

2.Parametric methods

In contrast to non-parametric methods, these methods enable the modeling of the distributions of the skin class and the non-skin class by incorporating hypotheses regarding the nature of these distributions. In order to wait for the two distributions, it is necessary to calculate the mean and variance parameters, among other technique-related parameters[4].

3.Explicit methods

One technique for detecting skin involves defining explicitly using a set of rules the boundaries that define the skin's beam in a particular color space.
As a result, in order to determine that a pixel in an image is a skin pixel, it must satisfy the following criteria [4]: **Threshold Up $<$ color skin$<$ Lower Threshold**

The benefit of this approach is how quickly and easily a pixel can be examined.

the following table 1.2 summarizes Some works done using this technique:

Year and Author	color space	Method of detection	dataset	Different types of skin	Different illumination	FP	FN	Accuracy
2013 Naji and Al[25]	HSV	LUT+ Thresholding	FEI +CVL+ LFW +FSKTM	yes	yes	2.04 %	0.63 %	98.51 %
2013 Osman and Hitam[45]	RGB	Based on regions+LDA	TDSD+UChile+SIdb	yes	no	13.4%	NA	98.35%
2013 Razmjooy and Al[40]	RGB	ANN	Bao	no	no	25 %	4.16%	70.84%
2014 Al-Mohair and Al[26]	RGB+ YIQ+ L*a*b+ YCrCb	ANN	Humanae	yes	no	NA	NA	93.02%
2015 Siddiqui and Wasif[41]	RGB	Thresholding	NA	no	no	14.20 %	NA	88.30 %
2016 Nadian-Ghomsheh[42]	YCrCb+ HSV +YUV+ XYZ+ RGBN	Histogramme	Compaq	yes	yes	14.48%	NA	95%

2017 Mahmoodi and al [46]	YCrCb	Thresholding + diffusion	SDD	no	no	NA	NA	98%
2017 Varma and Al [43]	HSV + YCrCb	Histogram +GMM	ETHZ PASCAL+ Partheepan+ SFA	no	no	NA	NA	93.41%
2018 ThaoNguyen-Trang[34]	YUV	Bayesian+ Making up connected	NA	yes	NA	0.16%	0.78%	82.27%
2019 Shuo Chen[47]	HSV +ycbcr	method based on the fusion of skin color information and HOG feature	NA	NA	NA	NA	NA	NA
2020 A.A.Zaidan [44]	YIQ *RGB	MCDM	NA	NA	NA	NA	NA	NA
2021 Yuhui Zheng [48]	RGB * YCrCb	GAN-Generated	NA	NA	NA	NA	NA	NA
2022 Mazin R. Al-Hameed [49]	RGB	normalized cross-relation	NA	NA	NA	NA	NA	94%

Table 1.2: Existing works of face detection based on skin color i the last 10 years.

1.6 Low-Light Image Enhancement methods

Low-light image enhancement refers to the process of improving the visibility and quality of images captured under low-light conditions. There are several methods and techniques used for low-light image enhancement. Here are some commonly employed approaches:

1.6.1 Histogram equalization

Histogram equalization is a technique used in image processing and computer vision to enhance the contrast and improve the visual appearance of an image. The primary goal of histogram equalization is to spread out the intensity values of an image to cover the entire available range.We showcasing various categories for Histogram Equalization, along with famous techniques, their advantages, and drawbacks in the table 1.3:

category	famous technique	advantages	drawbacks
Global histogram equalization	DHE [50][51][52] DCLHE[53][54][55][56]	Simple, Effective, Fast, Uniform gray.	Output image washed out, Can not preserve details, Can not control contrast enhancement.
Local histogram equalization	AHE[57][58][59]	Preserve image local details. Control clipping enhancement. Reduce noise.	Long computation time. Artifacts . Brightness preservation. Manual parameters.

Sub-image histogram equalization	BBHE[60][61][62] DHE[63][64][65]	Preserve brightness. Better enhancement for low frequency bins. Preserve entropy.	Fails with images have nonsymmetric. Long commutation time . Difficult to decide the last recursive level.
Modified histogram equalization	MHE[66][67][68]	Better enhancement for low frequency bins. Preserve brightness. Reduce noise.	Preserve details. Difficult to find optimal threshold parameter . Computation time.
Exposure regions histogram equalization	ERHE[69][70][71]	Preserve brightness. Segmentation threshold depends on exposure parameter.	Details washed out in large spans.

Table 1.3: summary of HE-based contrast enhancement techniques.

1.6.2 color based

"Color based on low light enhancement" refers to the process of enhancing or improving the appearance and visibility of colors in low-light conditions. When lighting conditions are poor, such as in dimly lit environments or at night, the human eye may perceive colors as less vibrant and less distinguishable. Here are some related works that address low-light enhancement in a color based approach:

Paper	Advantages	Disadvantages
Enhancing the low quality images using Unsupervised Colour Correction Method (2010)[72].	UCM aims to improve the visual quality of underwater images by reducing color cast and increasing contrast. UCM can be integrated into existing image processing software or workflows, allowing for seamless incorporation into established pipelines or systems.	UCM may not incorporate the latest advancements in image processing techniques.
Automatic Low Light Image Enhancement Using Color Balance and Noise Reduction (2015)[73]	Adjusts color balance and reduces noise for improved visual quality.	Limited information on the specific algorithms used.

Table 1.4: color base existing work

1.6.3 Dehaze-based

Low-light enhancement and dehazing are two related problems in image processing that aim to improve the visibility and visual quality of images captured in challenging lighting conditions. While dehazing algorithms aim to remove the effects of atmospheric scattering and haze, low-light enhancement algorithms aim to improve the visibility of images captured in low light conditions.

Here are some related works that address low-light enhancement in a dehaze-based approach:

Paper	Advantages	Disadvantages
Low light enhancement algorithm for color images using intuitionistic fuzzy sets with histogram equalization.(2021)[74]	Estimates haze density to guide the enhancement process.	Limited information on the fusion-based approach used.
De-hazing and enhancement method for underwater and low-light images. (2021)[75]	The method aims to enhance the visibility of both underwater and low-light images by reducing haze and improving clarity	The proposed method may involve computationally intensive operations.

Table 1.5: Dehaze-based existing work

1.6.4 Retinex based

Retinex, a word created by fusing the words retina and cortex, implies that both the eyes and the brain are involved in the process. In terms of how colors are perceived, it is thought that the human vision system (HVS) is arbitrary .Under a range of lighting conditions, the human vision system makes sure that the perceived color of an object stays largely constant. This function facilitates object recognition .Retinex functions in the same way as the human visual system[76] .The model for image formation used in Retinex is as follows:

$$\mathbf{S}(x,y) = \mathbf{L}(x,y) * \mathbf{R}(x,y) \tag{1.1}$$

Every point (x,y) in the domain is equivalent to one pixel on the input image where the bivariate function S(x,y) represents the image .The illumination L(x,y) and reflectance R(x,y) images make up the image, which is made up of two separate images. To generate the Retinex effect, we can separate R(x,y) from L(x,y), but this is known to be a mathematically challenging problem .Numerous efforts to numerically estimate the illumination image have been made.

Types of Retinex

Category	Types of Retinex Algorithms
Path Based	Random walk. Rest mechanism. Random spray. Brownian path.
Centre Surround	Single-Scale Retinex. Multi-Scale Retinex. Multi-Scale Retinex with Color Restoration. Multi-Scale Retinex with Color Preservation. Retinex based adaptive filter. fast multi scale Retinex.
Recursive Matrix	Path computation by Recursive Matrix comparison.
Physics Based	Transform Retinex model to physical from by making it an optimization problem.

Table 1.6: Types of Retinex.

Center Surround Retinex algorithms are one of the four categories mentioned above that are frequently used in image processing for image enhancement. Especially these four:

- Single-Scale Retinex.
- Multi-Scale Retinex.
- Multi-Scale Retinex with Color Restoration.
- Multi-Scale Retinex with Color Preservation.

1.Single-Scale Retinex

Single-scale retinex (SSR) is the difference between the image at a given pixel (x, y) and the center-surround average of that pixel (x,y). The calculation of the average of the above surrounding pixels serves as the basis for the inverse square spatial function for a given pixel And to calculate the surrounding average (for instance, a Gaussian distribution) that satisfies the aforementioned requirements, we can use any high pass filter. The retinex image for each i-th channel in an image is, if the Gaussian function (GG) is thought of as the center-surround function, as follows:

$$SSRi(x, y) = \log\left(Ii(x, y)\right) - \log\left(G_\sigma * Ii\right)(x, y) \tag{1.2}$$

- **Advantages:**
  1. SSR is a simple and computationally efficient algorithm, making it suitable for real-time image processing applications.
  2. SSR preserves the overall color balance of the image while enhancing the contrast, making it ideal for natural image enhancement.
  3. SSR can be used to remove haze and improve visibility in outdoor images.
- **Disadvantages:**
  1. SSR works on a single scale, meaning it cannot enhance the contrast at multiple scales simultaneously.
  2. SSR may produce artifacts in the image, such as halos around objects, especially when the image contains sharp transitions in luminance.
  3. SSR may not be effective in enhancing the contrast in highly saturated or highly noisy images.

2.Multi Scale Retinex

Because the selection of varies for different images in order to achieve good results, and different scale values enhance different parts of an image, we can combine SSR of various scales, assign weightage to each scale, and take the sum of all weighted-SSR images. The Multi-scale Retinex (MSR) of an image is the weighted average of n single-scale retinex images for various values.

$$MSR_i(x, y) = \sum_{n=1}^{N} w_n \cdot SSR_i(x, y) \tag{1.3}$$

Normalize the MSR output for range [0-255] given by the following equation because the output MSRi(x,y) image may contain negative real values and the range of values is not suitable for image representation, i.e. not in range [0-255].

$$MSR_i(x, y) = \frac{255 \cdot MSR_i(x, y) - \min(MSR_i)}{\max(MSR_i) - \min(MSR_i)} \tag{1.4}$$

- **Advantages:**

    1. MSR can enhance the contrast at multiple scales simultaneously, allowing for a more comprehensive enhancement of the image.
    2. MSR is effective in enhancing the contrast in highly saturated or noisy images.
    3. MSR can improve the visibility of fine details in the image while also removing the overall haze.
    4. MSR can preserve the color balance of the image while enhancing the contrast, making it ideal for natural image enhancement.

- **Disadvantages:**

    1. MSR is computationally more complex than SSR, which can make it slower and more resource-intensive.
    2. MSR can produce artifacts in the image, such as halos around objects, especially when the image contains sharp transitions in luminance.
    3. MSR may not be effective in enhancing the contrast in images with highly complex structures or patterns.

3.Multi Scale Retinex with Color Restoration

Multi-Scale Retinex with Color Restoration (MSRCR) is an image enhancement algorithm that combines the concepts of the Retinex algorithm, multi-scale image processing, and color restoration techniques. The goal of MSRCR is to improve the visual appearance of images by enhancing their contrast, brightness, and color rendition.

- **Advantages:**

    1. Multi-Scale Retinex with Color Restoration is capable of enhancing the details in both dark and bright areas of an image, making it more visually appealing and easier to interpret.
    2. The algorithm is relatively fast and can be applied to real-time video streams or high-resolution images with minimal delay.
    3. The MSRCR algorithm is effective at removing the effects of color cast or color imbalance, which can be introduced due to differences in lighting conditions or camera sensors.

4. The algorithm is robust and can work well even in challenging lighting conditions or when dealing with low-quality images.

- **Disadvantages:**

1. Multi-Scale Retinex with Color Restoration can sometimes produce overly bright or overly saturated images, which can distort the original content of the image and make it look unrealistic.
2. The algorithm can sometimes fail to properly restore the colors in an image, especially when dealing with images that have a high degree of color variation.
3. MSRCR can be computationally intensive when applied to very large or complex images, requiring powerful hardware or specialized computing resources.
4. The algorithm can sometimes introduce artifacts or noise into an image, which can be distracting or negatively impact the image quality.

4.Multi Scale Retinex with Color Preservation

Multi-Scale Retinex with Color Preservation (MSRCP) is an advanced version of the Multi-Scale Retinex with Color Restoration (MSRCR) algorithm that adds an additional step to preserve the colors in the original image.

$$MSRCp(x, y) = G[MSR(x, y) * CP(x, y) - b] \tag{1.5}$$

- **Advantages:**

1. MSRCP is capable of preserving the color accuracy and consistency of an image while enhancing its overall visual quality, making it more appealing and easier to interpret.
2. The algorithm is effective at removing color cast or color imbalance, which can be introduced due to differences in lighting conditions or camera sensors, while maintaining the natural color appearance of the image.
3. MSRCP is a robust algorithm that can work well even in challenging lighting conditions or when dealing with low-quality images.
4. The algorithm can produce high-quality results even when applied to large or complex images, making it suitable for a wide range of applications.

- **Disadvantages:**

  1. MSRCP can be computationally intensive, especially when applied to very large or complex images, requiring powerful hardware or specialized computing resources.
  2. The algorithm may produce oversaturated or unrealistic colors in some cases, depending on the specific image content and the parameters used in the algorithm.
  3. MSRCP can sometimes introduce artifacts or noise into an image, which can be distracting or negatively impact the image quality.
  4. The algorithm requires careful parameter tuning to achieve optimal results, and the performance of the algorithm may vary depending on the specific use case and image content.

Details on the various studies on retinex types used are provided in the table below:

Retinex type	**Existing works**
Single-Scale Retinex	[77][78]
Multi-Scale Retinex	[79][80][81]
Multi-Scale Retinex with Color Restoration	[82][83]
Multi-Scale Retinex with Color Preservation	[84][85][86]

Table 1.7: Retinex Existing works.

1.7 skin detection in low light enhancement works

1.7.1 Single-Stage Face Detection Under Extremely Low-Light Conditions

The paper presents a single-stage low-light face detection method that addresses the challenge of detecting faces in low-light images. The authors propose an improved MSRCR method for enhancing the image quality while preserving colors. They demonstrate that their method outperforms others in preserving low-resolution face details. They also utilize the Pyramidbox algorithm, known for its effectiveness in detecting faces of different scales, and perform multi-scale tests to improve the model's performance. The results are integrated using the Soft-NMS method. The proposed method achieves high accuracy and obtains excellent results on the DARK FACE dataset, demonstrating its effectiveness in low-light face detection.[87]

1.7.2 Benchmarking Low-Light Image Enhancement and Beyond

The paper presents a systematic review and evaluation of single-image low-light enhancement algorithms. It introduces the VE-LOL dataset, which includes paired low/normal-light images and face images with annotated bounding boxes. The study evaluates low-level vision enhancements using various metrics and measures the impact of these enhancements on face detection in low-light conditions using state-of-the-art methods. Additionally, the authors propose a novel approach that combines low-light enhancement and face detection into a unified model. Experiments on the VE-LOL dataset provide a comparative analysis of existing algorithms, highlight their limitations, and suggest future research directions. The dataset also supports the "Face Detection in Low Light Conditions" track of the CVPR UG2+ Challenge.[88]

1.7.3 Unsupervised Face Detection in the Dark

The paper addresses the challenge of low-light face detection, which is crucial for applications like nighttime autonomous driving and city surveillance. Existing face detection models lack generality and flexibility as they heavily rely on annotated low-light data. To overcome this limitation, the authors propose a novel approach that adapts face detectors from normal light to low light without requiring low-light annotations. They introduce the High-Low Adaptation (HLA) framework, which consists of bidirectional low-level adaptation and multitask high-level adaptation. In the low-level adaptation, dark images are enhanced and normal-light images are degraded, narrowing the gap between the two domains. In the high-level adaptation, context-based and contrastive learning methods are combined to align features from different domains. Experimental results demonstrate that their HLA-Face v2 model achieves superior low-light face detection performance, even in the absence of low-light annotations. The authors also highlight the potential of their adaptation scheme for improving supervised learning and generic object detection tasks. The project related to this work is publicly available at the provided URL.[89]

1.8 Conclusion

In conclusion, skin detection in low light conditions is a challenging task in computer vision and image processing. However, there have been significant advances in this field in recent years, particularly with the application of Retinex theory and related techniques. The use of Retinex-based algorithms, including single-scale and multi-scale Retinex, as well as their variations such as MSRCR, has shown promising results for low-light image enhancement and skin detection. Additionally, the use of color restoration and preservation techniques has further improved the performance of these algorithms.

Furthermore, the combination of Retinex-based algorithms with other techniques such as adaptive histogram equalization, Gaussian mixture models, and machine learning-based approaches has led to further improvements in skin detection in low light conditions. However, there are still some challenges that need to be addressed, such as the detection of skin in complex lighting conditions and the handling of diverse skin tones. Nevertheless, the recent advances in this field provide a strong foundation for future research in low-light skin detection and enhancement.

Chapter 2

Conception

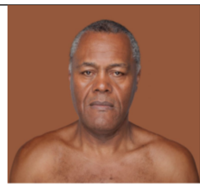
2.1 Introduction

In this project, we propose a system capable of detecting human skin in low light environments using a hybrid approach. Our system combines an improved retinex light enhancement method, specifically the Improved MultiScale Retinex with Color Restoration (MSRCR), with a multi-skin region detector based on popular color spaces such as YCbCr, RGB, and HSV. The goal is to compensate for low light degradation, enhance color information, and restore natural colors in real-world images. In the following, we will detail The different stages of design and implementation of our system as well as the different results achieved, as well as difficulties at different stages of development.

2.2 data preparation

In the first, we were looking for a dataset containing human skins in a dark environment. We found dark face dataset, but it does not contain the ground truth about skin and lighting. So we searched other datasets related to skin of different ethnicities to find the appropriate field/range for every skin tone, we found sfa , Humanae , Pratheepan dataset and CelebAMask-HQ. we found the LoL dataset to test the effectiveness of improving lighting because it contains images and their references in the case of light and dark.

2.2.1 data collection

data	Description	example
Humanæ[90]	"Humanæ" is an ongoing photographic project by artist Angélica Dass that aims to capture the true colors of humanity beyond racial labels. The project features portraits of nearly 4,000 volunteers from diverse backgrounds, including individuals from different countries, cultures, and social situations. Each portrait's background is tinted with a color tone derived from an 11 x 11 pixel sample taken from the subject's nose. The project has captured over 4,000 images in 36 cities across 20 countries, including locations in Europe, North America, South America, Asia, and Africa.	
Pratheepan Dataset [91]	The dataset consists of images randomly downloaded from Google for the purpose of human skin detection research. The images were captured using various cameras, exhibiting different color enhancements and taken under different lighting conditions. The dataset is organized into four folders: • FacePhoto - Single subject, simple background, Total Images = 32 • FamilyPhoto - Multiple subjects, complex background, Total Images = 46 • GroundT_FacePhoto - The groundtruth images for FacePhoto • GroundT_FamilyPhoto - The groundtruth images for FamilyPhoto	
SFA [92]	The SFA dataset is created for computer vision research, focusing on human skin color and texture as features. It is built using face images from FERET and AR datasets, with skin and non-skin samples extracted along with ground truth annotations for skin detection. The samples vary in size from 1 pixel to 35x35 pixels, totaling 3354 skin samples and 5590 non-skin samples for each dimension. Validation using artificial neural networks achieves an accuracy of around 93%. Comparisons with the UCI dataset show a nearly 4% improvement in image segmentation.	

CelebAMask-HQ[93]	CelebAMask-HQ is a large-scale face image dataset that consists of 30,000 high-resolution face images selected from the CelebA dataset by following CelebA-HQ. Each image in the dataset is accompanied by a segmentation mask of facial attributes corresponding to CelebA. The segmentation masks in CelebAMask-HQ have been manually-annotated with a size of 512 x 512 pixels and include 19 classes. These classes encompass various facial components and accessories such as skin, nose, eyes, eyebrows, ears, mouth, lips, hair, hat, eyeglass, earring, necklace, neck, and cloth. The CelebAMask-HQ dataset is particularly valuable for training and evaluating algorithms in the domains of face parsing, face recognition, and GANs for face generation and editing.	
dark face[94]	The Dark Face dataset consists of 6,000 real-world low light images captured at night in various environments, including teaching buildings, streets, and parks. These images are labeled with bounding boxes around human faces, serving as training and validation sets. Additionally, the dataset includes 9,000 unlabeled low-light images from the same settings. A unique set of 789 paired low-light/normal-light images captured in controlled lighting conditions is also provided. Although not all of these images contain faces, they can be used for training purposes. The dataset includes a hold-out testing set of 4,000 low-light images with annotated human face bounding boxes. Overall, the Dark Face dataset offers valuable resources for low-light image analysis, particularly for tasks related to human face detection and recognition.	
LOL[95]	The LOL dataset comprises 500 pairs of low-light and normal-light images, with 485 pairs designated for training and 15 pairs for testing. The low-light images exhibit noise resulting from the photo capture process. The majority of the images depict indoor scenes, and all images have a resolution of 400×600 pixels. The dataset serves as a valuable resource for researchers working on low-light image processing and enhancement, providing opportunities for algorithm development and evaluation.	

Table 2.1: data Description.

2.2.2 Data preprocessing

- We performed a background cleaning process on the images from the Humanae dataset to mitigate the negative impact of the uniform skin color background on the results of skin detection. By removing the background, we aimed to improve the accuracy and reliability of our skin detection algorithm.
- We have made an addition to the Pratheepane dataset by including a skin face file. This skin face file will serve as a valuable resource for calculating the color ranges of different skin tones within the dataset.

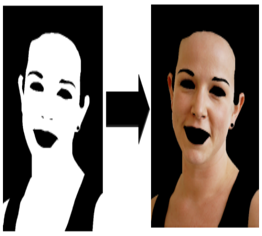


Figure 2.1: convert binary format into skin image for pratheepan dataset.

- We have made an important addition to the SFA dataset by including a ground truth file. This ground truth file will serve as a valuable resource for calculating metrics related to detection accuracy and evaluation.

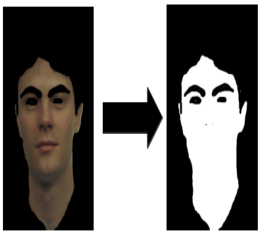


Figure 2.2: convert skin image into binary format for SFA dataset.

2.3 General conception

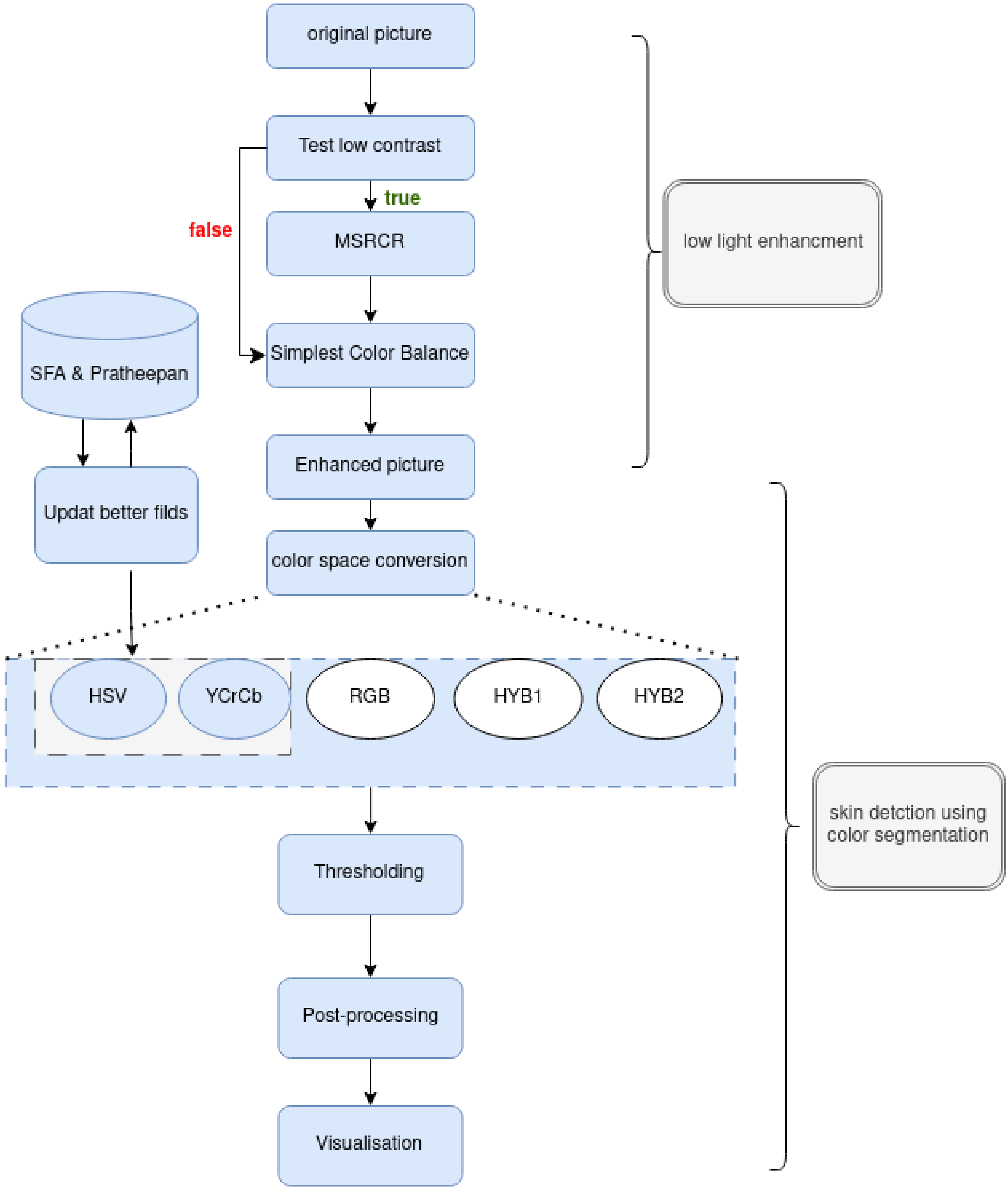


Figure 2.3: Our method for skin detection in low light enhancment

2.3.1 Low light enhancement

In the Low Light enhancement stage, we go through several steps to improve the visibility and quality of photos taken in low light conditions. Let's break down and explain each step:

1.test low contrast

The "test low contrast" algorithm is a method for determining whether an image is low contrast or not. The basic idea behind this algorithm is to compute the standard deviation of pixel intensities in the image and compare it with a threshold value. If the standard deviation is below the threshold, the image is considered to be low contrast. The algorithm can be summarized as follows:

1. Convert the image to grayscale.

2. Compute the mean intensity of the image.

3. Compute the standard deviation of the intensity values in the image.

4. Compute the contrast fraction, which is the ratio of the standard deviation to the mean intensity.

5. If the contrast fraction is below a certain threshold, the image is considered to be low contrast.

we have set The threshold value used in step 5 is to 0.4, although this can vary depending on the specific application.
We suggest using the "test low contrast" algorithm as a preliminary step to determine whether to use color balancing algorithm or a more complex method like MSRCR-CB to handle image lighting. If the "test low contrast" algorithm indicates that the image has low contrast, we use our MSRCR-CB algorithm to enhance the image's contrast and details. MSRCR-CB is an advanced method that uses multiscale Retinex processing to improve local contrast in the image, thereby enhancing overall contrast and reducing color discrepancies caused by uneven lighting conditions.

If the "test low contrast" algorithm indicates that the image has sufficient contrast, then we apply the "simplest color balancing" algorithm to correct the image's color and details, resulting in more natural and visually appealing results.

Overall, this approach can be a useful method to automatically determine the appropriate image processing algorithm based on the image's characteristics, although it may require fine-tuning to determine optimal threshold values for the "test low contrast" algorithm and to ensure proper implementation of color balancing and MSRCR-CB algorithms.

2.Multi-Scale Retinex with Color Restoration

The Multi-Scale Retinex with Color Restoration (MSRCR) algorithm enhances the colors of an image by combining the output of the Multi-Scale Retinex (MSR) algorithm with a Color Restoration Function (CRF). This is done to restore the original colors of the input image when the MSR output appears colorless.

The MSRCR calculation for each pixel (x, y) in the i-th channel is obtained by multiplying the MSR value MSRi(x, y) with the CRF value CRFi(x, y):

$$MSRCR_i(x, y) = MSR_i(x, y) \cdot CRF_i(x, y) \tag{2.1}$$

The CRF value CRFi(x, y) depends on the ratio of the composition of the pixel's i-th channel value to the sum of all channel values at that pixel. It is calculated as:

$$CRF_i(x, y) = \beta \left[\log(\alpha \cdot I_{i'}(x, y))\right] \tag{2.2}$$

Where I'i(x, y) is the chromaticity coordinates for the i-th channel at position (x, y), calculated by dividing the pixel's i-th channel value by the sum of all channel values:

$$I'_i(x, y) = \frac{I_i(x, y)}{\sum_{c=0}^{k-1} I_c(x, y)} \tag{2.3}$$

In the above equation, k represents the number of image channels, α is a parameter controlling non-linearity, and β is a parameter controlling the overall gain. The CRF equation can be further simplified as:

$$CRF_i(x, y) = \beta \left[\log(\alpha \cdot I_i(x, y)) - \log\left(\sum_{c=0}^{k-1} I_c(x, y)\right)\right] \tag{2.4}$$

To improve the contrast results, the MSRCR equation can be modified to include gain (G) and offset (b) values:

$$MSRCR_i(x, y) = G\left[MSR_i(x, y) \cdot CRF_i(x, y) - b\right] \tag{2.5}$$

here is a brief explanation of what each parameter may represent:

sigma-list: a list of standard deviations for the Gaussian filters used to create the Gaussian pyramid.

G: a parameter controlling the strength of the color restoration effect.

b: a parameter controlling the saturation of the enhanced image.

alpha: a parameter controlling the overall contrast enhancement.

beta: a parameter controlling the strength of the Retinex enhancement.

By incorporating the gain and offset, the MSRCR algorithm can provide enhanced contrast and color restoration in the image.

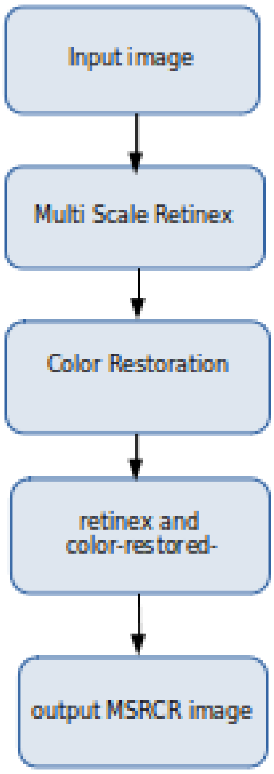


Figure 2.4: MSRCR algorithm steps

Here are the stages that the MSRCR algorithm goes through, from input to output:

1. The input image is first converted to a floating-point representation and then added by 1.0 to ensure that all pixel values are positive.

2. The multi Scale Retinex function is applied to the image using the sigma list parameter to compute a multi-scale retinex image, which estimates the illumination component of the image.

3. The color Restoration function is then applied to the retinex image along with the alpha and beta parameters to restore the color of the image.

4. The retinex and color-restored images are then combined using the G, b parameters to produce the enhanced image.

5. The enhanced image is then normalized so that each color channel has values in the range [0, 255] by scaling the pixel values to this range.

6. Finally, The enhanced image is converted to an unsigned 8-bit integer representation and returned as the output of the MSRCR function. Reconstruction of the final enhanced image by combining the enhanced scales using a weighted average.

In our study, we selected the parameters in the MSRCR technique from [96] that served as a reference to find the best parameters from the table below.

Image	Resolution	$\sigma1$	$\sigma2$	$\sigma3$	G	α	β	b
Airial	256 $*$256	13.18	99.01	177.22	189	113	39	-25
Palace	256 $*$256	20.19	127.82	192.81	133	111	33	-27
Big-ben	256 $*$256	67.51	119.87	201.01	161	117	44	-19
Memoriel	256 $*$256	57.99	134.15	197.19	198	119	36	-15
House	256 $*$256	51.20	116.90	216.81	173	122	36	-12

Table 2.2: MSRCR parameters tuned using additional test images.

We will see the metrics results for MSRCR parameters tuned using additional test images on the dataset LOL in table 3.15
Based on extensive experimentation and evaluation on the LOL dataset, the following parameter values have been determined to provide the best results for the Multi-Scale Retinex with Color Restoration (MSRCR) algorithm:

- Sigma-list: The values 57.99, 134.15, and 197.19 for sigma-list should be used for the Gaussian filters in the algorithm. These values enhance contrast and brightness, resulting in visually pleasing outcomes across different frequency bands.

- G: Set G to 198.19 for optimal color restoration. This value ensures a well-balanced color balance in the enhanced image, preserving and enhancing natural colors effectively.

- b: The value -15 for b controls the saturation level of the enhanced image. It provides a moderate level of saturation without introducing undesirable color artifacts, striking a balance between vibrant colors and a realistic appearance.

- Alpha:Use an alpha value of 198 for moderate contrast enhancement. This value improves the overall visual quality of the output while preserving image details.

- Beta: Set beta to 36 for a subtle yet effective Retinex enhancement. This value avoids an overly exaggerated effect while still enhancing the image's overall appearance.

It's important to note that these parameter values were selected based on their performance on the LOL dataset.

3.simplest method for color balancing

The biggest problem after the MSRCR step is that the color was Enhanced, but not color balanced is said to have a color cast, since everything in the image appears to have been shifted towards one color or another. Color balancing may be thought in terms of removing this color cast. Color balancing an image affects not only the neutrals, but other colors as well.

The idea is that in a well-balanced photo, the brightest color should be white and the darkest black.

Thus, we can remove the color cast from an image by simply stretching, as much as it can, the values of the three channels Red, Green, Blue (R, G, B), so that they occupy the maximal possible range [0, 255] by applying an affine transform ax+b to each channel.

Since many images contain a few aberrant pixels that already occupy the 0 and 255 values, In order to deal with outliers the proposed method saturates a small percentage of the pixels with the highest values to 255 and a small percentage of the pixels with the lowest values to 0, Notice that this saturation can create flat white regions or flat black regions that look unnatural. Thus, the percentage of saturated pixels must be as small as possible.

If there was a colored ambient light, for example electric light where R and G dominate, the color balance will enhance the B channel. Thus the ambient light will lose its yellowish hue. Although it does not necessarily improve the image, the simplest color balance always increases its readability.

Algorithm 1 Simplest Color Balance Algorithm

// Build the cumulative histogram
for $i = 0$ to $N - 1$ **do**
    histo[image[i]] $\leftarrow$ histo[image[i]] $+ 1$
end for
for $i = 1$ to 255 **do**
    histo[i] $\leftarrow$ histo[i] + histo[$i - 1$]
end for
// Search v_{min} and v_{max}
$v_{\text{min}} \leftarrow 0$
while histo[$v_{\text{min}} + 1$] $\leq N \times \frac{s1}{100}$ **do**
    $v_{\text{min}} \leftarrow v_{\text{min}} + 1$
end while
$v_{\text{max}} \leftarrow 255 - 1$
while histo[$v_{\text{max}} - 1$] $> N \times \left(1 - \frac{s2}{100}\right)$ **do**
    $v_{\text{max}} \leftarrow v_{\text{max}} - 1$
end while
if $v_{\text{max}} < 255 - 1$ **then**
    $v_{\text{max}} \leftarrow v_{\text{max}} + 1$
end if
// Saturate the pixels
for $i = 0$ to $N - 1$ **do**
    if image[i] $< v_{\text{min}}$ **then**
        image[i] $\leftarrow v_{\text{min}}$
    end if
    if image[i] $> v_{\text{max}}$ **then**
        image[i] $\leftarrow v_{\text{max}}$
    end if
end for
// Rescale the pixels
for $i = 0$ to $N - 1$ **do**
    image[i] $\leftarrow$ (image[i] $- v_{\text{min}}) \times \frac{255}{v_{\text{max}} - v_{\text{min}}}$
end for

The algorithm works as follows:

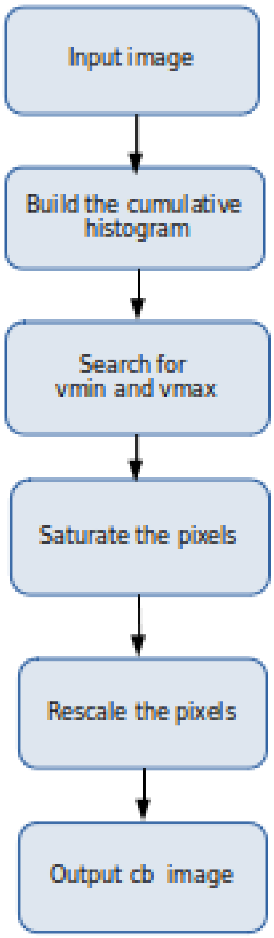


Figure 2.5: The simplest color balance algorithm steps

1. Build the cumulative histogram: The algorithm first builds a histogram of the input image by counting the number of pixels of each color intensity level. Then, it calculates the cumulative histogram by summing up the counts of each intensity level and all its lower levels.

2. Search for vmin and vmax: The algorithm searches for the minimum and maximum intensity levels (vmin and vmax) that contain a certain percentage of pixels in the image. Specifically, it starts from the lowest intensity level and increases vmin until the number of pixels with intensity levels lower than vmin is less than or equal to N $\times$ s1%100, where N is the total number of pixels in the image. Similarly, it starts from the highest intensity level and decreases vmax until the number of pixels with intensity levels higher than vmax is less than or equal to N $\times$ (1-s2%100).

3. Saturate the pixels: The algorithm then saturates the pixel values that are outside the

range [vmin, vmax]. That is, it sets the pixel values lower than vmin to vmin and the pixel values higher than vmax to vmax.

4. Rescale the pixels: Finally, the algorithm rescales the pixel values within the range [vmin, vmax] to the full intensity range [0, 255]. That is, it maps the pixel values x in [vmin, vmax] to the new values y in [0, 255] according to the formula: y = (x - vmin) × 255 / (vmax - vmin).

4.MSRCR-CB

Multiscale Retinex with Color Restoration with Color Balance (MSRCR-CB) is an image enhancement technology that combines two methods: Multiscale Retinex with Color Restoration (MSRCR) and color balance. It is designed to improve the visual quality of low-light images by improving contrast, brightness, and color balance.
MSRCR-CB has been shown to produce better results than other low-light enhancement methods in several studies. However, parameterization of the algorithm is crucial to achieving good results. The List Sigma parameter should be set appropriately for the image being processed, and the G and b parameters should be set carefully to avoid excessive contrast and negative pixel values in the result. The Table 3.15 proves the effectiveness of this technique.

2.3.2 skin detection with Skin color segmentation

In the skin detection stage, various color spaces are explored to determine the best fields for accurately detecting and segmenting human skin tones. The most commonly used color spaces for skin detection are RGB (Red, Green, Blue), YCrCb (Luma, Chroma red, Chroma blue), and HSV (Hue, Saturation, Value). Let's discuss each color space and its significance in skin detection:

1.RGB

Skin color segmentation using RGB color space involves identifying skin pixels based on their red, green, and blue color values. There are various approaches to perform this segmentation, but a common one involves setting a threshold on the RGB values. The threshold can be determined based on the average or median values of skin pixels in an image or using a predefined threshold value.

$$
\begin{aligned}
&(R > 95 \textbf{ AND } G > 40 \textbf{ AND } B > 20) \\
&\textbf{AND } ((\max(R, G, B) - \min(R, G, B)) > 15) \\
&\textbf{AND } (|R - G| > 15 \textbf{ AND } R > G \textbf{ AND } R > B) \\
&\textbf{AND } (R > G \textbf{ AND } B > G)
\end{aligned} \tag{2.6}
$$

can be used for skin color segmentation in RGB color space , and we chose this threshold because it is the most popular .

2.YCrCb

kin color segmentation using YCbCr color space involves identifying skin pixels based on their luminance (Y) and chrominance (Cr and Cb) values. The YCrCb color space is commonly used in image and video processing applications, as it separates the color information from the luminance information. To perform skin color segmentation in YCbCr color space, a threshold can be set on the Cb and Cr values. Skin pixels generally have Cr and Cb values within a specific range, which can be determined based on the characteristics of the skin color. We found many possibilities of them:

$$0 < Y < 255 \text{ AND } 135 \leq C_r \leq 180 \text{ AND } 85 \leq C_b \leq 135 \tag{2.7}$$

$$0 < Y < 255 \text{ AND } 133 \leq C_r \leq 175 \text{ AND } 85 \leq C_b \leq 140 \tag{2.8}$$

$$0 < Y < 255 \text{ AND } 138 \leq C_r \leq 173 \text{ AND } 67 \leq C_b \leq 133 \tag{2.9}$$

$$0 < Y < 255 \text{ AND } 133 \leq C_r \leq 180 \text{ AND } 77 \leq C_b \leq 140 \tag{2.10}$$

The best field is 2.9, according to numerous tests on the various datasets we have compiled in the table 3.17 .

Extraction of histograms of the field from the skin fact of the SFA dataset and the prthepane dataset:

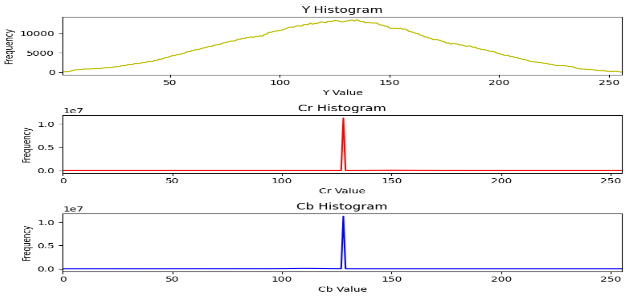
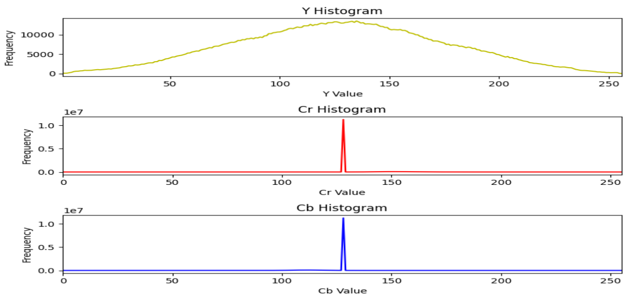
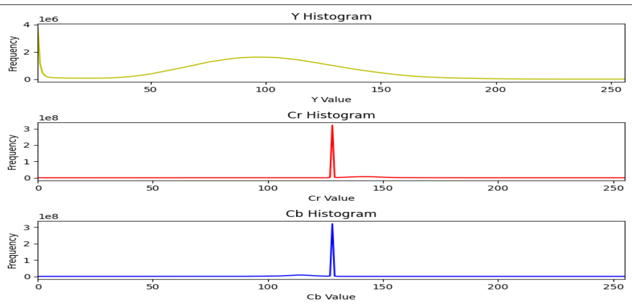
Data	**YCbCr Histogram**
pratheepane face	
pratheepane family	
sfa	

Table 2.3: YCrCb histogram for sfa and pratheepan dataset.

We note that y is distributed over the entire field. As for cr and cb, there is a peak value that covers the rest of the values. Therefore, we will divide the field to see the boundaries of the field clearly.

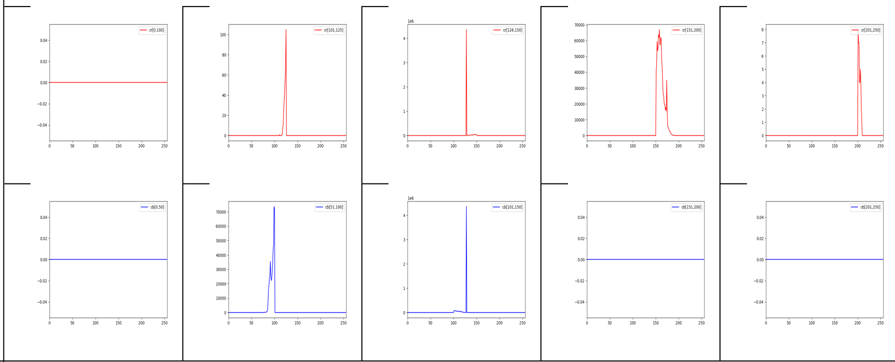
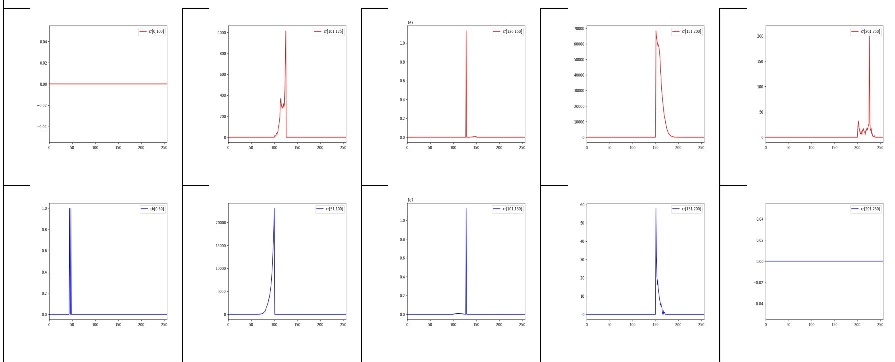
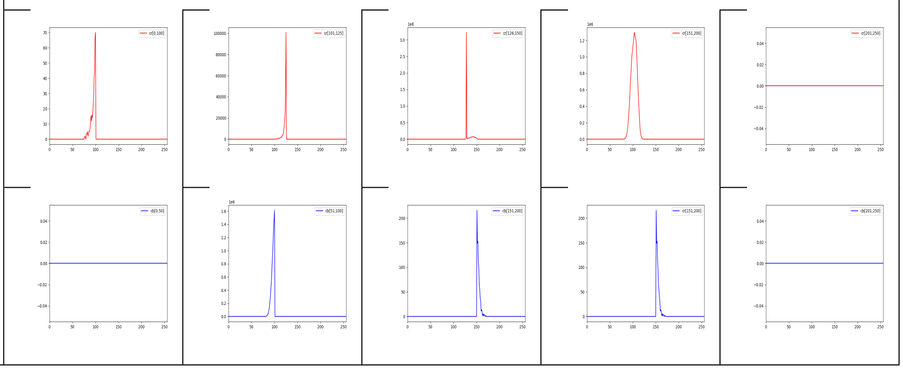
Data	Cr Cb detail
pratheepane face	$140 < Cr < 175$ $80 < Cb < 133$ 
pratheepane family	$145 < Cr < 173$ $70 < Cb < 130$ 
sfa	$140 < Cr < 173$ $70 < Cb < 130$ 

Table 2.4: Detailed Cr and Cb graph of the sfa and pratheepan data set.

Our initial choice of field aligns closely with the subject depicted in the graph, and it is gratifying to observe that this alignment has yielded positive outcomes.

3. HSV

Skin color segmentation using HSV (Hue, Saturation, Value) color space involves identifying skin pixels based on their hue, saturation, and value components. The HSV color space is often used in image processing applications because it separates color information from brightness and allows more intuitive control over color-related operations. To perform skin color segmentation in HSV color space, a threshold can be set on the hue, saturation, and value components.

$$0 < H < 50 \text{ AND } 10 \leq S \leq 200 \text{ AND } 80 \leq V \leq 255 \tag{2.11}$$

$$0 < H < 33 \text{ AND } 58 \leq S \leq 255 \text{ AND } 30 \leq V \leq 255 \tag{2.12}$$

$$0 < H < 25 \text{ AND } 40 \leq S \leq 255 \text{ AND } 67 \leq V \leq 255 \tag{2.13}$$

$$0 < H < 120 \text{ AND } 50 \leq S \leq 150 \text{ AND } 0 \leq V \leq 255 \tag{2.14}$$

$$0 < H < 17 \text{ AND } 15 \leq S \leq 170 \text{ AND } 0 \leq V \leq 255 \tag{2.15}$$

$$0 < H < 33 \text{ AND } 58 \leq S \leq 150 \text{ AND } 30 \leq V \leq 255 \tag{2.16}$$

$$0 < H < 25 \text{ AND } 40 \leq S \leq 255 \text{ AND } 0 \leq V \leq 255 \tag{2.17}$$

$$0 < H < 15 \text{ AND } 10 \leq S \leq 68 \text{ AND } 0 \leq V \leq 255 \tag{2.18}$$

The best field is 2.11, according to numerous tests on the various datasets we have compiled in the table 3.18.

Extraction of histograms of the field from the skin fact of the SFA dataset and the prthepane dataset:

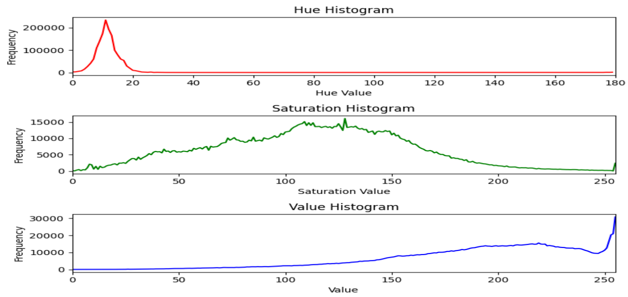
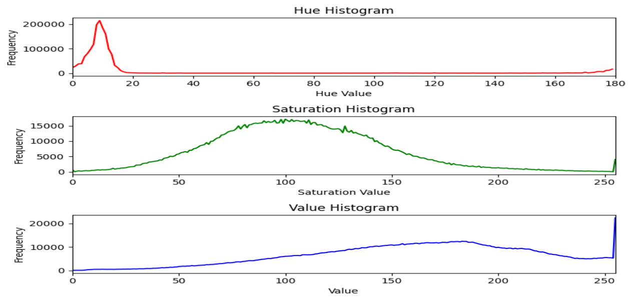
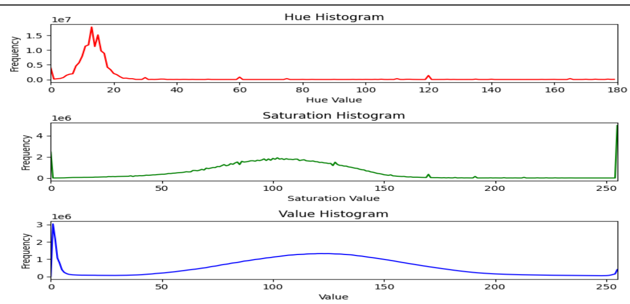
data	hsv histogram	intrval
pratheepane face		• $0 < H < 20$ • $20 < S < 200$ • $75 < V < 255$
pratheepane family		• $0 < H < 20$ • $25 < S < 200$ • $50 < V < 255$
sfa		• $0 < H < 20$ • $50 < S < 255$ • $0 < V < 200$

Table 2.5: HSV histogram for sfa and pratheepan dataset

So :0<H<20 AND min (20,25,50)<S< min(200,200,255) AND max (75,50,0)<S< max(255,255,200)

$$0 < H < 20 \textbf{ AND } 20 \leq S \leq 200 \textbf{ AND } 75 \leq V \leq 255 \tag{2.19}$$

Ultimately the best field is2.19 our calculator file, and according to numerous tests on different datasets we have compiled it into the table 3.18.

4.hybridization

In skin detection, hybridization can refer to the combination of different color spaces and techniques to improve the accuracy and reliability of skin detection. Skin detection algorithms often use multiple color spaces, such as RGB, HSV, and YCbCr, to detect skin pixels in an image. Each color space has its own advantages and limitations, and by combining them using hybridization techniques, the accuracy and robustness of skin detection can be improved.

- **hybridization 01:**
  ((YCrCb or hsv) xor (rgb or hsv)) xor (YCrCb or rgb)):
  The expression ((YCrCb or hsv) xor (rgb or hsv)) xor (YCrCb or rgb)) represents a logical operation that combines the results of multiple skin detection techniques. The "or" operation represents a logical "union" of the results of skin detection in different color spaces. For example, the term YCbCr or hsv means that the algorithm is detecting skin pixels in either the YCrCb color space or the HSV color space, and combining the results into a single mask.
  The "xor" operation represents a logical "exclusive or" of the results of different skin detection techniques. The term (YCrCb or hsv) xor (rgb or hsv) means that the algorithm is detecting skin pixels in either the YCbCr or HSV color spaces, or in the RGB or HSV color spaces, but not both. This can help to reduce false positives and improve the accuracy of skin detection. Finally, the outermost "xor" operation combines the results of the previous operation with the results of skin detection in the YCbCr or RGB color spaces, which are then combined using the "or" operation.
  Overall, this expression represents a hybrid skin detection algorithm that combines multiple color spaces and logical operations to detect skin pixels in an image. By using a combination of color spaces and logical operations, the algorithm can improve the accuracy and reliability of skin detection in a variety of lighting conditions and skin tones.
  NOTE:

  - merge skin detection 1: ((YCrCb or hsv) xor (rgb or hsv)) xor (YCrCb or rgb).
  - merge skin detection 2: ((YCrCb and hsv) xor (rgb and hsv)) xor (YCrCb and rgb).
  - merge skin detection 3: ((YCrCb or hsv) and (rgb or hsv)) and (YCrCb or rgb).

  After the experiments, we ensure that all three combinations (skin discovery fusion 1, skin discovery fusion 2, and skin discovery fusion 3) give the same results.

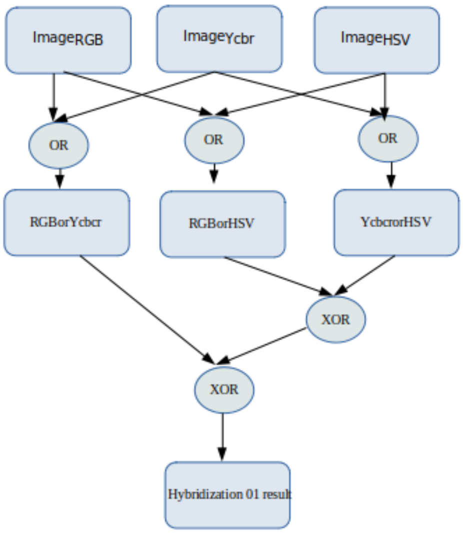


Figure 2.6: Hybridization 1.

- **hybridization 02:**

  ((YCrCb or hsv) or (rgb or hsv)) and (YCrCb or rgb): The expression ((YCrCb or hsv) or (rgb or hsv)) and (YCrCb or rgb) represents a logical operation that combines the results of multiple skin detection techniques using the "or" and "and" logical operators.

  The "or" operator represents a logical "union" of the results of skin detection in different color spaces. For example, the term YCrCb or hsv means that the algorithm is detecting skin pixels in either the YCbCr color space or the HSV color space. Similarly, the term rgb or hsv means that skin pixels are detected in either the RGB color space or the HSV color space. The "or" operation combines these two sets of results, including any pixels that are detected as skin in either color space.

  The "and" operator represents a logical "intersection" of the results of skin detection. In this case, the expression (YCrCb or hsv) or (rgb or hsv) combines the results of skin detection in the YCrCb or HSV color spaces with the results in the RGB or HSV color spaces. Then, the expression (YCrCb or hsv) or (rgb or hsv) is combined with the results of skin detection in the YCbCr color space using the "or" operation.

  By using this expression, we merge the skin detection results from the YCbCr color space, HSV color space, and RGB color space. The resulting mask includes the pixels detected as skin in any of these color spaces. This hybrid skin detection algorithm, incorporating multiple color spaces and logical operations, can enhance the accuracy and effectiveness of skin detection across various lighting conditions and skin tones. The choice of using the "or" and "and" operators in this expression allows for a more inclusive approach, potentially improving sensitivity in detecting skin pixels.

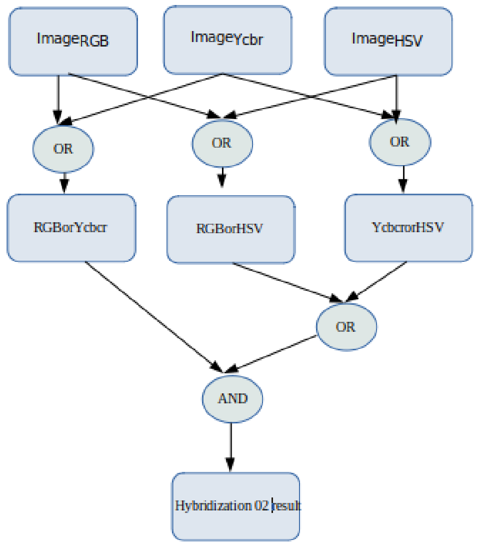


Figure 2.7: Hybridization 2.

- chose the first hybridization in the first, because it gives the best results that we see in the Table 3.19, and after entering our hsv, the first hybridization becomes good in cases of images full of noise, such as the pratheepan dataset, and the second hybridization for images of close faces, such as the sfa dataset, and the Table 3.20 proves to us that.

5.Post-processing

Post-processing in skin detection refers to additional steps or techniques applied after the initial skin detection process to refine the results or enhance the accuracy of skin detection algorithms. The technique we used in our study:

Morphological processes: such as erosion, dilation, opening, and closing, , are commonly used in image processing to manipulate and enhance images, including skin areas.
Erosion: Erosion is a morphological process that erodes or shrinks the boundaries of objects in an image. It can be used to smooth the edges of the exposed skin areas, making them appear more refined.

- Dilation: Dilation is the opposite of erosion and is used to expand or grow the boundaries of objects in an image. It can be applied to fill gaps and connect adjacent skin areas, making the skin appear more continuous.

- Opening: Opening is a combination of erosion followed by dilation. It helps to remove small details or noise while preserving the overall structure of objects. Opening can be used to refine the skin areas by removing small imperfections while maintaining the general shape.

- Closing: Closing is a combination of dilation followed by erosion. It helps to close small gaps or holes in objects. In the context of skin areas, closing can be used to fill small gaps or discontinuities, making the skin appear smoother and more connected.

The results of this techniques are shown in the table 3.21

2.4 conclusion

In this chapter, we discussed the conception phase of our skin detection system for low light environments. We highlighted the importance of data preparation, including data collection, data cleaning, and data preprocessing. Additionally, we presented the general conception of the system, which involves low light enhancement and skin detection using skin color segmentation.

Chapter 3

Implementation and results

3.1 Introduction

The development environment is an essential part of the software development process. It includes hardware and software tools that developers use to write and test code for their application.
In this chapter, we will learn about the development environment and software tools used to develop our application. We will discuss hardware components, such as the computer, monitors, and peripherals used, as well as software tools and libraries, including integrated development environments , text editors, programming languages, and frameworks.
In addition, we will cover the different stages of implementing our system, any challenges we faced during development, and the results we have achieved so far with our system.

3.2 Development environment

3.2.1 Hardware environment

We used a computer that has the following characteristics:
Type: PC /lenovo.
Processor:Intel(R) Celeron(R) CPU N2840 @ 2.16GHz 2.16 GHz
Installed memory (RAM): 2,00 Go .
System type: 64-bit operating system, x64 processor.

3.2.2 Software Environment

python

is a computer programming language often used to build websites and software, automate tasks, and conduct data analysis. Python is a general-purpose language, meaning it can be used to create a variety of different programs and isn't specialized for any specific problems.

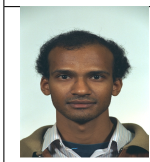
package for Python

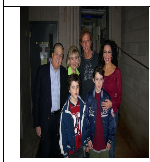
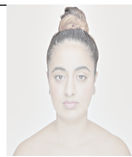
For application	OS, glob, matplotlib, cv2, numpy.
For metrics	sklearn.metrics, precision-score, call-score.

Table 3.1: package for Python

3.3 Observable effects

3.3.1 Results of the color balancing algorithm and ”Msrcr-cb”

data	original image	color balancing image	msrcr	msrcr-cb image
sfa				
				
parthepan face photo				
				

parthepan family photo				
				
humanea				
				

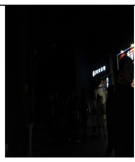
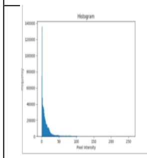
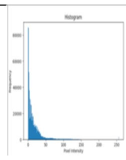
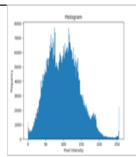
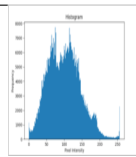
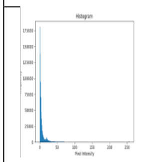
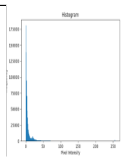
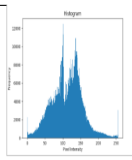
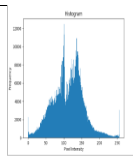
				
dark face				
				
				

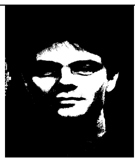
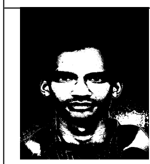
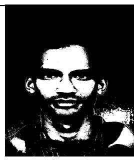
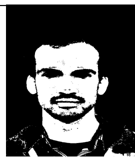
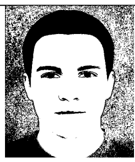
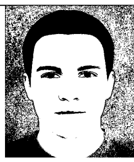
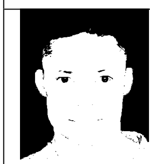
Table 3.2: Some results of the color balancing algorithm and "Msrcr "and "Msrcr-cb " in different databases with the most ethnicities and different luminance.

In the databases SFA, Pratheepan, and Human, it has been observed that color balance generally produces better results compared to "msrcr" and "Msrcr-cb".This could be due to the fact that "Msrcr"is specifically designed to work in low-light conditions and may not be effective in other lighting situations. On the other hand, color balance can be used to address a variety of color and lighting issues in an image and, as a result, it can yield more diverse and improved outcomes. Therefore, color balance may be a preferable option for enhancing the visual quality of images in this dataset. It should also be noted that the worst performance of"Msrcr"was observed in human-related images, as it is a processing rule that is not natural and the "Msrcr"algorithm is specifically designed for nature images.

Furthermore, the Dark Face database has indicated that"Msrcr-cb" is crucial for enhancing dark images and color contrast. This is because "Msrcr-cb" is specifically designed to improve low-light images by enhancing contrast and reducing noise. Therefore, "Msrcr-cb" proves to be an effective technique for enhancing the visual quality of dark images in this dataset. Overall, the choice of the technique employed to enhance an image depends on the specific characteristics of the dataset under analysis. In some cases, color balance may be a more effective technique, while in other cases, ”Msrcr-cb”may be more efficient. It is also worth noting that performing color balancing after applying ”msrcr” is an important step in restoring the colors in an image. However, both approaches can be valuable in enhancing the visual quality of images and facilitating their analysis or interpretation.

3.3.2 Skin detection results

RGB results

data	hsv mask	hsv mask color balancing	hsv mask msrcr	hhsv mask msrcr-cb
sfa				
				
parthepan face photo				
				

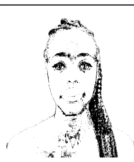
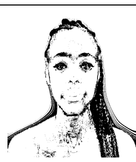
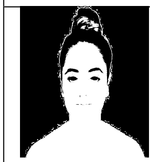
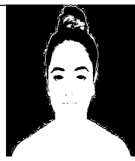
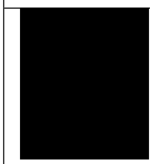
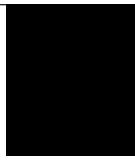
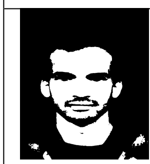
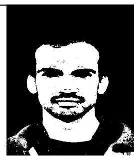
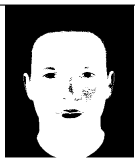
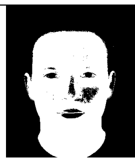
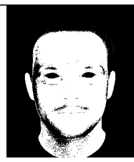
parthepan family photo				
				
humanea				
				
dark face				
				

Table 3.3: Some results of the skin detection with ”rgb ”and ”rgb-color-balancing” algorithm and ”rgb -msrcr ”and ”rgb -msrcr-cb ”in different databases with the most ethnicities and different luminance

Based on the information in the table above, we tested the RGB field we chose before and the RGB and”RGB -color balancing ” algorithms on three different databases: SFA, Pratheepan, and Humanae. We found that both algorithms performed well on these databases, with the ”RGB -color balancing ” algorithm leading to further improvements in accuracy and reduced error rates. However, when we tested the ”RGB -msrcr-cb ” algorithm on the same databases, we found that its performance was weaker compared to the RGB and ”RGB -color balancing

" algorithms. This may be because the "RGB -msrcr-cb " algorithm was designed for low-light images and may not be suitable for skin detection under normal lighting conditions. We also tested the "RGB -msrcr-cb "algorithm on the DRAK FACE database and found good results. This may be because the DRAK FACE database contains images captured under low-light conditions, which may be more suitable for the "RGB -msrcr-cb " algorithm. Overall, the results indicate that the RGB and "RGB -color balancing " algorithms are effective for skin detection in different databases with different ethnicities and lighting levels, while the "RGB -msrcr-cb " algorithm may be more suitable for low-light images. However, further experimentation and evaluation may be needed to confirm these results and determine the optimal algorithm for different scenarios.

YCrCb results

data	ycrcb mask	ycrcb mask color balancing	ycrcb mask msrcr	ycrcb mask msrcr-cb
sfa				
				
parthepan face photo				
				

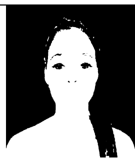
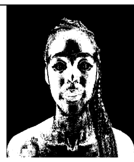
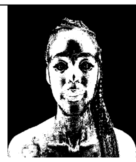
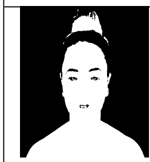
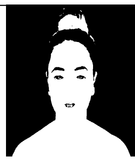
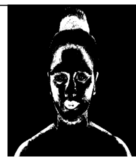
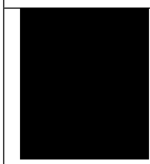
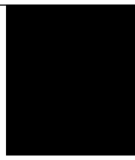
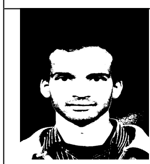
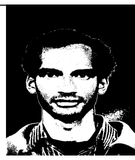
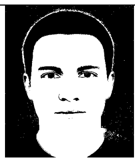
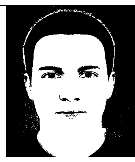
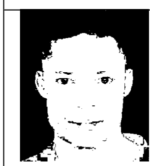
parthepan family photo				
				
humanea				
				
dark face				
				

Table 3.4: Some results of the skin detection with ”YCrCb ”and ”YCrCb -color balancing ”algorithm and ”YCrCb-msrcr ”and ”YCrCb-msrcr-cb ”in different databases with the most ethnicities and different luminance.

Based on the information in the table above, we tested the YCbCr field we chose before and the YCrCb and ”YCrCb -color balancing ” algorithms on three different databases: SFA, Pratheepan, and Humanae. We found that both algorithms performed well on these databases, with the ”YCrCb -color balancing ”algorithm leading to further improvements in accuracy and reduced error rates. However, when we tested the ”YCrCb-msrcr-cb ” algorithm on the same databases, we found that its performance was weaker compared to the Ycbcr and ”YCrCb

-color balancing "algorithms. This may be because the "YCrCb-msrcr-cb " algorithm was designed for low-light images and may not be suitable for skin detection under normal lighting conditions. We also tested the"YCrCb-msrcr-cb " algorithm on the DRAK FACE database and found good results. This may be because the DRAK FACE database contains images captured under low-light conditions, which may be more suitable for the "YCrCb-msrcr-cb " algorithm. Overall, the results indicate that the YCbCr and "YCrCb -color balancing " algorithms are effective for skin detection in different databases with different ethnicities and lighting levels, while the "YCrCb-msrcr-cb " algorithm may be more suitable for low-light images. However, further experimentation and evaluation may be needed to confirm these results and determine the optimal algorithm for different scenarios.

HSV results

data	hsv mask	hsv mask color balancing	hsv mask msrcr	hhsv mask msrcr-cb
sfa				
				
parthepan face photo				
				

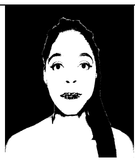
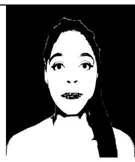
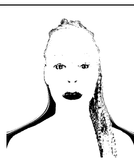
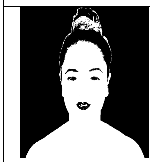
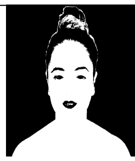
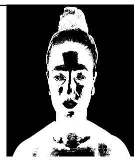
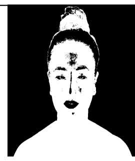
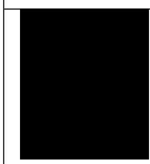
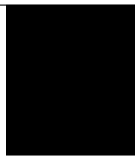
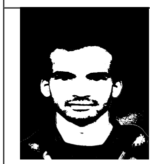
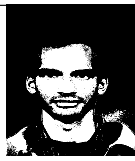
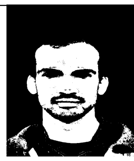
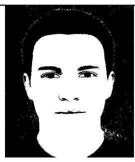
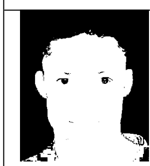
parthepan family photo				
				
humanea				
				
dark face				
				

Table 3.5: Some results of the skin detection with ”HSV ”and ”HSV-color-balancing” algorithm and ”HSV -msrcr ”and ”HSV -msrcr-cb ”in different databases with the most ethnicities and different luminance

Based on the information in the table above, we tested the HSV field we chose before and the HSV and ”HSV-color-balancing” algorithms on three different databases: SFA, Pratheepan, and Humanae. We found that both algorithms performed well on these databases, with the ”HSV-color-balancing” algorithm leading to further improvements in accuracy and reduced error rates. However, when we tested the ”HSV-color-balancing” algorithm on the same databases, we found that its performance was weaker compared to the HSV and ”HSV-color-balancing” algorithms.

This may be because the "HSV-color-balancing" algorithm was designed for low-light images and may not be suitable for skin detection under normal lighting conditions. We also tested the"HSV-color-balancing" algorithm on the DRAK FACE database and found good results. This may be because the DRAK FACE database contains images captured under low-light conditions, which may be more suitable for the "HSV-color-balancing" algorithm. Overall, the results indicate that the HSV and"HSV-color-balancing" algorithms are effective for skin detection in different databases with different ethnicities and lighting levels, while the "HSV-color-balancing"algorithm may be more suitable for low-light images. However, further experimentation and evaluation may be needed to confirm these results and determine the optimal algorithm for different scenarios.

hybridization 1 results

data	hyb1 mask	hyb1 mask color balancing	hyb1 mask msrcr	hyb1 mask msrcr-cb
sfa				
				
parthepan face photo				
				

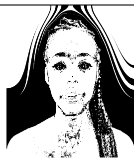
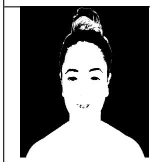
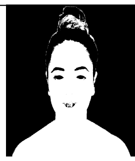
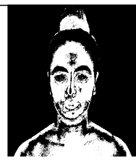
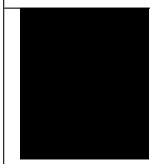
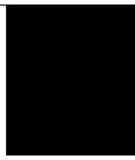
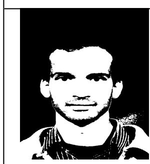
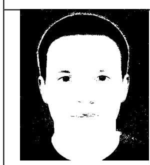
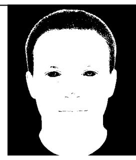
parthepan family photo				
				
humanea				
				
dark face				
				

Table 3.6: Some results of the skin detection with ”hyb1 ”and ”hyb1-color-balancing” algorithm and ”hyb1 -msrcr ”and ”hyb1 -msrcr-cb ”in different databases with the most ethnicities and different luminance

Based on the information in the table above, we tested the hybridization 1 and ” hybridization 1-color balancing” algorithms on three different databases: SFA, Pratheepan, and Humanae. We found that both algorithms performed well on these databases, with the ” hybridization 1-color balancing” algorithm leading to further improvements in accuracy and reduced error rates. However, when we tested the ”hybridization 1-msrcr-cb ” algorithm on the same databases, we found that its performance was weaker compared to the HSV and ” hybridization 1-color balancing" algorithms. This may be because the "hybridization 1-msrcr-cb " algorithm was designed for low-light images and may not be suitable for skin detection under normal lighting conditions. We also tested the "hybridization 1-msrcr-cb " algorithm on the DRAK FACE database and found good results. This may be because the DRAK FACE database contains images captured under low-light conditions, which may be more suitable for the "hybridization 1-msrcr-cb " algorithm. Overall, the results indicate that the hybridization and " hybridization 1-color balancing" algorithms are effective for skin detection in different databases with different ethnicities and lighting levels, while the "hybridization 1-msrcr-cb "algorithm may be more suitable for low-light images. However, further experimentation and evaluation may be needed to confirm these results and determine the optimal algorithm for different scenarios. It seems to us that our calculated ranges yields the best results among other color fields.

hybridization 2 results

data	hyb2 mask	hyb2 mask color balancing	hyb2 mask msrcr	hyb2 mask msrcr-cb
sfa				
				
parthepan face photo				
				

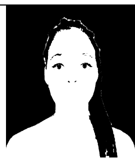
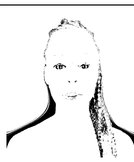
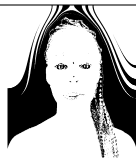
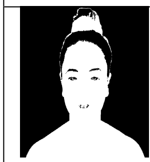
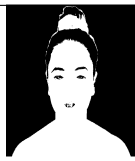
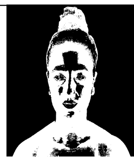
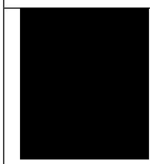
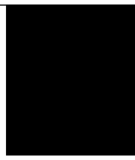
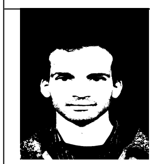
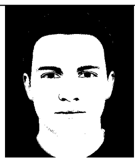
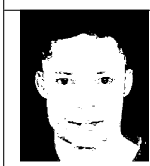
parthepan family photo				
				
humanea				
				
dark face				
				

Table 3.7: Some results of the skin detection with "hyb2 "and "hyb2-color-balancing" algorithm and "hyb2 -msrcr "and "hyb2 -msrcr-cb "in different databases with the most ethnicities and different luminance

Based on the information in the table above, we tested the hybridization 2 and " hybridization 2-color balancing" algorithms on three different databases: SFA, Pratheepan, and Humanae. We found that both algorithms performed well on these databases, with the " hybridization 2-color balancing" algorithm leading to further improvements in accuracy and reduced error rates. However, when we tested the "hybridization 2-msrcr-cb " algorithm on the same databases, we found that its performance was weaker compared to the HSV and " hybridization 2-color balancing” algorithms. This may be because the ”hybridization 2-msrcr-cb ” algorithm was designed for low-light images and may not be suitable for skin detection under normal lighting conditions. We also tested the ”hybridization 2-msrcr-cb ” algorithm on the DRAK FACE database and found good results. This may be because the DRAK FACE database contains images captured under low-light conditions, which may be more suitable for the”hybridization 2-msrcr-cb ”algorithm. Overall, the results indicate that the hybridization and ” hybridization 2-color balancing” algorithms are effective for skin detection in different databases with different ethnicities and lighting levels, while the”hybridization 2-msrcr-cb ”algorithm may be more suitable for low-light images. However, further experimentation and evaluation may be needed to confirm these results and determine the optimal algorithm for different scenarios. It seems to us that our calculated ranges yields the best results among other color fields.

Our HSV results

data	hsv mask	hsv mask color balancing	hsv mask msrcr	hsv mask msrcr-cb
sfa				
				
parthepan face photo				
				

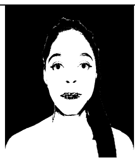
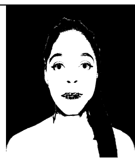
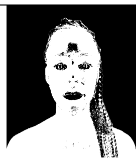
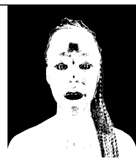
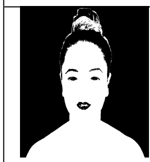
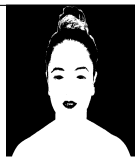
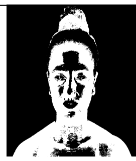
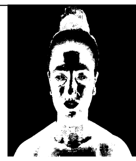
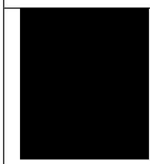
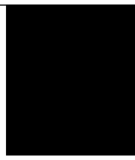
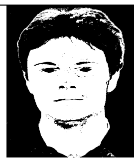
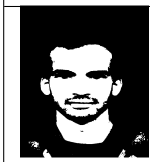
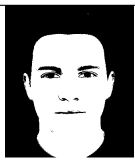
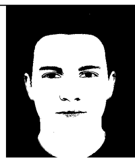
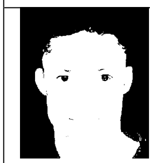
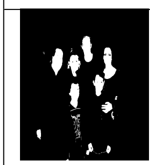
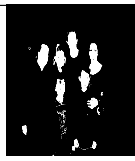
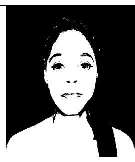
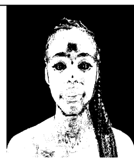
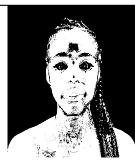
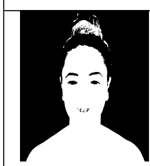
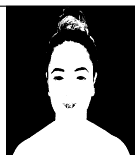
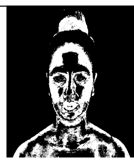
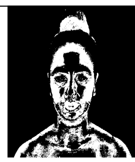
parthepan family photo				
				
humanea				
				
dark face				
				

Table 3.8: Some results of the skin detection with ”our HSV ”and ”our HSV-color-balancing” algorithm and ”our HSV -msrcr ”and ”ourHSV -msrcr-cb ”in different databases with the most ethnicities and different luminance

hybridization 1 with our hsv results

data	hyb1 mask	hyb1 mask color balancing	hyb1 mask msrcr	hyb1 mask msrcr-cb
sfa				
				
parthepan face photo				
				
parthepan family photo				
				
humanea				
				

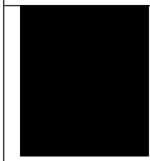
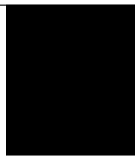
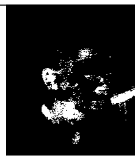
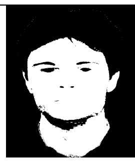
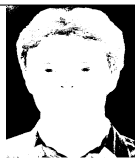
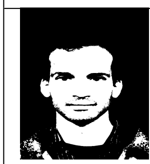
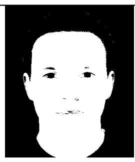
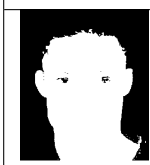
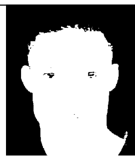
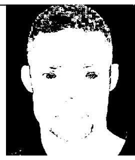
dark face				
				

Table 3.9: Some results of the skin detection with ”hyb1 with our hsv ”and ”hyb1-color-balancing” algorithm and ”hyb1 -msrcr ”and ”hyb1-msrcr-cb ”in different databases with the most ethnicities and different luminance

hybridization 2 with our hsv results

data	hyb2 mask	hyb2 mask color balancing	hyb2 mask msrcr	hyb2 mask msrcr-cb
sfa				
				
parthepan face photo				
				

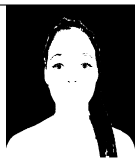
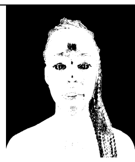
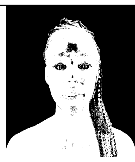
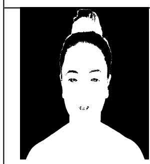
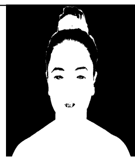
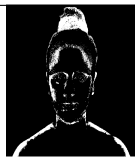
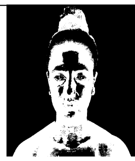
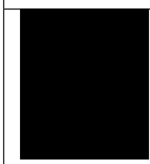
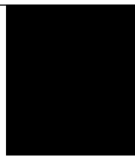
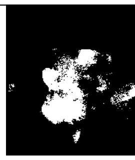
parthepan family photo				
				
humanea				
				
dark face				
				

Table 3.10: Some results of the skin detection with "hyb2 with our hsv "and "hyb2-color-balancing" algorithm and "hyb2 -msrcr "and "hyb2 -msrcr-cb "in different databases with the most ethnicities and different luminance

3.3.3 Results of the best fields on different ethnicities

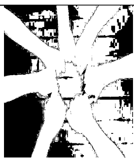
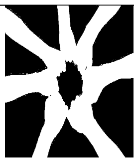
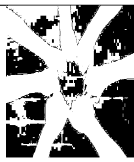
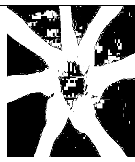
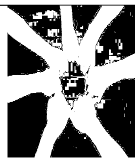
orignal	rgb mask	ycbcr mask	hsv mask	hybridization 1	hybridization 2
					
					

Table 3.11: Results of the best fields on different ethnicities

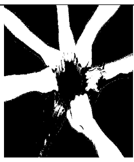
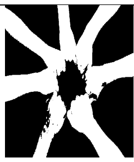
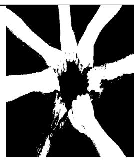
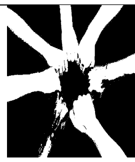
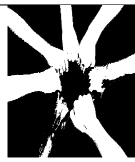
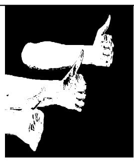
orignal	rgb mask	ycbcr mask	hsv mask	hybridization 1	hybridization 2
					
					

Table 3.12: Results of the best fields on different ethnicities with color balancing

The findings of our research demonstrate that this approach yields favorable results across different ethnicities. It is worth noting that the incorporation of color balancing techniques has significantly increased the accuracy and fairness of our results. By applying RGB, YCbCr, and HSV masks in conjunction with hybridization, we have achieved a comprehensive understanding of a diverse range of skin tones and ensured equitable representation. Furthermore, it is evident that the balancing algorithm has improved the results. These advancements have further strengthened our commitment to inclusivity and provided a solid foundation for future investigations in ethnicity-based analysis.

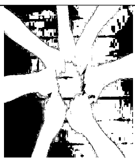
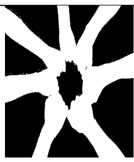
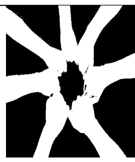
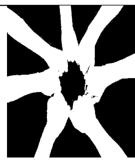
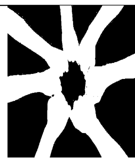
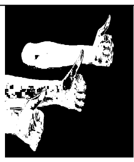
orignal	rgb mask	ycbcr mask	our hsv mask	hybridization 1	hybridization 2
					
					

Table 3.13: Results of the our hsv field on different ethnicities

Our research findings demonstrate that our approach yields favorable results across different ethnicities. Notably, the incorporation of color balancing techniques has significantly enhanced the accuracy and fairness of our outcomes. By applying RGB, YCbCr, and our HSV masks in combination with hybridization, we have achieved a more comprehensive understanding of the diverse range of skin tones and ensured equitable representation. These advancements have further reinforced our commitment to inclusivity and provided a solid foundation for future investigations into ethnicity-based analysis.

3.3.4 Enhanced Skin Detection in Dark Environments: Illustrative Results

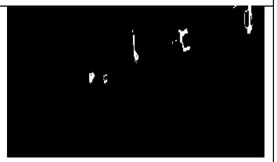
<table>
<tr><td rowspan="3">original image</td><td rowspan="3"></td><td colspan="3">mask</td></tr>
<tr><td>RGB</td><td>YCrCb</td><td>HSV</td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td rowspan="3">image enhanced</td><td rowspan="3"></td><td colspan="3">our mask</td></tr>
<tr><td>OUR HSV</td><td>OUR HYB1</td><td>OUR HYB2</td></tr>
<tr><td></td><td></td><td></td></tr>
</table>

Table 3.14: Results of Skin Detection Method in Dark Environment

The table above illustrates the results of our method for detecting skin in a dark environment. It consists of two sections: the original image and the enhanced image with corresponding masks.

In the "Original Image" section, we have a dark face photo as the input image. This image represents a challenging scenario where the lighting conditions are not favorable for skin detection.

Next, we provide three different types of masks computed from the original image: RGB, YCrCb, and HSV. These masks highlight the areas in the image that are likely to contain skin pixels. Each mask is shown as a separate image in the table.

Moving on to the "Our Image Enhanced" section, we present the enhanced version of the original image, where we have applied our skin detection algorithm. This enhanced image aims to improve the visibility and accuracy of the detected skin regions.

Similar to the previous section, we provide three different masks computed from our enhanced image: OUR HSV, OUR HYB1, and OUR HYB2. These masks represent the skin regions detected by our algorithm using different color spaces and processing techniques. Each mask is shown as a separate image in the table.

By comparing the original masks with our enhanced masks, it is evident that our method successfully identifies skin regions even in a dark environment. The enhanced masks demonstrate improved accuracy and better discrimination of skin pixels.

Overall, these illustrative results showcase the efficiency of our method for detecting skin in challenging lighting conditions, providing a valuable tool for various applications such as facial recognition, image analysis, and computer vision tasks.

3.4 Quantitative results

3.4.1 Quantitative results for low light enhancement

We will use the LOL database to test the results of the" msrcr and " msrcr-cb " algorithm at MSRCR parameters in table 2.2:

algo	MSRCR			MSRCR-CB		
metrics	vif	psnr	rte	vif	psnr	rte
arial	0.65	27.64	0.44	0.73	27.75	0.39
palace	0.67	27.75	0.42	0.76	28.56	0.37
palace	0.703	27.80	0.416	0.77	28.57	0.348
arial	0.706	27.80	0.415	0.78	28.67	0.347
arial	0.701	27.75	0.42	0.77	28.57	0.35

Table 3.15: Comparison of Metrics for msrcr and msrcr-cb Datasets.

Note:

- the RTE value ranges from 0 (completely identical images) to 1 (completely different images). Therefore, lower RTE values indicate better image quality.
- the VIF metric ranges from 0 to 1, where 0 represents completely different images and 1 represents identical images. A lower VIF score indicates a higher level of dissimilarity or degradation in image quality.
- the PSNR value is a measure of the similarity between two images, and higher values indicate greater similarity. The PSNR value can range from 0 (completely different images) to infinity (identical images).

$$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right)$$

Where:

MAX is the maximum possible pixel value (e.g., 255 for an 8-bit image). MSE (Mean Squared Error) is the average squared difference between the original and distorted/compressed versions of the signal.

PSNR provides a quantitative measure of the quality degradation in terms of signal fidelity. Higher PSNR values indicate better quality and lower levels of distortion or compression artifacts. Here are a few examples of PSNR thresholds for image and video compression:

Excellent quality: PSNR > 40 dB

Good quality: PSNR > 30 dB

Fair quality: PSNR > 20 dB

Poor quality: PSNR < 20 dB

low	high	msrcr	msrcr-cb
			

Table 3.16: test the results of the" msrcr and " msrcr-cb " algorithm with lol database

3.4.2 Quantitative results for skin detection

Metric for choosing the best field for Ycrcb:

metrics	ycrcb filds	Sfa	Pratheepan Dataset Face Photo	Pratheepan Dataset Family Photo
map	2.7	85.40%	66.13%	45.15%
	2.8	83.40%	63.20%	44.15%
	2.9	88.5%	68.16%	46.15%
	2.10	83.4%	63.16%	44.18%
iou	2.7	59.48%	53.13%	27.15%
	2.8	54.42%	50.13%	25.15%
	2.9	60.40%	55.13%	29.15%
	2.10	54.40%	50.13%	25.15%

Table 3.17: Metric for choosing the best field for YCrCb.

Metric for choosing the best field for HSV:

metrics	HSV fields	Sfa	Pratheepan Dataset Face Photo	Pratheepan Dataset Family Photo
map	2.11	77.40%	71.13%	45.15%
	2.12	67.61%	63.20%	43%
	2.13	75.3%	69.56%	44.15%
	2.14	63.2%	53.30%	40.13%
	2.15	71.3%	65.16%	43.18%
	2.16	64.8%	57.20%	41.18%
	2.17	76.2%	60.31%	44.18%
	2.18	36.6%	15.66%	10.18%
	2.19	79%	73.8%	50%
iou	2.11	65.4%	59.13%	24.15%
	2.12	60.40%	56.20%	20.18%
	2.13	62.20%	58.16%	24.15%
	2.14	50.46%	43.16%	16.18%
	2.15	59.43%	54.16%	23.18%
	2.16	63.48%	53.16%	22.18%
	2.17	57.48%	53.16%	22.18%
	2.18	18.48%	10.16%	8.18%
	2.19	70%	62.8%	32%

Table 3.18: Metric for choosing the best field for HSV.

metrics	mask	Sfa	Sfa-cb	Pratheepan Dataset FacePhoto	Pratheepan Dataset Face Photo-cb	Pratheepan Dataset Family Photo	Pratheepan Dataset Family Photo-cb	CelebA Mask-HQ	CelebA Mask-HQ -cb
map	RGB	81.3%	78%	69.4%	71.3%	49%	51.7%	63.7%	64.3%
	HSV	77.4%	72%	71%	75%	43%	45%	59.1%	59.1%
	ycrcb	88.5%	83.7%	66%	73%	44%	47%	61.7%	58.9%
	hyb1	91.2%	89%	72%	77%	48%	51%	63.6%	62%
	hyb2	87.3%	88.1%	67%	75%	45%	48%	60.1%	59.9%
iou	RGB	60.8%	51.9	56.5%	58.3%	31.3%	32.2%	47.4%	48%
	HSV	65.4%	59.1%	59%	62%	24%	26%	43%	43%
	ycrcb	71.5%	74%	53%	61%	27%	30%	45.5%	42.8%
	hyb1	67.7%	63.7%	60%	65%	31%	33%	47.4	47.5
	hyb2	65.2%	65.8%	57%	63%	29%	30%	43.8	43.5

Table 3.19: Quantitative results for skin detction and skin detection with color balancing in sfa ;Pratheepan and CelebAMask-HQ database

metrics	mask	Sfa	Sfa-cb	Pratheepan Dataset Face Photo	Pratheepan Dataset Face Photo-cb	Pratheepan Dataset Family Photo	Pratheepan Dataset Family Photo-cb	CelebA Mask-HQ	CelebA Mask-HQ -cb
map	our HSV	79%	73.9%	73%	76.7%	47.8%	54.3%	60%	59.4%
	hyb1	84.3	80.8%	71.4%	76.1%	52.3%	55%	63.1%	62%
	hyb2	86.8	85.5	68.6%	74.8%	45%	48%	60.1%	59.9%
iou	our HSV	70%	70.06%	62.8%	66.6%	32%	35.5%	44%	43.5%
	hyb1	73.4%	70.8%	60.8%	65.3%	34.3%	36.4%	47.7%	52%
	hyb2	78%	76.5	56%	62.5%	29%	30.2%	43.8%	44.3%

Table 3.20: Quantitative results for skin detection with our hsv and with color balancing in sfa ;Pratheepan and CelebAMask-HQ database

metrics	mask	Sfa	Sfa-cb	Pratheepan Dataset Face Photo	Pratheepan Dataset Face Photo-cb	Pratheepan Dataset Family Photo	Pratheepan Dataset Family Photo-cb	CelebA Mask-HQ	CelebA Mask-HQ -cb
map	our HSV	91.8%	90.1%	74.9%	78.6%	50.8%	56.3%	60.7%	59.7%
	hyb1	89.5	91%	72.4%	77%	53.2%	57%	63%	62.4%
	hyb2	86.9%	85.5	69.6%	74.8%	46.3%	50.1%	60.3%	60.8%
iou	our HSV	72%	73%	64%	67.9%	33.6%	36.5%	44.2%	43.8%
	hyb1	80.1%	71.9%	60.8%	65.3%	35.3%	37.6%	46.8%	46.2%
	hyb2	78.8%	77.5	56.5%	63.5%	29.8%	32.5%	44%	44.5%

Table 3.21: Quantitative results for skin detection with our hsv and with color balancing and post-procissing in sfa , Pratheepan and CelebAMask-HQ database

We have noticed that in the SFA database, there is a drop in hits when color balancing is used. This is because the database contains many images exposed to high light conditions, which affects our results. The table below shows our view

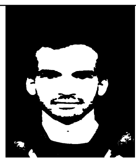
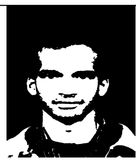
original image	mask example	mask example with Cb
		
	precision: 80.6% iou:77.4%	precision: 75.8% iou:65.7%
		
	precision: 68.7% iou:63.9%	precision: 90.8% iou:78.6%

Table 3.22: the difference that color balancing makes on an exposed and underexposed image in the sfa database.

We have noted that the results on the celebA-HQ dataset do not show similar improvement to the other datasets. This is because the mask used in the dataset only covers the face and not the skin, which leads to incorrect information regarding the neck and hands. We provide an example of this in Table 3.23.

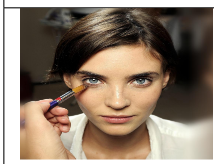
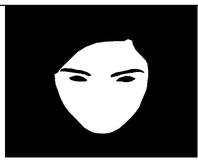
original image	groundtruth	our mask
		

Table 3.23: Difference between celebA-HQ groundtruth and our mask

3.5 Challenges and Difficulties

Throughout the development process, we encountered several challenges and difficulties. Some of the key obstacles include:

- Limited visibility of skin tones in low light conditions.
- Handling noise and artifacts in the collected dataset.
- Finding an optimal balance between sensitivity and specificity in skin detection.
- Diversity of skin tones.
- Limited training data. .

3.6 conclusion

In the implementation phase of our project, we focused on utilizing the development environment and software tools to achieve our goals. We carefully considered the hardware and software components necessary for efficient coding and testing. Throughout this phase, we observed the effects of various algorithms and techniques, such as the color balancing algorithm and the "Msrcr-cb" method for image enhancement, as well as our skin detection algorithm. We also conducted quantitative analysis to measure the impact of our implementation, obtaining numerical results for low light enhancement and skin detection. Despite facing challenges and difficulties, we successfully addressed them and made significant progress in improving our system's performance and functionality. Moving forward, we will continue refining our system and addressing any remaining challenges to further enhance its capabilities.

General Conclusion

Based on the information provided in the previous sections, it can be concluded that skin detection is a crucial process in computer vision, with applications ranging from gesture analysis to person identification and image retrieval. The challenges faced by skin detection methods include varying lighting conditions, color variance, and image quality.

To address these challenges, researchers have proposed color-based and texture-based methods. Color-based methods utilize color information, while texture-based methods rely on texture characteristics to differentiate between skin and non-skin regions. These approaches have shown effectiveness in identifying skin regions in images and videos.

In low-light conditions, skin detection becomes even more challenging due to degraded image quality. Retinex-based enhancement techniques offer a solution by improving the quality of low-light images, thereby enhancing the performance of skin detection algorithms.

A wide variety of face detection methods have been proposed in recent years for skin segmentation. However, most of them do not take the low-light problem seriously. And they assumed that faces are easily available for processing. That is why we proposed a new face detection method in a complex lighting environment based on the hybridization of: firstly, enhanced retinex light enhancement "Enhanced MultiSclae Retinex with Color Restoration (MSRCR) and (SCB), so the first is based on light compensation and the second is based on color enhancement", and, multi-skin region detector based on the most well-known color spaces (Ycbcr, RGB, HSV), and the choice is based on robustness if each in a situation.

The multi-scale Retinex with color restoration (MSRCR) algorithm was applied to enhance the input images captured in a complex real world environment, aiming to minimize the impacts of varying light conditions without deteriorating colors. it was combined with the simplest Color Balance algorithm to correct the color cast, since in MSRCR the color was Enhanced, but not color balanced. The enhanced images was entered to the next step of skin segmentation which uses an hybridization of RGBHSVCbCr by combining the best threshold of every color space. Experimental evaluation on various public databases has demonstrated the effectiveness of our proposed approaches, outperforming existing techniques in terms of quality enhancement and efficiency. This advancement in skin detection enables more accurate and reliable results in challenging lighting conditions.

In conclusion, skin detection methods combined with low-light enhancement techniques significantly contribute to the field of computer vision. They improve the accuracy and reliability of skin detection, benefiting a wide range of applications. Further research in this area can lead to additional advancements and improvements in computer vision systems.

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