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Skin Lesion Segmentation Using Adaptive Color Segmentation and Decision Tree

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Abstract

A decision tree operates as a predictive model in machine learning, utilizing a structured hierarchy of rules for the decision-making process. This model is graphically depicted through a tree-like structure, where each node symbolizes a decision point, and the ensuing branches represent the resultant outcomes of these decisions. This method proves particularly efficacious in addressing both classification and regression challenges, offering clear interpretability through its graphical illustration of the connections between input features and predicted outcomes. In the domain of image processing, color image segmentation serves as a crucial preliminary step for various applications. Specifically, the segmentation of skin lesions holds significant importance in image analysis, notably in the classification of lesions within dermoscopy images. Image segmentation involves the categorization of image pixels into uniform regions based on attributes like color, texture, and luminosity. The primary objective here is to delineate the area of interest from the healthy surrounding tissue. In methods reliant on threshold-based segmentation, the effectiveness of the segmentation hinges on the accurate selection of an appropriate threshold.

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1 Introduction

The organ system of the human body is comprised of numerous organs, each serving a specific function. The skin, in particular, is a vital organ that serves as the body's outer covering. Disorders affecting the skin are categorised as skin diseases, which are among the most common medical conditions affecting people worldwide. Skin and subcutaneous tissue disorders represent a major category of non-lethal ailments (Süt et al., 2020). A substantial number of these disorders are attributed to infectious agents, including bacteria, viruses, fungi, and parasites, leading to conditions such as cellulitis, pyoderma, and scabies, as well as assorted fungal and viral infections. Infectious diseases in this category are most commonly manifested as skin and soft tissue infections, which often present with various rashes accompanied by fever (Yeroushalmi et al., 2020). Infections of the skin (Arief et al., 2024) and soft tissues represent a significant category of infections, encompassing a range of conditions such as cellulitis, erysipelas, impetigo, ecthyma, folliculitis, furuncle, boil, abscess, infections related to trauma, desquamation ulcers, necrotizing fasciitis, Fournier's gangrene, and infections due to human or animal bites. It is important to note that this information is presented in an objective and unbiased manner, using clear and concise language with a logical flow of information. The presentation, etiology, and severity of these infections can vary considerably (Silverberg, 2021; Yeroushalmi et al., 2020).

The diagnosis of traditional exanthems, including measles, dengue, rubella, erythema infectiosum, roseola, and varicella, relies on evaluating both the distinctive features of rashes and accompanying symptoms. Furthermore, there exist atypical exanthems which may coincide with fever or additional clinical signs (Ganesan et al., 2023). These atypical presentations can result from infections or may arise due to hypersensitivity reactions that induce toxicity (Muzumdar et al., 2019). Some of these conditions present diagnostic challenges, but those that arise in emergency medical situations and create urgent diagnostic and therapeutic dilemmas are the most crucial (Patel et al., 2021).

Skin lesions, which manifest as abnormal alterations in the tissue either on or below the skin's surface, often extend irregularly beyond their normal confines compared to adjacent tissue. This outcome frequently occurs as a consequence of prolonged exposure to ultraviolet (UV) radiation. Lesions of this type are classified into two categories, namely benign skin tumors, including nevi, and malignant tumors. The latter represent the least prevalent but most severe form of skin cancer. In recent years, advancements in computer-aided diagnosis have facilitated the early detection of skin cancer through the analysis of dermoscopy images (Sinthura et al., 2020). The procedure entails the extraction of an array of characteristics from the given images, encompassing statistical attributes, shape features, textural characteristics, and relational properties. These features are subsequently utilized to train traditional machine learning (Srinivasa Rao et al., 2023; Jelena & Srđan, 2023) models, which are capable of differentiating between lesions and healthy skin (Benyahia et al., 2021). The diagnostic process for skin lesions has undergone notable advancements in recent years, resulting in more precise and accurate methods for identifying various conditions, particularly in the assessment of structural features like lesion borders, pigmentation, dots/clusters, and lines. These evaluation methods have become increasingly sophisticated, necessitating more time for accurate detection. Consequently, effective and precise detection techniques for these structural elements are essential for facilitating early diagnosis. In the field of computer vision and image processing, edge detection and image segmentation (Sánchez-Ancajima et al., 2022) are fundamental techniques that form an indispensable foundation upon which numerous other processes and techniques are based. Edge detection identifies abrupt changes in pixel intensity to delineate object boundaries within an image, whereas image segmentation divides an image into smaller sections based on distinct characteristics. These techniques are instrumental in recognizing and assessing key structural components such as lesion borders and pigmented areas. Although these methods may prolong the evaluation time, they significantly enhance the accuracy and efficiency of the diagnostic process. It is imperative to acknowledge that despite the critical role of technology, the medical assessment and human interpretation remain indispensable in the diagnosis of skin lesions.

Although the assessment of structural areas may necessitate a greater investment of time, this technology can facilitate the prompt identification of dermatological conditions. The combination of sophisticated technology with human expertise can facilitate the diagnosis process and enhance comprehension of dermatological conditions (Liu et al., 2019). Moreover, edge detection can be defined as a process of reducing the size of an image by filtering out irrelevant and excessive information while preserving the important details. It is commonly used in image segmentation, which involves dividing an image into distinct regions that represent different objects. Edge detection and image segmentation are among the most frequently utilized tasks in the domains of computer vision and image processing. Edge detection can be defined as the process of identifying the boundaries of an image (Zhao et al., 2021). It involves filtering out less relevant and excessive information to preserve important details. Edge detection can also be used for image segmentation, dividing an image into regions representing different objects. Earlier diagnosis of malignant disease increases the probability of favorable prognosis. Malignant cells demonstrate an inclination toward aberrant proliferation and function, and the production of melanin by melanoma cells may evoke an immunologic response, which is reflected in the clinicopathologic presentation of the affected tissue (Albittar et al., 2020)

2 Related Work

Research in the domain of decision trees for medical image analysis has been a significant focus in efforts to improve diagnostic accuracy and efficiency. Previous studies have explored various methods and techniques for implementing decision trees to analyze medical images, including radiology and other medical imaging. Some journals present innovative approaches in building decision trees that can accurately classify specific diseases or medical conditions based on features extracted from these images. The application of decision tree technology in medical images also considers aspects of security and interpretability, which are crucial in supporting accurate clinical decisions. Despite the significant progress made, there are still challenges and opportunities to further enhance the performance of decision tree systems in medical imaging. This will make a positive contribution to medical practices and patient care.

In image processing, segmentation is the process of partitioning an image into discrete regions, or segments, based on the characteristics of the pixels within each region. These features include texture, intensity, and color, thereby ensuring that the segmented image contains sufficient information for analysis and classification. In order to assess the degree of homogeneity within an image of a dermatological lesion, one may consider utilising attributes or features of said image. For instance, the intensity of pixel values may be employed as a metric in this assessment. The skin lesion image segmentation process aims to separate lesion images with healthy classification and images indicated to be affected by skin disease based on the features of the skin image to be used in the classification process. Segmentation of skin lesions on a thresholding basis can be classified as point-based or pixel-based, depending on the threshold estimation approach, and generally has difficulty estimating effective thresholds due to dermoscopy artifacts (Hasan et al., 2020; Hasan et al., 2023). Research approach conducted (Sivaraj et al., 2020) segmenting on a threshold basis by segmenting into several pixels in gray images, pixel intensity values on citara that have a value less than T are considered images that are not affected by skin cancer. Research approach conducted (Gangwar, 2021) It adds K-means clustering and active contour to the Chan-Vese method by ignoring edges in the image and minimizing energy functions. The process is carried out repeatedly, while in the k-means method the segmentation process is carried out on the desired area using k clusters. Research conducted (Hegde et al., 2018) perform the segmentation process using HED Segmentation. The findings indicate that: (a) Linear Discriminant Analysis (LDA) demonstrates superior performance in both binary and multi-class classification scenarios when utilizing color-based features; (b) Support Vector Machines (SVM) achieve enhanced accuracy with texture features across both binary and multi-class classifiers; (c) when integrating both types of features, LDA and SVM classifiers exhibit improved effectiveness in binary and multi-class classification contexts, respectively. Research conducted (Hameed et al., 2020) performs the segmentation process using the Otsu method. The input images used are common skin lesions such as acne, eczema, psoriasis, melanoma with a total of 1800 images with an accuracy of 83% using Support Vector Machine. The segmentation results are then used as input in the classification process. The classification method employed (ALEnezi, 2019) involves multi-SVM classifying three distinct classes with 100% accuracy. Similarly, also uses the Otsu thresholding method for image segmentation. The process of separating foreground and background images involves adjusting thresholds to reduce or increase the variance between classes (Senan et al., 2021) propose a different approach to segmentation by using the active contour method based on surface evolution. This process involves the separation of parameters and geometric groups, the definition of parameters as parametric active contours, and the definition of geometric active contours based on the evolution of the curve itself. Choudhary et al., (2022) used the Otsu method for image segmentation, specifically Otsu Multilevel thresholding with IM Quantize using 2-level thresholds. Similarly (AlDera & Othman, 2022) employed the Otsu method for image segmentation, considering color, sharpness, brightness, and intensity of the image. On the other hand (Breslavets et al., 2022) utilized an artificial neural network method for psoriasis image segmentation, achieving an MPE of 70% (Joseph & Olugbara, 2021) combined Otsu Thresholding with Color Histogram Clustering (CHC) for preprocessing analysis using a saliency method. The process involves extracting dominant foreground objects from lesion images based on their color, intensity, contrast, and brightness relative to the background. Finally (Gangwar, 2021) utilises the Global Thresholding OTSU method in combination with K-means clustering. This involves iterating the global thresholding stage by applying a single threshold value to the entire image until the difference between the previous and new threshold values can be ignored. This involves iterating the global threshold by applying a single threshold to the entire image until the difference between the previous and new thresholds can be ignored.

3 Review

1) Skin Lesion Image Segmentation

The skin image segmentation process aims to eliminate irrelevant information for a more detailed classification process (Adeyinka & Viriri, 2018). Various challenges are encountered when segmenting skin lesion images, such as the presence of hair, multicolored lesions, specular reflections, and other artifacts. The literature presents several algorithms addressing the accurate segmentation of skin lesion areas, including threshold-based, edge and contour-based, and region-based methods. However, these segmentation methods may lack robustness in cases of low-contrast images and exhibit decreased performance in complex images with substantial artifact volumes. In this study, we have endeavored to utilize these diverse methods for clustering skin lesion areas and subsequently classifying them based on the proposed algorithm.

2) HSV Color Model

HSV is a color model that delineates colors in a manner akin to human visual perception. Hue denotes the type of color visible to the human eye, such as red or green, and this attribute corresponds to the eye's detection of different light wavelengths. Saturation describes the degree of purity of a color, indicating the absence or presence of white light mixed with the hue. A fully saturated color, devoid of any white light, exhibits 100% saturation, whereas the introduction of white light reduces saturation towards zero. Value, often termed brightness, quantifies the lightness or darkness of a color, perceived as variations in brightness from white through various shades of gray to black, commonly referred to as the gray scale. An example demonstrating the transformation from RGB (Red, Green, Blue) to HSV color space is depicted in Figure 1.

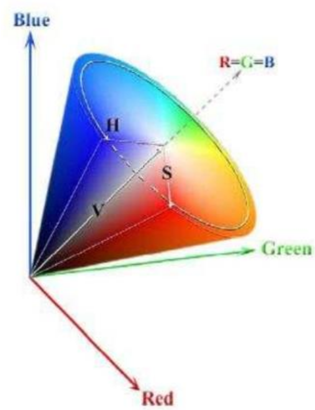


Figure 1: The RGB Colour Model

A perceptual HSV color model, which is non-linear with respect to the fundamental RGB color model, has been developed for use in areas such as computer vision and facial recognition. This enhanced color model consists of three main elements: hue, saturation, and value. The hue element denotes the color as perceived by the human eye, the saturation element reflects the color's intensity regarding its purity from white light, and the value element assesses the color's brightness or luminosity.

4 Proposed Methodology

Figure 2 provides a visual demonstration of the proposed methodology for skin pixel segmentation utilizing the HSV model. The HSV (hue, saturation, value) color space offers several advantages over the RGB (red, green, blue) color space. Perhaps most importantly, it represents colors in a more intuitive manner, making them easier for humans to understand. The RGB color space employs an intricate mixture of intensities from three fundamental primary color components (red, green, and blue), which can prove challenging to comprehend visually. The non-linear perceptual model separates color components into hue (tint), saturation, and value. This provides a more intuitive method of controlling the properties of color. The proposed methodology employs the HSV color model for the detection and segmentation of skin lesions. Derived from the RGB model, the HSV color space comprises three components: hue, saturation, and value. Hue is defined as the color, with varying angles representing distinct hues.

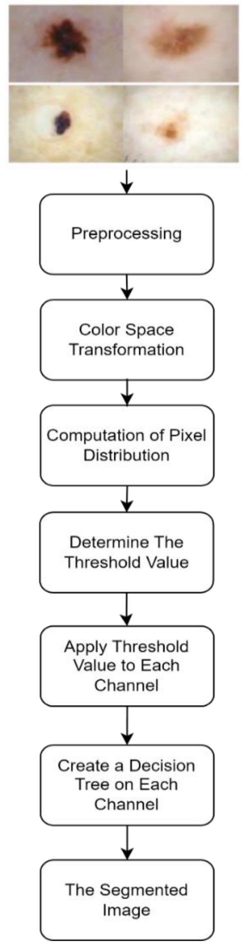


Figure 2: Proposed Methodology

1) Preprocessing

During the preprocessing phases, images varying in size often contain disparate numbers of features. To mitigate this variability and standardize input, image dimensions are adjusted. This resizing process not only normalizes the number of features across different images but also diminishes processing time and augments the efficiency of the system. Specifically, the original resolution of an image, initially at 768 × 560 pixels, is systematically altered to a uniform size of 224 x 224 pixels.

2) The Sketch Removal Stage

The next stage involves removing sketches from a portion of the image by cropping it to obtain the desired region (Figure 2). Some images have circular sketches that degrade segmentation performance, so it is important to eliminate them before the segmentation process by examining the diagonal of the image and obtaining the average values from these three pixel channels. These values are saved for comparison with a threshold. The algorithm searches for the first and last positions where the average pixel value is higher than the threshold. With this information, it is determined where the points on the diagonal of the image are, indicating the start and end of the sketch. In the second step, the lesion image is cropped based on these points, and then the algorithm checks both diagonals. This ensures that the region of interest is correct, even if the sketch is not in the center."

3) The Stage of Hair Removal

The process of removing hair in dermoscopy images is equally crucial in the segmentation and classification process. Failure to address this can result in suboptimal segmentation outcomes. The following steps are involved in the hair removal process as part of noise reduction:

1. Calculate the hair ratio index in the image.
2. If the ratio index is > 2, then.
3. Perform a median filter on the RGB image.
4. Multiply the calculated image with the median filter by an edge mask to obtain pixel values on the mask.
5. Calculate the maximum value to replace hair pixels in the original image with the median value.

4) Calculation of Pixel Distribution

Each pixel is taken as the smallest unit, and the frequency of its occurrence is recorded for each brightness level or color. The results of calculating this pixel distribution provide information about the brightness or color distribution in the image, forming a histogram that reflects the pattern of pixel intensity distribution. Hue specifies the color aspect within the model, with varying angles of hue corresponding to distinct colors. For instance, angles ranging from 0 to 60 degrees are indicative of the color red. This model is constructed upon the foundational color space model through a specific mathematical transformation. The equation (1) is given as,

$$H = \begin{cases} 0 + \dfrac{43 \times |G-B|}{Max\,(R,G,B) - Min\,(R,G,B)}, Max\,(R,G,B) = R \\ 85 + \dfrac{43 \times |B-R|}{Max\,(R,G,B) - Min\,(R,G,B)}, Max\,(R,G,B) = G \\ 171 + \dfrac{43 \times |R-G|}{Max\,(R,G,B) - Min\,(R,G,B)}, Max\,(R,G,B) = B \end{cases}$$

$$S = 255 \times \begin{cases} \dfrac{Max(R,G,B) - Min(R,G,B)}{Max\,(R,G,B)} \end{cases}$$

$$V = Max\,(R,G,B) \tag{1}$$

5) Pruning

Once the decision tree for the candidates has been formed, a pruning process is initiated. The objective of this procedure is to eliminate irrevelant decision nodes (Nugroho et al., 2023), this process is integral to removing superfluous decision nodes, which enhances both the decision tree's visualization clarity and its predictive accuracy. Initially, candidate trees are susceptible to excessive complexity due to unrestricted expansion—this occurs until all attributes or samples are exhausted, or when all samples correspond to a single class label. The pruning of the decision tree is executed in two main steps, as illustrated in Figure 3. The first step targets pruning to adjust to the training data, which, although improving fit, risks overfitting. This involves substituting decision nodes with the most frequently utilized branches or leaf nodes that demonstrate higher classification accuracy with the training data. The objective here is to discard decision nodes that may have been inadvertently added during the stochastic construction process and are detrimental to the tree’s classification accuracy. This step is repeated until no further node replacement enhances accuracy or the tree is reduced to only leaf nodes. The second step aims to bolster generalization of the tree beyond the training data set. It includes replacing decision nodes with branches that are used frequently, adjusting the tree only if such replacements lead to a higher estimated error rate. This approach shifts the focus from classification accuracy on training data to minimizing the overall estimated error rate. The primary goal of this step is to prevent overfitting—a condition where the tree fits the training data too tightly but performs poorly on unseen data. The strategy entails minimizing the error rate of each subtree to enhance the tree's ability to generalize, thereby reducing the estimated error rate across the training data.

5 Results and Discussion

1) Setting Threshold Values

The next step involves applying optimal threshold values to the three channels of the HSV image. Careful selection of these thresholds is essential to ensure accurate segmentation of skin pixels, after determining the threshold values for the three channels, the next process involves constructing a decision tree. The threshold values in the decision tree are manually set at nodes, and the determination of threshold values is used to identify significant changes in image intensity at object boundaries. The decision tree in the HSV color space is presented in Figure 3.

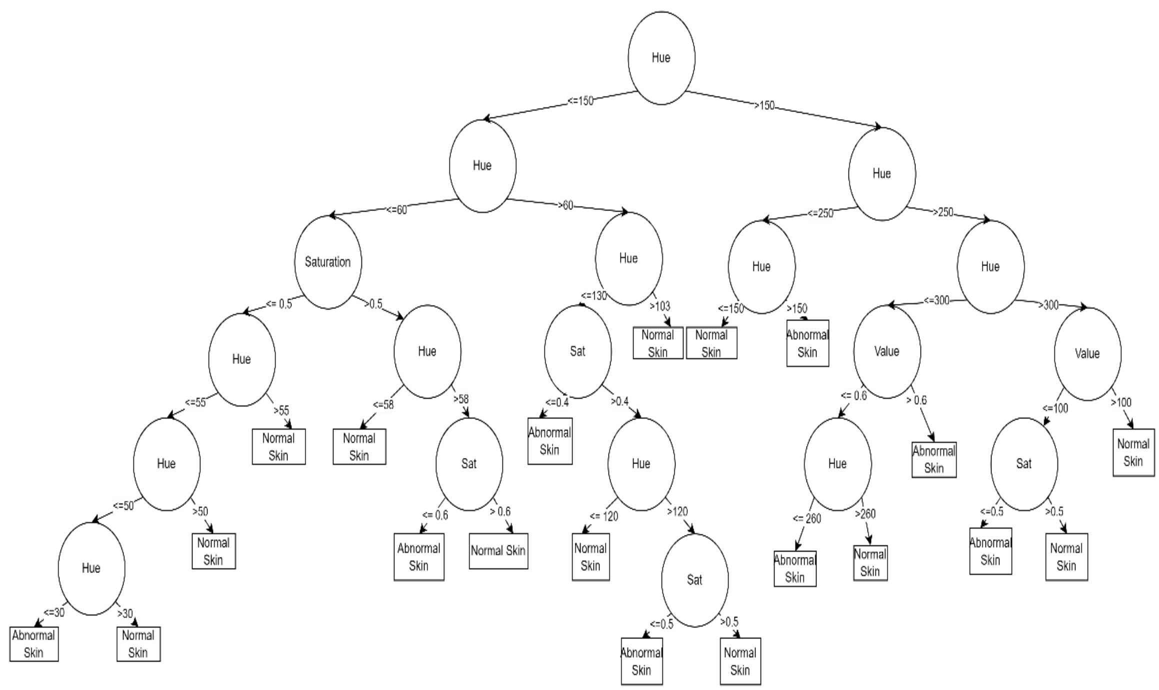


Figure 3: Hue, Saturation, Value Decision Tree

The figure 3 depicts a decision tree used to segment skin lesions by setting thresholds based on HSV (Hue, Saturation, Value) values. This tree is structured with a series of nodes that represent decisions based on specific threshold values of these HSV components. Here's a breakdown of how the decision tree works to search for thresholds to classify skin lesions. The decision process starts with the Hue component at the topmost node. If the Hue value is less than or equal to 150, the decision follows the left branch; if it's greater than 150, it moves to the right branch. This split helps separate the data based on a fundamental color property of the skin lesion.

Subsequent Decisions: As the tree branches out, additional decisions are made based on the Saturation and Value components, as well as further refinement of the Hue thresholds. For instance:

1. If the Hue is less than or equal to 60, the decision moves towards checking the Saturation value (e.g., <= 0.5).
2. At various other nodes, checks for different ranges of Hue (e.g., <= 55, > 250) lead to further branching.

2) Classifying Normal and Abnormal Skin

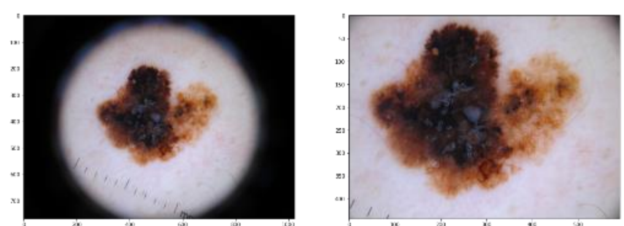
The end nodes (leaf nodes) of the tree classify the skin as either Normal Skin or Abnormal Skin based on the thresholds applied throughout the decision process. If the Hue is less than or equal to 60 and the Saturation is less than or equal to 0.5, the skin is classified as Normal Skin. Other branches lead to different classifications based on thresholds of Hue, Saturation, and Value.

3) Threshold Exploration

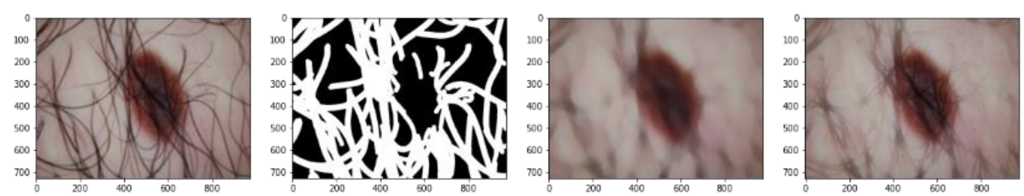
The tree structure systematically explores different thresholds to identify patterns in the skin lesion data. By adjusting these thresholds, the model attempts to segregate the image into regions of normal and abnormal skin, making it easier to identify lesions that require further attention.

4) Segmentation

The image to undergo the segmentation process undergoes preprocessing as depicted in Figure 3. This task is carried out to anticipate the possibility of suboptimal segmentation results due to disruptive noise in the segmentation process. Some preprocessed results are presented in Figure 4.



(a)



(b)

Figure 4: Preprocessing Results (a) Hasil Vignette Removal, (b) Preprocessing Results with Hair Removal on the Lesion Image

An RGB color image is divided into red, green, and blue channels. The maximum and minimum values of the R, G, and B components are then identified. As illustrated in Figure (4.a), a masking technique uses the pixel values from these channels. Original Image and Adaptive Threshold Value shown in Figure 5,6. Different threshold levels are applied to the R, G, and B channels respectively. Image Intensity Level and The Outcome of RGB based Skin Color Segmentation shown in Figure 7, 8.

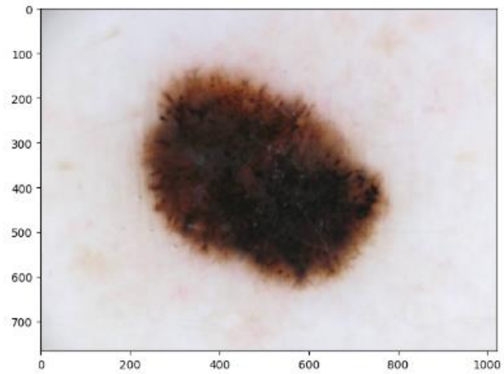


Figure 5: Original Image

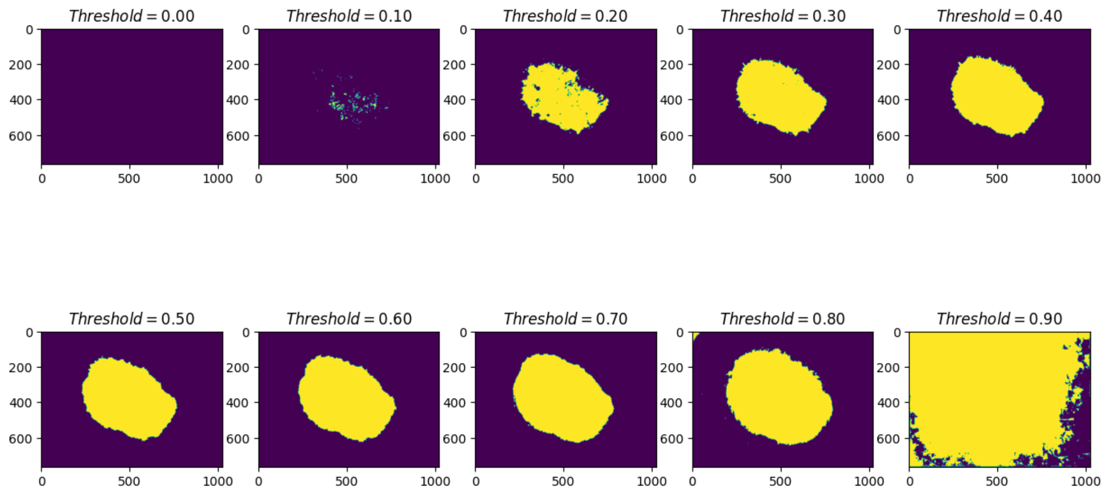


Figure 6: Adaptive Threshold Value

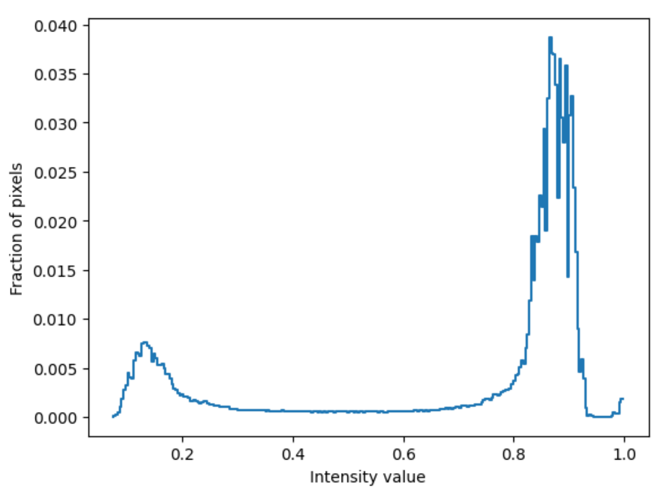


Figure 7: Image Intensity Level

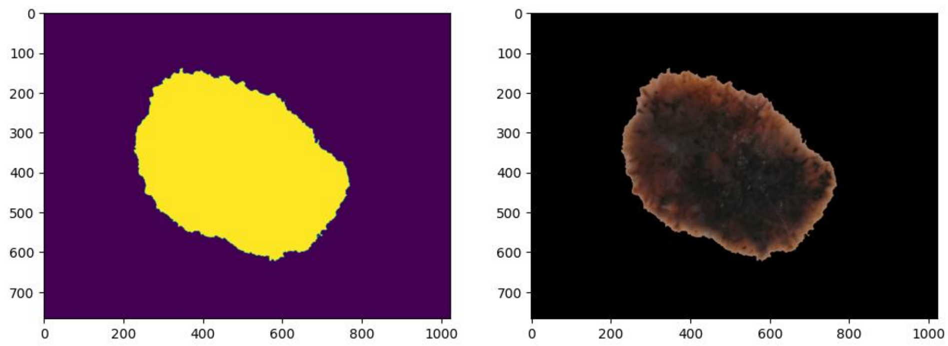
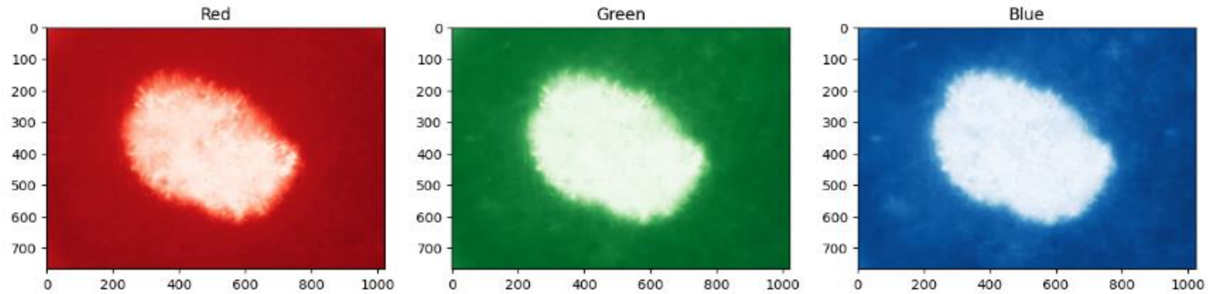
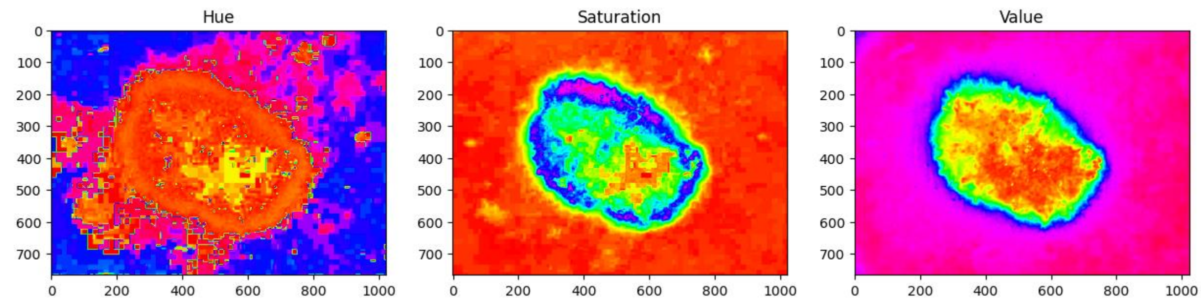


Figure 8: The Outcome of RGB based Skin Color Segmentation

The results of the skin identification process utilising the HSV model are illustrated in Figure 9. The process is initiated by transforming the image from the RGB to the HSV colour model. Fig. 9(a) shows the original test image, and Fig. 9(b) displays its transformation into the HSV format.



(a)



(b)

Figure 9: (a) Test Image in RGB, (b) HSV Space

The Hue, Saturation, Value color model segments an image into three components: Hue, Saturation, and Value. Hue specifies the color of the image, Saturation indicates the extent of white mixed with the hue, ranging from zero to one hundred percent, and Value measures the brightness or intensity of the image. Additionally, histograms are used to graphically represent the distribution of pixels across various channels, as demonstrated in Fig. 10.

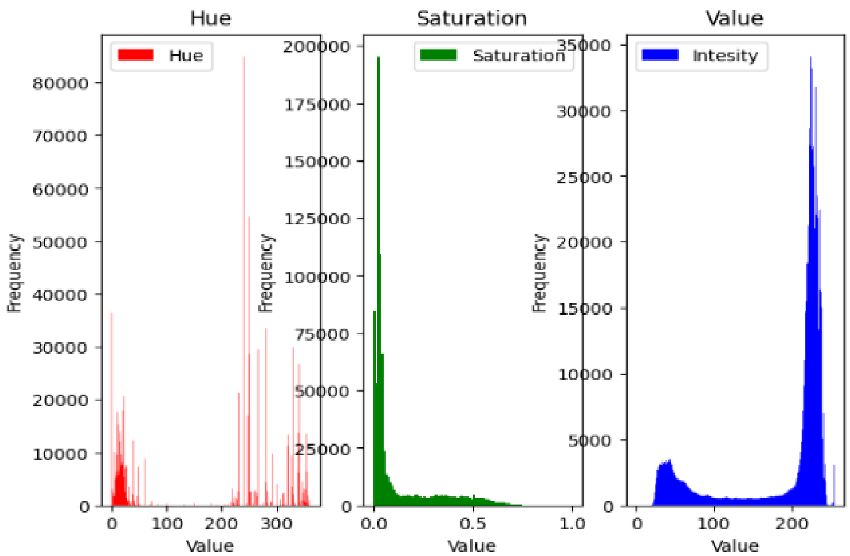


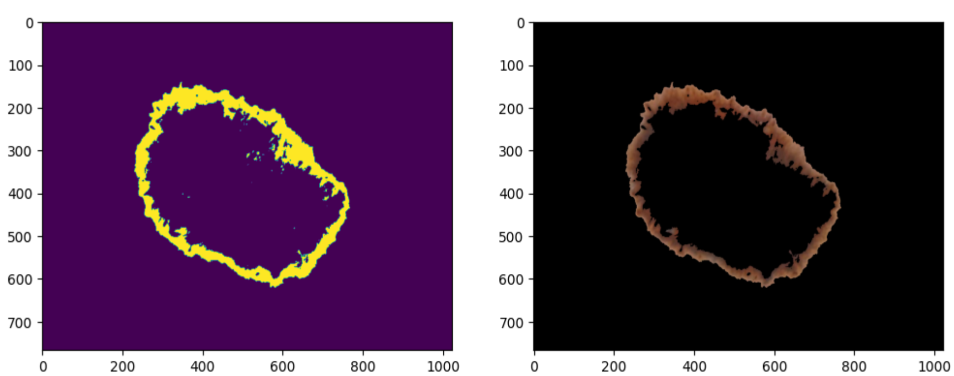
Figure 10: The Distribution of Pixels Across the Three Channels of the HSV Color Space

The hue, saturation, and value (HSV) test image was subjected to a thresholding process, wherein the three primary channels were evaluated. The selection of optimal threshold values is of particular importance for the accurate segmentation of skin elements. In this approach, a binary image of the skin is generated by employing the precise values for optimal thresholding that are optimal for the segmentation of skin color, as illustrated in Table 1.

Tabel 1: Threshold Values

No	Color Space	Min Threshold	Max Threshold	Optimal Threshold
1	Hue	0.0	200	< 100
2	Saturation	0.5	1.00	> 0.4
3	Value	20	250	> 100

The methodology employed for the segmentation of skin color is illustrated in Fig. 8. Binary images, created by applying threshold values to the hue, saturation, and value channels of the image, are illustrated in Figure 11 for each respective channel.



(a) (b)

Figure 11: The Skin Color Segmentation Result

6 Conclusion

It is evident that the HSV (Hue, Saturation, Value) color space offers several advantages over the RGB (Red, Green, Blue) color space. Primarily, HSV aligns more closely with human color perception by deconstructing color into intuitive components such as hue, saturation, and value. This separation into distinct aspects of color tone, purity, and brightness enhances the understanding and manipulation of color attributes. Our proposed methodology highlights the efficacy of the HSV model in the precise identification and segmentation of skin color pixels. While there are various color models each tailored to specific applications with unique characteristics, the effectiveness of our proposed scheme hinges critically on the accurate selection of threshold values for each channel. Inaccurate thresholds can lead to suboptimal outcomes. In our approach, we utilize the HSV color model specifically for skin pixel segmentation, demonstrating its practical utility in this application.

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