Foundation Makeup Shade Recommendation using Computer Vision Based on Skin Tone Recognition

MSc Research Project
Data Analytics

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Project Submission Sheet
School of Computing

Student Name:	Sanica Kamble
Student ID:	x21130701
Programme:	Data Analytics
Year:	2022
Module:	MSc Research Project
Supervisor:	Anderson Augusto Simiscuka
Submission Due Date:	15/12/2022
Project Title:	Foundation Makeup Shade Recommendation using Computer Vision Based on Skin Tone Recognition
Word Count:	8337
Page Count:	21

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Foundation Makeup Shade Recommendation using Computer Vision Based on Skin Tone Recognition

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Abstract

Skin detection has a wide range of uses in fields including surveillance, criminal justice, and health, among others, and has shown to be a fantastic innovation. In order to recommend or advise the best matching foundation shade to users, this research focuses on skin detection, which involves extracting the skin tone RGB values from face photos belonging to different ethnic groups. This method, which is based on a three-tier architecture, addresses three components of the process: skin detection, identifying the skin tone, and recommending the foundation shade, brand and product that is most appropriate. Three color-space models have been compared for the detection of skin and skin tones: HSV color space with Gaussian blur, HSV color space alone, and a mix of HSV and YCrCb color space with histogram equalization and Otsu's image segmentation. For each of the three methodologies, the difference between the calculated RGB skin tone values and the actual RGB skin tone values has been measured using the delta-E metric. By producing the lowest Delta-E average value of 17.51427022, the color-model using a mix of the HSV and YCrCb color spaces outperformed the other two techniques.
Keywords- RGB, HSV, YCrCb, Delta-E, Histogram Equalization, Image Segmentation, Skin Tone, Skin Detection, Color Space

1 Introduction

In order to deliver results that are tailored to users' interests, platforms like Netflix, Amazon, and Google, which are used every day by practically all users, have undergone significant development. But as of yet, no comparable advancement has been made in applications based on makeup. There is now a standard for beauty, and people's ideas of it have changed as a result of the development of social media, social culture changes, advancements in cosmetics production, etc. It is crucial in the beauty sector to be able to offer products that would improve the users' appearance. Moreover, the advent of gender-neutral cosmetics has significantly changed the customer base of the enormous, globally distributed, and diverse beauty sector (AZUMA; 2021). Therefore, it is essential that the beauty applications begin offering tailored recommendations rather than broad ones. The makeup applications do offer some general recommendations based on the user's prior purchases or searches, or in some cases, a user is required to complete a quiz in order to receive the best makeup recommendations. This is quite stressful because not every user is likely to be aware of their own physical characteristics, and so such quizzes have a tendency to become overly technical and overwhelm the user. In order to make the skin appear even toned and enhance the appearance of additional cosmetics like lipstick, blush, etc., foundation or base makeup must match the skin tone. Because of the in-store cosmetic trial, it was simple to obtain the ideal foundation colour to match skin before COVID-19, but this practice has since been outlawed globally for reasons of public health and safety. Although COVID-19 is gradually being phased out and corporations may start in-store makeup trials once more, it turns out that this method is still not hygienic. The potential health risks associated with exchanging used makeup are highlighted in research done by (Bashir and Lambert; 2020) for UK consumers, and according to the authors' research on used makeup products and used makeup applicators, it was discovered that these were contaminated with different types of bacteria like *Staphylococcus aureus*, *Escherichia coli*, and *Citrobacter freundii*. Therefore, there needs to be a simple, user-friendly, and hygienic method for consumers to select the appropriate foundation shade. Skin detection technology using color spaces appears to be a potential solution due to its lightweight, quick, and straightforward implementation and deployment in terminal applications (He; 2021).

Skin detection has many applications namely, real time surveillance (Shifa et al.; 2020a), healthcare for detecting cancer or skin defects, bio-metrics (Lionnie and Alaydrus; 2018), criminal justice, detection of fake faces (Chen et al.; 2022), etc. as discussed in section 2.1. It is possible to apply same or similar concept in makeup domain as well. By guiding customers in the selection of the appropriate makeup shade and preventing them from squandering money on cosmetics with the incorrect foundation shades based on presumptions, this research project will have **major contribution towards the diverse client base of the beauty sector**.

The objective of this research project is to study and implement various skin detection techniques using different combinations of color spaces to address the research question, **"How can Computer Vision based skin tone recognition improve the effectiveness of makeup recommender systems in determining best suited foundation makeup shades?"**. First technique will be implemented using combination of HSV and YCrCb color spaces along with histogram equalization and Otsu's image segmentation. Second technique will be implemented using HSV color space along with Gaussian blur. Lastly only HSV color space will be implemented. All of these techniques will be implemented on human facial coloured images belonging to different ethnic groups. These skin detection techniques will not only be used to detect skin but also to detect skin tones of all the individuals in the images. Skin tones will be in RGB value format. These skin tone RGB values will be then compared with the ground truth RGB values of the skin tone to measure the errors and skin tone color similarities and dissimilarities using Delta-E metric. The three mentioned skin detection techniques will be compared based on the average Delta-E value obtained and the technique with least Delta-E average value will be selected for finding the best matching foundation shade from the dataset consisting of different foundation shades of various foundations products of different makeup brands.

This research paper discusses skin detection techniques using color spaces in section 2 related work. Methodology of the research will be discussed in section 3. Section 4 discusses on design components of all the three skin detection techniques. Section 5 describes the detailed implementation steps of the three techniques proposed and section 6 focuses on evaluation of the results. With section 7 the research will be concluded by discussing upon the overall research and the results obtained by each technique and also the future advancements will be discussed.

2 Related Work

Skin, skin tone, and face detection methods have been the subject of extensive research in the past for use in the realms of beauty, fashion, crime, medical, surveillance, etc. The subsections that follow provide a critical overview of the approaches, strategies, or surveys connected to the research of makeup, the identification of skin tones, commercial and non-commercial applications of Delta-E metric and recommender systems.

2.1 Skin detection using Color Spaces

HSV color model and SLIC Superpixels image segmentation algorithm is used by (Nikolskaia et al.; 2018) for skin detection in colored images. The author also uses histogram graphs to represent images and its features for human faces belonging to different nationalities. Naive Bayes classifier is used by this author to classify the skin pixels in the image. The author provides a detailed step by step approach of the implementation and also mentions the importance of using images of people belonging to different races for more accurate results. The challenges faced by this author like hair color pixels similar to dark skin tone are falsely classified as skin pixels and the background objects or any other objects like clothes present in the image which are of skin color are also falsely classified as skin pixels, are very common challenges when it comes to skin identification. The author moreover describes how using of image segmentation makes the classification process easier.

Skin detection technique was used by (He; 2021) in order to determine whether a person is wearing mask or not. This research is based on COVID-19 scenario when wearing a mask was mandatory in public places. The author's idea was to eliminate human resource used for regulating the mask wearing rule and automate the process. The author has used ellipse skin model for skin detection. Before the images captured via camera are run through ellipse skin model, they are first converted from RGB to YCrCb color space after carefully studying the advantages of YCrCb color space over HSI and HSV color spaces, its ease of calculation process and simple representation of spatial coordinates and minimum overlap between skin and non-skin colored pixels providing great results in skin color clustering. A non-linear transformation is performed on the YCrCb color space image and all the pixels in the image are traversed through to check whether it complies with the ellipse skin model. The grey pixels that comply with the ellipse skin model are set to 255 representing skin pixels and the one's that do not are set to 0 representing non-skin pixels thus masking the image to accurately identify skin colored pixels in the image. The author has made great points related to challenges of skin identification due to uneven illumination of the images leading to inaccurate results. The author also stated how these skin models do not require training data and hence eliminate the overhead of training process, they require less computational power and resources, have faster detection speed and are easier to deploy in the terminal devices than that of machine learning and deep learning models.

The study presented by (Yen and Yang; 2020) is based on skin color detection to be able to apply in the expert systems in the future for the females to be able to get customized cosmetic suggestions based on their skin color. The approach in this study is based on identifying the points in the face image to get the skin color values and calculate the average skin color value based on the values obtained by the chosen points on the face. The author has made use of YCrCb color space and k-means clustering and has developed algorithms called as FaceRGB and ColorFCM to automatically detect skin tones from big data consisting of female face images.

The research presented by (Hussain and Al-Bayati; 2019) to detect human face using skin color properties uses simple HSV color model to identify the skin colored pixels in the images. The authors explain how H channel is used from the HSV color space to identify the skin region from the images. The face images are originally in RGB color space which are converted to HSV color space wherein the H value has certain thresholding values that helps is classifying the pixels as skin and non-skin pixels. Using this a boundary region is set in an image which is used to mask the background and non-skin pixels to obtain the just the face from an image.

The research based on face detection using skin color feature by (Li et al.; 2020) uses YCrCb color space to detect skin color pixels in the image. Along with this color model the author has also applied two dimensional Gaussian model where the mean and variance of the Gaussian distribution is calculated to obtain the skin color. The author mentions that YCrCb color model is not extremely influenced by the external brightness and hence is the best choice in detecting skin regions in the image. The author performed various comparative experiments using images having multiple human faces and images having single human face. The results showed that the proposed method works best with the images having one human face however the detection frame is lost when the images have multiple human faces.

A comparative study done by (Lumini and Nanni; 2020) on different skin detection approaches using various public datasets presents experimental analysis between pixel based algorithms, spatial analysis algorithms and deep learning algorithms. Various different parameters like time, image complexity, use case complexity, computational resources, precision, accuracy and need of parameter tuning are taken into consideration while comparing the results obtained by all the types of techniques or algorithms. The results correctly showed that pixel based skin detection techniques are very fast, simple to implement and consume less computational power and resources. However, they only give accurate results for images not having complex backgrounds and can only be used for simple scenarios or problems or use cases. Spatial analysis techniques are comparatively complex in implementation, are very inaccurate and need parameter tuning and are generally very slow. On the other hand, the deep learning techniques do achieve precise results however, they consume a lot of computational power and resources and better to be implemented for complex scenarios where there is no limitation over power and resource consumption. Lastly, the author comments on how skin detection is a complex process and with the fusion of various techniques accurate results can be achieved.

Research done by (Kolkur et al.; 2017) on human skin detection implements combination of 3 color model namely RGB, HSV and YCrCb to develop a threshold based algorithm. The author mentions how skin detection is influenced by brightness, contrast, transparency, illumination, and saturation present in the colored images and all of these factors are needed to be taken into consideration while processing the images using the color models to determine the human skin from the images. A detailed explanation of 3 used color models is provided by the author in the proposed research followed by the implementation of these on the Pratheepan dataset. The results are based on the number of pixels correctly classified as skin pixels using which the classification evaluation metrics accuracy and precision are calculated.

A robust technique proposed by (Chen et al.; 2022) for detecting GAN (Generative Adversial Networks) generated fake faces uses RGB and YCrCb color spaces along with and improvised xception technique. The author performed a comparative study between RGB, YCbCr, HSV, and Lab color models where RGB and YCbCr proved to be more robust and were able to give different results for different post-processing operations. Hence, the author made the clear choice of using RGB and YCrCb color spaces for the proposed implementation. These color models were used to detect JPEG compression and blurring post-processing operation that are present in GAN generated fake faces to improve the classification results.

Skin detection technique is implemented by (Shifa et al.; 2020b) for human face encryption for the purpose of privacy protection in real time surveillance applications. The proposed technique makes use of 3 color models like RGB, HSV and YCrCb for developing a Combined Threshold Rule (CTR) based skin segmentation to increase the accuracy of detecting skin and reducing false positives. The identified skin pixels are then blurred and selectively encrypted to protect the individual's privacy. These color spaces are used individually and combined for pre-processing, skin sampling and skin segmentation respectively.

The research based on skin detection done by (Buza et al.; 2018) is based on image color segmentation with histogram clustering. A combination of two color models namely HSV and YCrCb is used along with histogram equalization to define threshold values and it also separates the background and objects of interest in a colored image. Further Otsu's segmentation is also performed on the images. Combination of all of the mentioned is used in detecting the skin in an image. The technique was tested on face images and family images and the results show that the technique is best suited for face images that have large skin area and simple background and is able to achieve accurate results with very less error. However, for family images where skin area is less and has complex background the technique gives moderate results.

Comparative research conducted by (Lionnie and Alaydrus; 2018) compared 10 rules of skin color detection using various color spaces like RGB, HSV, YCbCr, CIE Lab and YIQ. This research is based on skin detection used in bio-metric identification. The precision of the proposed technique was done using 2 fold cross validation and by calculating Euclidean distance. Further the author also employed combination of HSV and YCrCb color spaces to check if the accuracy improves. The best precision was obtained by using YCbCr, CIE Lab and HSV color models and overall YCbCr color model gave 84.35 percent of precision which was the highest of all for binary images.

Another human skin detection research by (Varma and Behera; 2018) employs a combination of HSV and YCrCb color spaces for the pixel transformation and training. The author has implemented histogram processing, Gaussian model and a combination of histogram and Gaussian model in the three experiments for detecting human skin and compared the results of the three. The experiment was conducted on 3 different datasets namely ETHZ PASCAL dataset, Partheepan dataset and SFA dataset and the images were randomly selected for the study. The comparative results show that the fusion of histogram and Gaussian model has the highest accuracy of around 86 percent whereas histogram alone gives around 83 percent of accuracy and Gaussian model alone gives 81 percent of accuracy.

Authors (Hema and Kannan; 2020) in the research used HSV color space for image segmentation for the purpose of object detection. They developed an interactive GUI where the user can adjust the HSV threshold values in order to extract an object from the colored image. The authors describe the application of this technique in the various fields like medicine to detect cancer.

Authors (Mohammed et al.; 2020) explain how different color models perform different in various conditions and hence, it is important to make a informed decision with respect to the problem scenario. The authors compared the results of RGB color space and YCrCb color space used for skin detection and image segmentation. The results showed that YCrCb color model was able to obtain consistent results under varied illumination conditions whereas RGB model is very sensitive to lighting hence performed poorly.
A survey done by (Garcia-Lamont et al.; 2018) on different image segmentation techniques and color spaces and their real world application presents a detailed study on the features and working of these. The authors of this study explained the need of color space transformation. The color images are always in RGB color space as this is used to represent every color in the space, however this color space is not suitable for image segmentation due to high correlation between R, G and B components. Other color spaces like HSV, Lab, YCrCb colorspaces do not have these issue and hence are preferred color spaces for image segmentation process. Further the author discusses about the real world application of the color spaces and performs a qualitative evaluation of different image segmentation techniques.

2.2 Application of Delta-E

Research by (Karma; 2020) on measuring color dissimilarity outlines ways to measure the color difference using the Delta-E metric. Related works of this paper on color difference represents a valid acceptable range of Delta-E value while calculating the color difference which is a difference from 0-49 that can be termed as acceptable where the entire range of Delta-E is between 0 to 100. However, every scenario can have different acceptable tolerance and it should be analyzed through detailed study. Also, the related works on Distance and Similarity Measures states that RGB color space need to be transformed to a different color space which has uniform perception.
(Mahmoudi et al.; 2018) authors developed an interactive Color sensing AR based learning system which helped the kids to analyze the colors and learn the color names in Spanish. The sensors in the system are used to measure the color frequency to obtain the RGB code which is then sent to the cloud with the help of MQTT protocol. This color is then represented on the interactive tool's screen for the kids to learn. Further, Delta-E metric is used to calculate the errors of the sensors in translating the RGB colors.
Research done by the authors (Bhookya et al.; 2020) is based on the estimation of yield of chilly crop where image processing techniques have been used. Delta-E metric is used to identify the chilly crop from a colored image which is in the RGB color space which is then converted to Lab color space to calculate the Delta-E value. This delta-e value is used to differentiate the chilies in the picture from the background. The color of the chilies is an important factor in analyzing the ripened chilies ready to yield. By automating this process using image processing technique that accuracy required for the job has increased up to 97 percent and with this the need of manual labor is also eliminated.
Another research done by authors (Nemli et al.; 2018) used Delta-E metric to evaluate color and translucency matching of the maxillofacial prostheses reproduced using computerized system.
Yet another application of Delta-E seen in the research of (Ruiz-López et al.; 2022) based on evaluation of the color difference between natural teeth and dental implants.

2.3 Need for Makeup recommender systems

The differences between knowledge-based recommender systems are highlighted by a survey that (Ameen; 2019) reported in the study article on types of recommender systems. According to the author's research, rule-based recommender systems, which are a subset of knowledge-based recommender systems, are able to provide high-quality recommendations based on the precise constraints provided by the user as knowledge. This research proposal is particularly interested in rule-based recommender systems because skin tone will be provided as a constraint based knowledge to determine the foundation shade for the user.

(Elahi and Qi; 2020) have addressed a number of cold start issues with regard to recommender systems for clothing. In order to minimize cold start problems, the author also outlines a number of potential options for receiving input from a user who has just signed in to the system. This study explains how crucial it is to have a user's initial input when providing recommendations so that they are relevant. This issue is related to the suggested research topic.

According to a statistical analysis of sunscreen recommendations made by (Song et al.; 2021) based on surveys of dermatologists and popular news investigations, it is crucial to use sunscreen that is appropriate for your skin tone if you want to achieve effective outcomes. The goal of this research topic, which is to better understand how to apply facial cosmetics while recognizing skin tone, is supported by the author's research.

2.4 Importance of makeup

Effects of makeup on Brazilian women's self-esteem were discussed in the statistical analysis and survey conducted for the study by (Mafra et al.; 2022). Women's cosmetics usage inventory, sociodemographic data, general and social self-esteem, and self-ratings of their bodies were used to create the survey questionnaire. The overall study found that socially engaged women spent more money on cosmetics, while women who valued appearances spent more money and time on makeup. Conversely, women who loved their appearance and had greater general self-esteem spent less money on acquiring makeup. The fact that every woman uses makeup, even if not on a regular basis, is shown by this study, and this fact serves as the impetus for this research project.

The impact of cosmetics on a person's emotions, different brain regions, and their sense of self is wonderfully addressed by (de Souza Nuevo et al.; 2021). The concept of Visagism2 and how it enables people to communicate through their appearances was also mentioned by the author. In addition, the author conducted a thorough bibliographical search to comprehend different emotional and neurological components of makeup, which is explored and analyzed in detail. The author came to a conclusion by explaining how self-esteem is currently improved by makeup.

To summarize, section 2.1 justifies the choices made for selecting the color spaces models and also the common challenges faced during image processing and skin detection are discussed in detail. Section 2.2 justifies the choice of evaluation metric Delta-E for measuring accuracy of the color models in detecting skin tone. Sections 2.3 and 2.4 supports the objective behind choosing this research topic.

3 Methodology

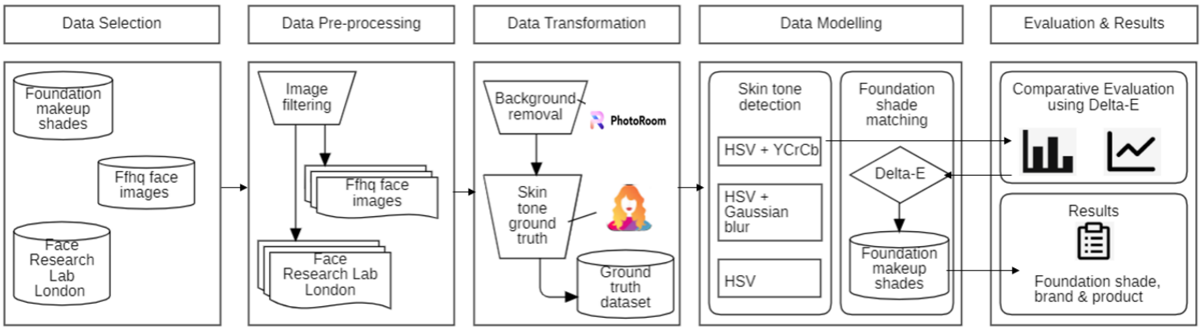


Figure 1: Research Methodology for Skin Tone Detection and Foundation Shade Matching

This section will describe the research approach, sources and choice of datasets, data models, choice of evaluation metrics and the type of results obtained. The research methodology for this research project consists of 5 steps as illustrated in Figure 1.

3.1 Data Selection

Three datasets have been gathered from various sources. First dataset is Ffhq[1] facial dataset that contains 70,000 high quality human facial images belonging to different ethnic groups and this dataset is being used for testing of the skin tone recognition models. Second dataset is face research lab London[2] dataset which is similar to Ffhq dataset and will be used for validation of the models. Third dataset consists of around 700 makeup foundation shades[3] of different products and brands.

3.2 Data Pre-processing

Ffhq dataset was studied and out of 70,000 images 1000 images were carefully selected so that they contain human facial images of various skin tones for the testing of the color space models. Finally, the images that contained multiple human faces, images that contained paint on the face and images with improper illumination that could produce inaccurate results as stated in the research of (He; 2021) and (Kolkur et al.; 2017) and hence, were removed from the dataset manually.

3.3 Data Transformation

Numerous background items, some of which resembled human skin color, were present in the facial photos. As discussed by Nikolskaia et al. (2018) and (Buza et al.; 2018)in their research on skin identification utilizing color spaces, such background could impair the accuracy of the color models. Because of this, the background of the facial photos from the ffhq and Face research lab London dataset was accurately eliminated using a web program called PhotoRoom[4], and it was replaced with ultramarine blue, a hue that is

[1]https://github.com/NVlabs/ffhq-dataset
[2]https://figshare.com/articles/dataset/Face$_{R}esearch_{L}ab_{L}ondon_{S}et$/5047666?$file = 8541955$
[3]https://www.kaggle.com/datasets/shivamb/makeup-shades-dataset
[4]https://app.photoroom.com/batch

entirely unrelated to shades of skin. These photographs are then uploaded in an Android software called Dressika[5] that was ran using a Windows OS emulator called BlueStacks in order to establish the hex color values for skin tone ground truth manually. This Android software analyzes a facial photograph to identify the skin, eye, and hair colors. The skin tone output from this software is utilized to use a color picker to get the precise hex color values for each of the corresponding facial photos.

3.4 Data Modelling

Three different combinations of color spaces models have been implemented in this research for comparative evaluation of skin tone recognition as follows,

1. HSV and YCrCb color spaces with histogram equalization and Otsu's image segmentation

2. HSV color space with Gaussian Blur

3. HSV color space

As discussed in section 2 of this paper, recent studies show that HSV is extensively used for object detection from images(Hema and Kannan; 2020) also it is easier to perform threshold classification to detect skin region from the images(Hussain and Al-Bayati; 2019). On the other hand, YCrCb is not easily influenced by excess or low illumination and hence is a good choice for such projects (Li et al.; 2020) and gives high accuracy (Lionnie and Alaydrus; 2018). Another study by (Buza et al.; 2018) proved a combination of HSV, YCrCb, histogram equalization and Otsu's image segmentation gives best accuracy for skin detection for images having one human face.
HSV Color Space: The RGB color system used by humans to define and experience color is far more similar to the HSV (Hue, Saturation, Value) color space. Humans primarily see hue as a color. Saturation refers to the quantity of white light that varies in hue. Value determines brightness and intensity. As hue (H) fluctuates from 0 to 1.0, the corresponding colors change from red through yellow, green, cyan, blue, and magenta before returning to red. The related colors (hues) range from unsaturated (gray shades) to completely saturated as saturation(S) varies from 0 to 1.0. (no white component). The appropriate hues increase brighter when value (V), or brightness, changes from 0 to 1.0. The HSV hue component has an angle distribution of 0° to 360°, all within a hexagon as shown in Figure 2 (Kolkur et al.; 2017). The following formula is used to calculate the HSV color space:

$$H = across \frac{\frac{1}{2}(2R - G - B)}{\sqrt{(R-G)^2 - (R-B)(G-B)}}$$

$$S = \frac{max(R,G,B) - min(R,G,B)}{max(R,G,B)}$$

$$V = max(R,G,B)$$

However, when the brightness is very low, HSV color model produces subpar results.
YCrCb Color Space: Luminance, chromatic blue, and chromatic red are referred to as the Y, Cb, and Cr components. This color space is extremely appealing for skin color

[5] https://standysoftware.com/dressika/

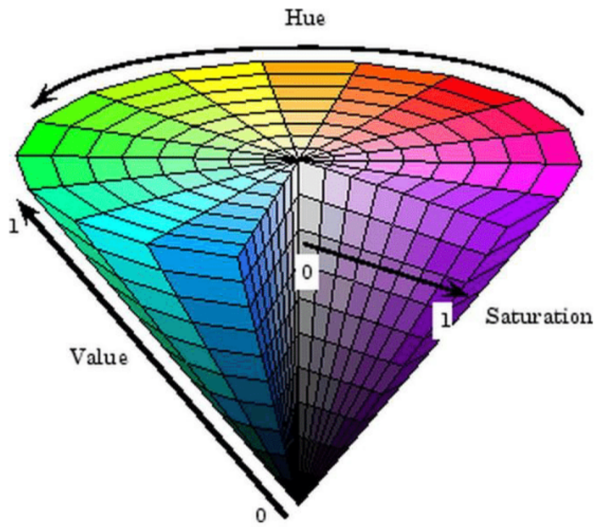


Figure 2: HSV Color Space

identification due to the straightforwardness in transforming RGB color space and is calculated as follows:

$$Y = 0.299R + 0.587G + 0.114B$$
$$C_b = R - Y$$
$$C_r = B - Y$$

Histogram Equalization: The intensity distribution of an image is graphically represented by a histogram. In plain terms, it shows how many pixels are involved in each intensity value taken into account. The number of pixels in each category of a color component is shown in a color histogram of an image as shown in Figure 3[6]. A computer

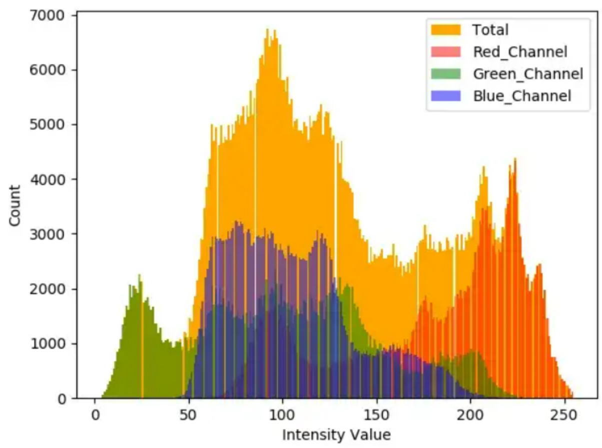


Figure 3: Image Histogram Representation

image processing method called "Histogram Equalization" is used to boost contrast in

[6]https://towardsdatascience.com/histograms-in-image-processing-with-skimage-python-be5938962935

images. It achieves this by effectively extending the intensity range of the image and spreading out the most common intensity levels. When the useful data is represented by close contrast values, this strategy typically boosts the overall contrast of images. This enables regions with lower local contrast to acquire higher contrast. Red, Green, and Blue parts of the image cannot each have their histogram equalization applied independently because doing so would drastically alter the image's color balance. In contrast, if the image is first transformed to a different color space, such as the HSL/HSV/YCrCb color space, the technique can then be used on the luminance or value channel without affecting the hue and saturation of the image.

Otsu's Image Segmentation: The OTSU technique (OTSU) is a global adaptive binarization threshold image segmentation algorithm that was proposed by Japanese researchers OTSU in 1979. This algorithm splits the image into foreground and background based on its gray scale properties and uses the highest inter class variance between the background and the target image as the threshold selection rule. The disparity between the two sections is greatest when the ideal threshold is used. The measure standard for the OTSU method is the greatest interclass variance. Variance is a crucial indicator of a uniform gray distribution; the higher the variance number, the larger the difference between the two graphed portions. Therefore, the likelihood of misclassification will be reduced as long as the variance between clusters is maximized, accomplishing the ideal segmentation of an image (Huang et al.; 2021).

Gaussian Blur: The Gaussian blur feature is produced by blurring (smoothing) an image with a Gaussian function in order to lower the noise level. It can be viewed as a nonuniform low-pass filter that protects low spatial frequency while lowering visual noise and insignificant features. One of the most crucial preprocessing procedures in all of computer vision and image processing is smoothing and blurring. We can lessen the quantity of high-frequency material, such as noise and edges, by smoothing an image before using methods like edge detection or thresholding. Although it may seem counter-intuitive, by removing some of the details from an image, we can more quickly locate the objects we are looking for. Additionally, it enables us to concentrate on the image's bigger structural elements.

3.5 Evaluation and Results

The three mentioned color spaces techniques mentioned in section 3.4 will be compared and evaluated on the basis on **accuracy using Delta-E** metric. As discussed in section 2.2 this metric is used to calculate the color difference or color similarity between objects or images where the two colors might be perceived as identical by human eyes but in reality, are quite different. While working with commercial applications or research it is very important that the delta-e value is under the acceptable threshold and hence, becomes an important and relevant measure of accuracy. However, as mentioned in research of (Karma; 2020) every scenario can have different threshold acceptance range of delta-e value as long it follows the standard range which is between 0-100. The author has mentioned all the ranges of delta-e where if the delta-e value is between 0-1 the colors are exactly same and if the value is between 11-49 the colors are similar than opposite. The value between 49-100 signifies that the colors are exactly opposite. **For this research the acceptable threshold is defined as 0-20**. Using this metric the distance between the ground truth skin tone values and the skin tone values calculated by proposed color spaces models will be calculated. The color model with the lowest average delta-e value, i.e., between 0 and 20, will then be chosen to suggest the foundation shade from foundation shades csv dataset that will best match a person's skin tone, and the foundation shade, brand, and product will be the study's conclusions.

4 Design Specification

This section will cover the architecture of the color spaces models implementation and illustrate screen mock-ups for the same. Figure 4 depicts the 3 tiered architecture of the proposed implementation. **1st tier** or client presentation layer displays the final result of foundation shade, brand and product. **2nd tier** or business logic layer performs all the data processing using color spaces models implemented using OpenCV in python programming language on the images to find the suitable foundation shade. **3rd tier** or data layer performs all the data pre-processing and data transformation activities on the datasets gathered for the research. Figure 5 illustrates the screen mockups created using

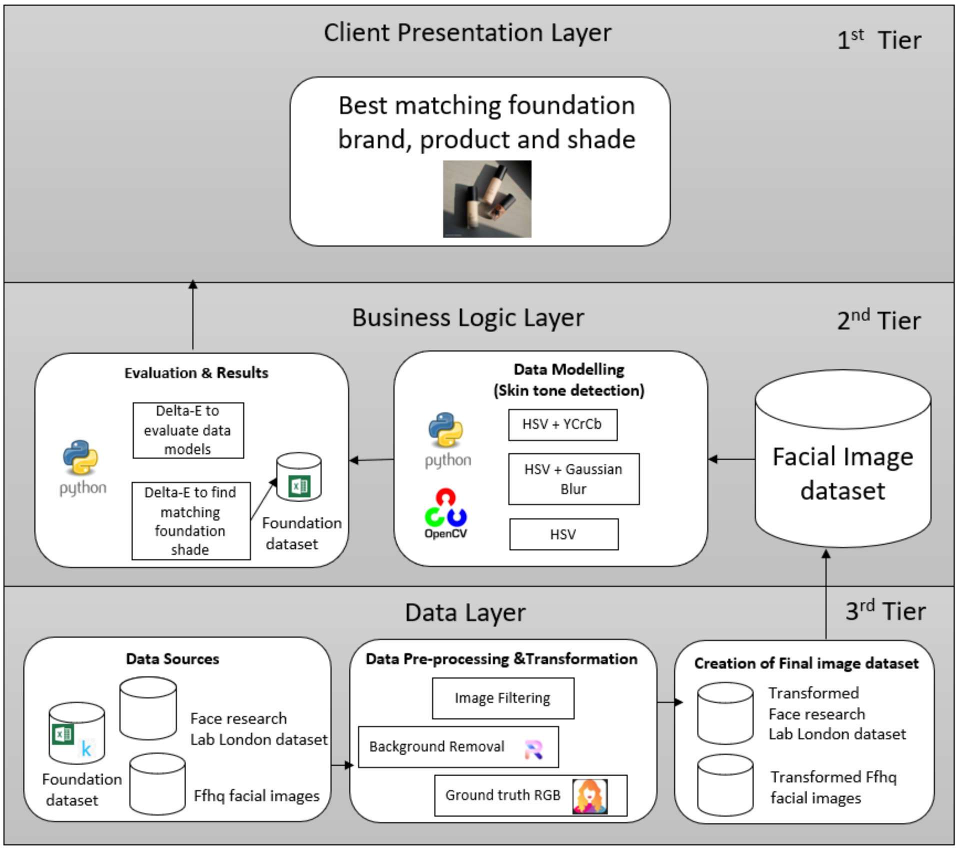
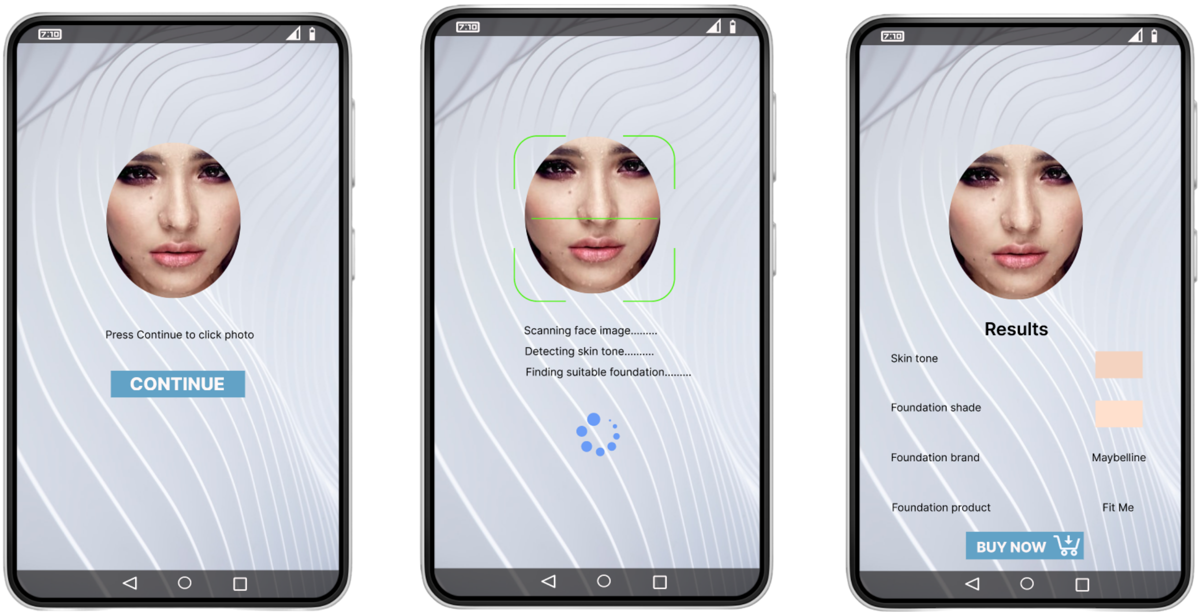


Figure 4: Skin Tone Detection and Foundation Shade Matching Implementation Architecture

Figma software for extra clarity on how the proposed technique would look like **if it is deployed on the terminal systems or if it is commercialized in any way**.



(a) User Clicks the Picture (b) Skin Tone Detection (c) Foundation Suggestion

Figure 5: Screen Mock-ups

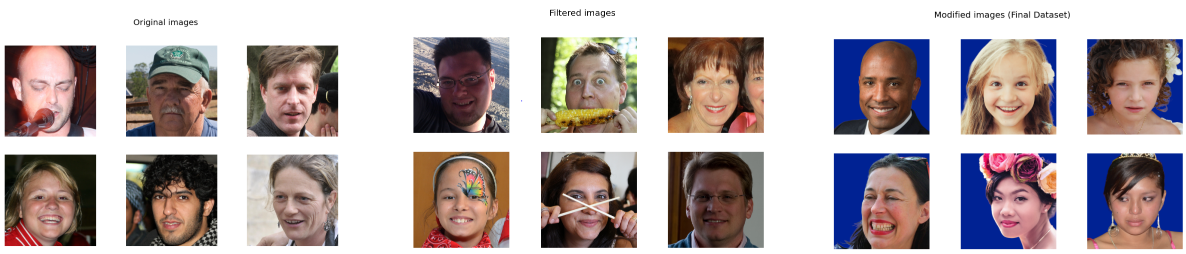
5 Implementation

The three color space models' end-to-end implementation as well as the environment setup for its development are presented in this section.

5.1 Setup and Configurations

Python 3.9.13 will be used to develop color spaces models and foundation matching code in Jupyter Notebooks created with Anaconda Navigator (anaconda3). The model processing will take place on a Windows 10 computer with a 2.40GHz 11th generation Intel Core i5 processor and 16GB RAM.

5.2 Preliminary Data Exploration



(a) Original Images (b) Filtered Images (c) Modified Images

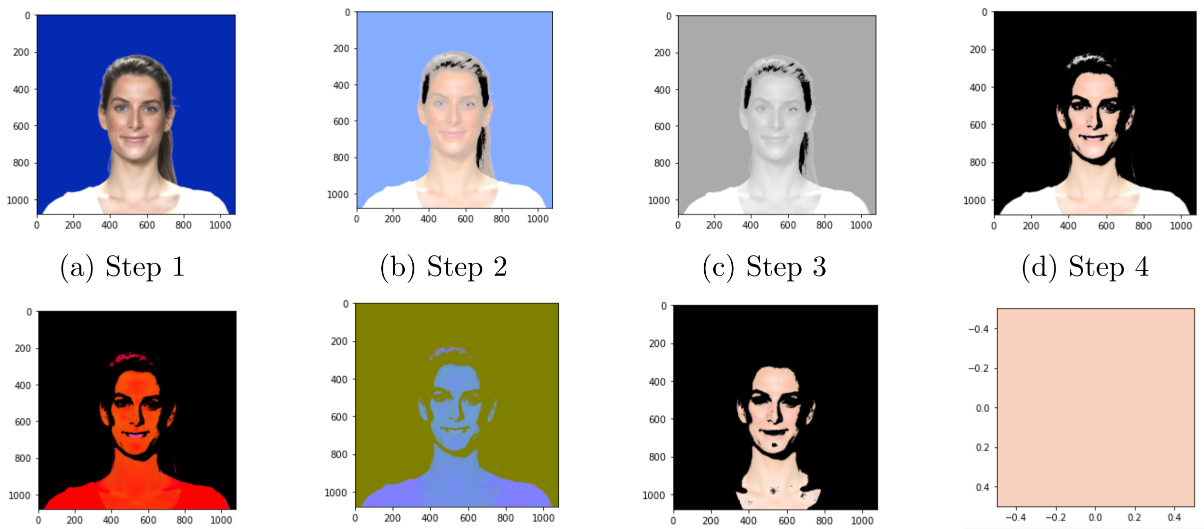
Figure 6: Ffhq Facial Dataset EDA

Figure 6 depicts EDA done on ffhq facial dataset. Figure 6a shows the original images in the dataset. Figure 6b shows images that were filtered or removed manually from the dataset due to the presence of excess of shadows, low illumination, multiple faces and objects or paint on the face that could have reduced the accuracy of the color spaces models. Figure 6c shows images that were modified using Photoroom web application to remove the background from the images to improve accuracy in the results and this will be the final dataset for the testing of the three color spaces models.

5.3 Implementation of Color Spaces Models for skin tone detection

The following sub-sections will provide a step-by-step implementation of color spaces done using OpenCV library in Python. There is no requirement of training phase for implementing color models (He; 2021) and hence these color models will be tested on different images of Ffhq facial dataset as follows.

5.3.1 HSV and YCrCb Color Spaces with Histogram Equalization and Otsu's Image Segmentation



(a) Step 1 (b) Step 2 (c) Step 3 (d) Step 4

(e) Step 5 (f) Step 6 (g) Step 7 and 8 (h) Step 9

Figure 7: HSV and YCrCb Implementation

1. Load the image from the directory using cv2.imread() method which store the colored image information in 3D numpy array which makes it easier to modify it for image processing tasks. Original image is shown in Figure 7a.

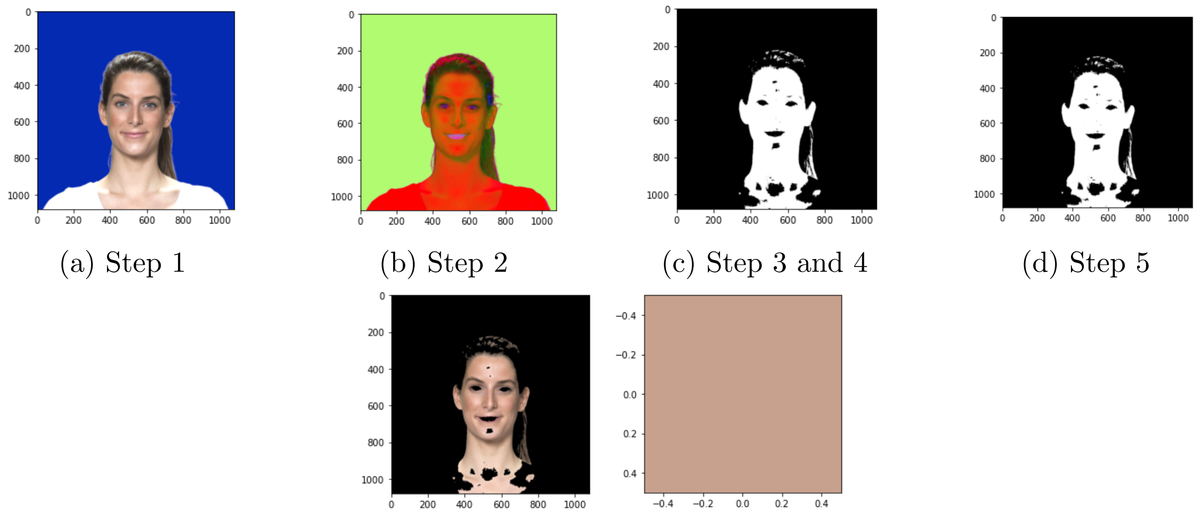
2. Perform histogram equalization on the color image which is originally in RGB color space by first converting it to YCrCb color space, select the Y(brightness) channel to perform histogram equalization on it as shown in Figure 7b.

3. Convert the RGB color space using cv2.COLOR_BGR2GRAY() method to GRAYSCALE image as shown in Figure 7c.

4. Perform Otsu's image binarization and thresholding segmentation on GRAYSCALE image to classify the image into background and foreground as shown in Figure 7d.

5. Convert the segmented image in HSV color space as shown in Figure 7e.
6. Convert the segmented image in YCrCb color space as shown in Figure 7f
7. Create a threshold classifier mask to classify the skin pixels and non-skin pixels in the segmented image by combining the properties of image converted in HSV and YCrCb color spaces in step 5 and 6 respectively.
8. Apply the threshold based classifier mask on the segmented image to obtain the skin pixels in the image as shown in Figure 7g.
9. Calculate the average skin tone RGB value by applying mean() method of numpy array on the R (red), G (green) and B (blue) channel separately. Figure 7h displays the average RGB skin tone of the image.

5.3.2 HSV Color Space with Gaussian Blur



(a) Step 1 (b) Step 2 (c) Step 3 and 4 (d) Step 5

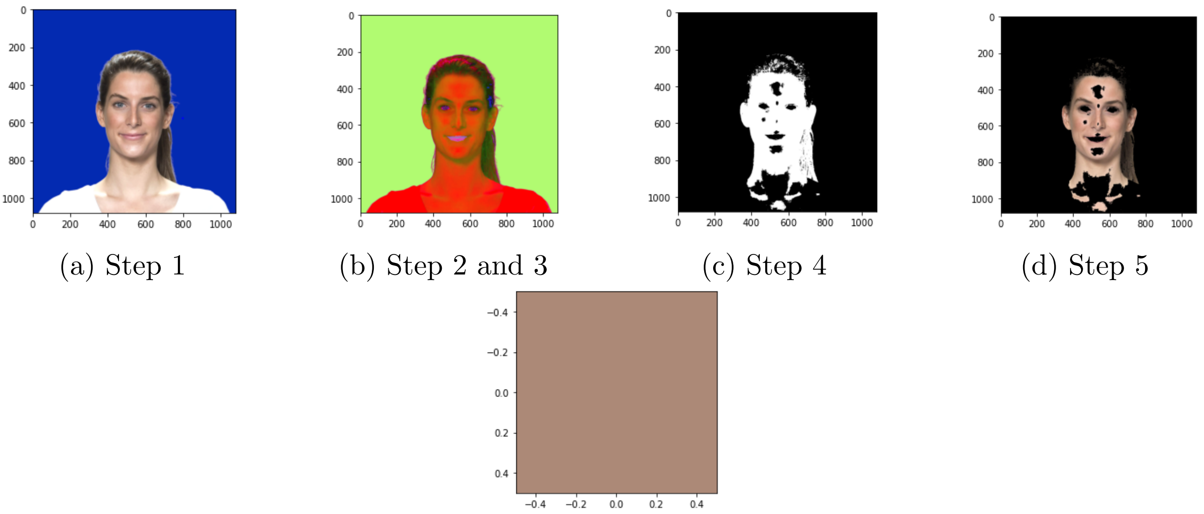
(e) Step 6 (f) Step 7

Figure 8: HSV Color Space with Gaussian Blur Implementation

1. Load the image using cv2.imread(). Figure 8a shows the original image.
2. Convert the image into HSV color space as shown in Figure 8b.
3. Define lower and upper threshold values of Hue, Saturation and Value. The lower threshold is set to [0, 48, 80] and upper threshold is set to [20, 255, 255].
4. Using the HSV defined threshold classifier create a mask to classify skin area and non-skin area from the image. Figure 8c shows the HSV threshold mask.
5. Clean the threshold mask using Gaussian blur filter. Figure 8d shows the cleaned HSV threshold mask.
6. Apply the cleaned threshold mask on the color image. Figure 8e shows final masked image where non-skin pixels and skin pixels are successfully classified.

7. Calculate the average RGB skin tone value using mean() method of numpy array applied on each channel of RGB color space. Figure 8f displays the average RGB skin tone of the image.

5.3.3 HSV Color Space



(a) Step 1 (b) Step 2 and 3 (c) Step 4 (d) Step 5

(e) Step 6

Figure 9: HSV Color Space Implementation

1. Load the image using cv2.imread(). Figure 9a shows the original image.
2. Change the RGB color space of the original image to HSV color space as shown in Figure 9b.
3. Define the minimum and maximum HSV threshold. The minimum threshold is set to [0, 58, 30] and maximum threshold is set to [33, 255, 255].
4. Create a threshold classifier using the HSV thresholds defined in step 2 to classify the skin and non-skin area in the image as shown in Figure 9c.
5. Apply the threshold classifier on the image to detect the skin pixels as shown in Figure 9d.
6. Calculate the average RGB skin tone value from the detected skin pixels as shown in Figure 9e.

6 Evaluation

The **accuracy** of the three color spaces models will be evaluated using **Delta-E metric** discussed in sections 2.2 and 3.5. The RBG skin tone values calculated by three color spaces models are recorded in the csv files against the ground truth skin tone HEX values for all the selected images in the ffhq facial dataset. Delta-E metric will be used to calculate the difference between the calculated skin tone and ground truth skin tone and determine the accuracy of the models. The model with the least average delta-e value

will be chosen to recommend the foundation makeup shade.
The ground truth hex value of skin tone will be converted to RGB color space. Now these calculated and ground truth RGB values will be converted to Lab color space since, Delta-E approximates how humans perceive color using the CIE Lab color space. Once these two colors are converted to Lab color space the Delta-E metric is calculated for all the facial images across three models using colormath library of Python. Figure 10 shows a combination of HSV and YCrCb color spaces along with Histogram equalization and Otsu's image segmentation performs better with an average **Delta-E value of 17.5** in accurately calculating the skin tone values closer to the ground truth skin tone values than other two color models. Execution time was also calculated for the three color models while processing each image and Figure 11 displays average execution time in seconds of three color models. Even though HSV + YCrCb color models takes slightly more time to execute, the accuracy is the major factor in determining the perfect foundation shade.

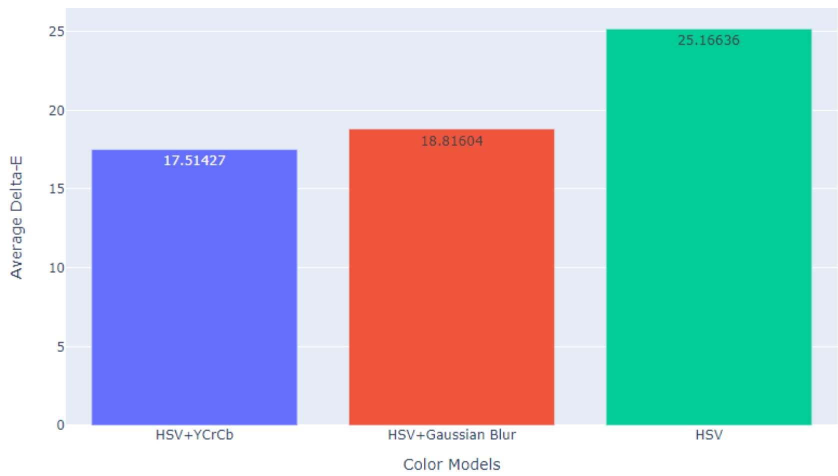


Figure 10: Average Delta-E of Color Space Models (the lower the better)

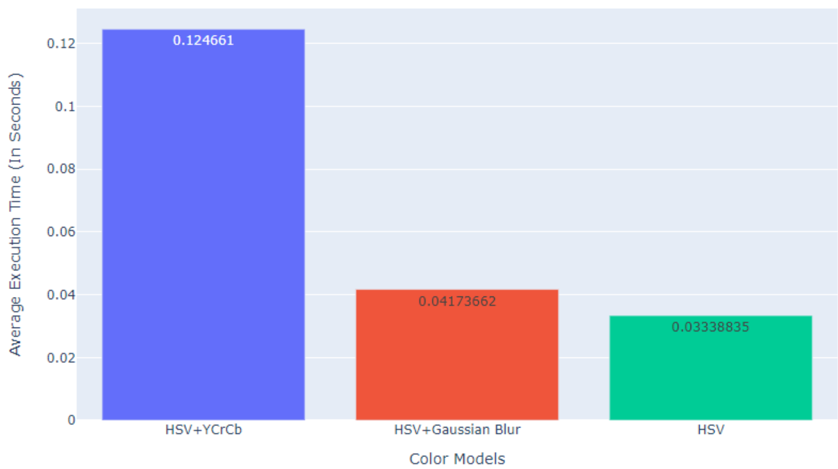


Figure 11: Average Execution Time of Color Space Models

Hence, with respect to the comparative evaluation, the average Delta-E value obtained for HSV + YCrCb model is between 0-20 which is in between the acceptable threshold defined for this research as discussed in section 3.5 and also the value is between 11-49 which signifies that the two colors are more similar than opposite (Karma; 2020). Hence, **HSV + YCrCb color model will be selected to recommend the foundation shade**. This color model was applied to Ffhq facial images (testing dataset) and Face Research Lab London facial images (validation dataset) to recommend foundation shade, brand and product. Figure 12 created in MS-Excel illustrates implementation of HSV + YCrCb color spaces model on validation dataset where foundation shade, brand and product are recommended for the facial images respectively based on the skin tone detected using the color model. The average Delta-E obtained for this dataset is **14.4044848**.

Image	HSV + YCrCb	Foundation Shade	Brand	Product
			L'OrÃ©al	True Match
			Maybelline	Fit Me
			EstÃ©e Lauder	Double Wear
			Dior	Diorskin Forever
			Nykaa	SKINgenius
			L'OrÃ©al	True Match

Figure 12: HSV + YCrCb Color Spaces Model Applied on Face Research Lab London Dataset (Validation Dataset)

6.1 Discussion

Table 1 represents model evaluation result comparison. Color model with a combination of HSV+YCrCb along with histogram equalization and Otsu's image segmentation performed better than other two color models. Model with HSV color space and Gaussian blur also gave somewhat better results and with respect to Delta-E value it is much closer to the best performing color model. HSV color space model gave extremely high value of Delta-E and hence proved that this color space alone would not be a sufficient solution. The last result in the table is of HSV + YCrCb color space model implemented on Validation dataset giving much lower Delta-E value of **14.4** the results of which are illustrated in Figure 12.

Table 1: Results Comparison

Model	**Delta-E (Accuracy)**	**Execution Time (s)**
HSV+YCrCb	**17.51427022**	0.124660951
HSV + Gaussian Blur	18.81604228	0.041736619
HSV	25.16636144	0.033388351
HSV + YCrCb (Validation)	14.4044848	0.317219884

As shown in Figure 12 HSV + YCrCb model has given quite decent results for skin tones ranging from light to medium (1st four images), however, for dark and extra dark/deep skin tones (last 2 images) the results are not up to the mark and since the skin tone detection was not as expected, the model has recommended incorrect foundation shades for these images. The major challenge faced during the research was unavailability of ground truth dataset and creating one manually was extremely time consuming and tedious job. The models accuracy would have improved in terms of Delta-E (accuracy) value or even model evaluation would have become easier if a ground truth dataset was available. With respect to dark and deepest skin tones the model definitely needs improvement since, histogram equalization tends to increase the contrast making the dark skin tones seem brighter than they are.

7 Conclusion and Future Work

The primary goal of this research study was to address the research question "How can Computer Vision-based skin tone recognition improve the effectiveness of makeup recommender systems in determining best suited foundation makeup shades?". To achieve this primary goal, three color spaces models were applied to publicly available facial image datasets, namely the Face Research Lab London dataset and the Ffhq facial image dataset, for a comparative evaluation of skin tone detection using Delta-E (accuracy) metric. The goal was to determine which color space model performed the best in order to identify matching foundation shade, brand, and product from the publicly available foundation shade dataset. Out of the three color spaces models, HSV + YCrCb color spaces with histogram equalization and Otsu's image segmentation obtained the least average Delta-E value of around 17.5 and hence was chosen to recommend matching foundation shade. HSV + Gaussian blur color model obtained the second best average Delta-E value of around 18.8 whereas HSV color model obtained the highest Delta-E value of around 25. Hence, as per the evaluation results, the proposed skin tone detection technique was fast in execution, lightweight and easy to implement and can definitely improve the effectiveness of foundation makeup recommender system. This research study's drawback is that the chosen color space model only performed successfully for skin tones that ranged from light to medium to moderately dark. Another limitation of this study was unavailability

of ground truth dataset.
By using an alternative histogram equalization method, such as Contrast-Limited Adaptive Histogram Equalization to improve contrast while keeping the naturalness (Chang et al.; 2018), and a better means of collecting ground truth datasets, the model can be enhanced in future work to accurately detect the darkest and deepest skin tone values.

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