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Enhancing Foundation Shade Suggestions through Skin Tone Identification

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Abstract*: As we concentrate on addressing the challenges in responsible beauty product recommendation, particularly when it involves comparing the product's color with a person's skin tone, similar as for foundation and robe p conditions. The features uprooted using the prints from illuminated terrain can be largely deceiving or indeed be inharmonious to be compared with the product attributes. Hence bad illumination condition can oppressively degrade quality of the recommendation. We introduce a machine learning frame for illumination assessment which classifies images into having moreover good or bad illumination condition. We also make an automatic stoner guidance tool which informs a stoner holding their camera if their illumination condition is good or bad. This way, the stoner is handed with rapid-fire feedback and can interactively control how the print is takenfor their recommendation. Only a many studies are devoted to this problem, substantially due to the lack of datasetthat's large, labeled, and different both in terms of skin tones and light patterns. Lack of similar dataset leads to neglecting skin tone diversity. Thus, we begin by constructing a different synthetic dataset that simulates colorfulskin tones and light patterns in addition to a being facial image dataset. Next, we train a Convolutional Neural Network (CNN) for illumination assessment that outperforms the being results using the synthetic dataset. Eventually, we dissect how the work improves the shade recommendation for colorful foundation products.*

Keywords: RGB, HSV, YCrCb, Delta-E, Histogram Equalization, Image Segmentation, Skin Tone, Skin Detection,Color Space

I. INTRODUCTION

A numerous beauty product recommendation systems bear information on both the products and guests' preferences (5). Traditionally, guests' preferences are collected through series of questions and answers. Still, numerous guests don't know how to answer similar technical beauty- related questions, and the recommendation produced may not feel worth the time they spent (1). On the other hand, prophetic models to infer information about the guests may not lead to accurate results. An indispensableroute to reduce the hedge for beauty product recommendation is to use camera images as input and give skin care or makeup recommendations grounded on the facial features estimated from the images. Still, it's challenging to prize facial features fromprints unless they're taken under a good illumination condition. The stoner may not be paying attention to the illumination condition while taking the stoner may not be paying attention to the illumination condition while taking prints figure 1 effect of using prints under different illumination conditions on shade recommendation for foundation and robe products. Only well- illuminated face print (middle) results in recommending medium range tones as intended. The same stoner is given disagreeing recommendations in the other two cases. Synthetic face images are used because of sequestration reasons and having further control over illumination/ skin tone variations. Prints, but the prints taken under poor illumination conditions largely impact how face features similar as skin conditions, makeup, tone, etc. are inferred. See Figure 1. The products recommended groundedon clashing or incorrect point values redounded from a set of inadequately illuminated face prints may indeed give a recommendation that's worse than recommending arbitrary products. While tracking the face illumination condition is largely important for perfecting recommendation, only a many studies have been conducted to address this problem performing in a many automatic models available for this purpose(5). Our approach is to apply an automatic model to directly inform the stoner holding a camera to take picture if the light condition is good or bad, which allows the stoner to be picky about what print to be used for the recommendation. Specifically, the tool displays the outgrowth of the illumination assessment model (moreover good or bad) to the stoner holding their camera, which also encourages them to interactively change the camera position or terrain until they see the light condition being good. One indispensable approach is to take any image from the stoner and attempt to rightly infer features (2). Still, some studies don't consider images taken under poor illumination conditions or bear images that meet special conditions, similar as holding a color estimation card. It's also unclear how important point conclusion varies if else illuminated prints of the same person are used by the system. Whilethese being results may reduce the time demanded for the stoner to interact with their camera, our approach gives the stoner a direct control over meet special conditions, similar as holding a color estimation card. It's also unclear how important point conclusion varies if else illuminated.

II. RELATED WORK

One of the studies on face illumination quality assessment is conducted by Sellahewa and Jassim (2). Their system, still, is limited by taking a reference image which reduces the connection of their approach. Another system by Truong etal. (3) Approaches illumination assessment by comprising over image partitions. This fashion is too simple to regard for different illumination scripts. Analogous pixel averaging is also used in a recent study by Hernandez- Ortega etal. (1). In another study by Terhorst etal.(2), pixel- position face quality is considered rather than image- position, which is considered in our study.

Numerous other previous studies have concentrated on face quality assessment in general, i.e., considering different factors similar as head disguise, noise, sharpness, and illumination. One of similar studies is performed by Chen etal. (5), to elect images of high quality for the downstream task of face recognition. This group of studies still aren't suitable to give an unequivocal signal about the bad illumination condition, which is the main thing of this study.

One of the challenges that has averted the development of an automatic illumination assessment model is the lack of a large dataset of faces under colorful lighting conditions. Being face datasets are substantially under neutral illumination, or captured in- the-wild with unbridled illumination. The bones that include images of colorful lighting conditions are moreover not labeled or limited to a small number of subjects. To fill this gap, Zhang etal. (5) Constructed a largescale dataset of face images with synthetic illumination patterns, labeled grounded on their quality. To construct the dataset, one subject took prints at colorful lighting conditions. These patterns were also transferred to being face datasets similar as YaleB (6), PIE (8), and FERET (7). To transfer light patterns, an illumination transfer algorithm through edge-conserving pollutants proposed in (6) was used. This fashion still works under the supposition of analogous face shape between source and target, it requires anterior faces, and fails under violent lighting conditions. Another debit of the study by Zhang etal.(4) is that their illumination assessment model fails when fed with dark skin tone faces and classifies utmost of them as bad lighting. As bandied in a study by Babnik and Struc, face quality assessment models largely favour light- colored faces (2). Disentangling skin tone and illumination is still an open problem (8), and machine literacy models aren't suitable to assess illumination quality unless they're either trained on an inclusive and representative dataset, or fed with background information (6). Asking the druggies to include background in their prints, still, results in low resolution faces, for utmost of the mobile bias, reducing the performance of the consequent faceprocessing operations.

Contributions

Achieving a representative dataset is expensive and time- consuming. For this reason, in this work, we propose to first increasethe diversity of a face dataset by bluffing light to dark skin tones. Bluffing skin tones has the benefit of adding the diversity without collecting similar data. Accordingly, 200 illumination are defined and transferred to the dataset, using the Deep Single- Image portrayal Relighting (DPR) model (3). This model is suitable to transfer a target illumination to a source portrayal image. Unlike Reference (6), DPR isn't confined to anterior and same shape source and reference faces, and it can handle harsh lighting. Its limitation, still, is that light and skin tone aren't impeccably disentangled and some skin color is transferred along

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illumination. Thus, for each skin tone, we transfer illumination defined on the same tone. The constructed dataset is also used to train a MobileNetv2 (8) model to classify faces as good/ bad illuminated.

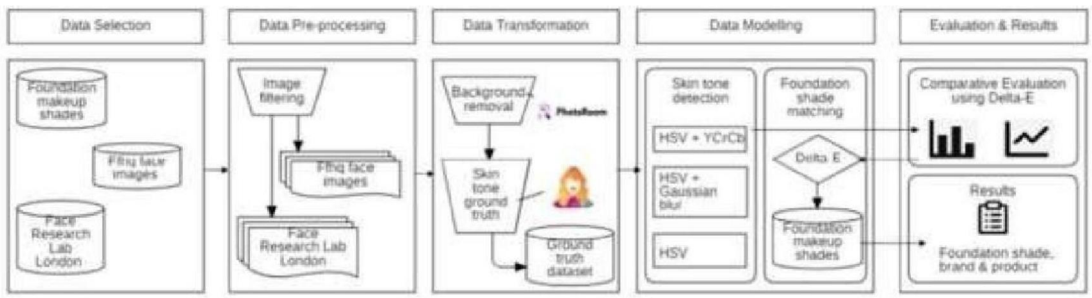


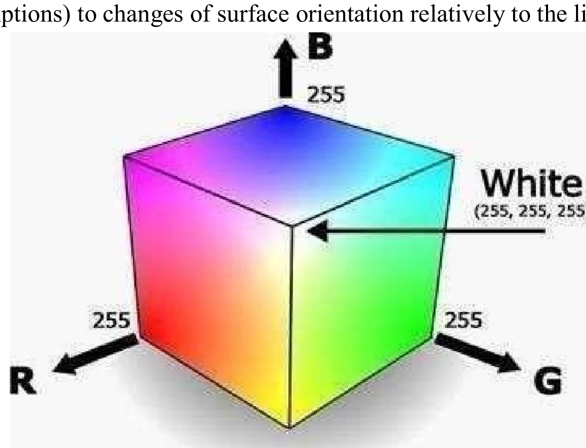
Figure 1: Research Methodology for Skin Tone Detection and Foundation Shade Matching

The proposed illumination assessment model is used in perfecting beauty product recommendation grounded on stoner's face print. We illustrate how the recaptured product shade is significantly different than the shade we should recoup grounded on the real face features similar as skin tone, under proper illumination. The rest of this paper is organized as follows our proposed frame, including illumination assessment and beauty product recommendation, is described in Section 2, followed by the trialsin Section 3. Eventually, Section 4 concludes the study.

Red, Green, and Blue (RGB) Color Model

RGB color space is widely used and is normally the default color space for storing and representing digital im- ages. We can get any other color space from a linear or non-linear transformation of RGB [1]. The RGB color space is the color space used by computers, graphics cards and monitors or LCDs. As shown in fig.1 it consists of three components, red, green and blue, the primary colors. Any color can be obtained by mixing the three base colors. Depending on how much is taken from each base color, any color can be created. Reversing this technique, a specific color can be broken down into its red, blue and greencomponents as shown in equation 1 to equation 3 [1]. These values can be used to find out similar colored pixels from the image. [7] Explains skin color detection based on RGB color space. Normalized RGB is a representation that is easily obtained from the RGB values by a simple normalization procedure [1].

A remarkable property of this representation is that for matte surfaces, while ignoring ambient light, normalized RGB is invariant (under certain assumptions) to changes of surface orientation relatively to the light source [4].



YCbCr (Luminance, Chrominance) Color Model

YCbCr is an encoded non-linear RGB signal, commonly used by European television studios and for image compression work. As shown in fig. 2 color is represented by luma (which is luminance computed from non- linear RGB) constructed

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as a weighted sum of RGB values [4]. YCbCr is a commonly used color space in digital video domain. Because the representation makes it easy to get rid of some redundant color information, it is used in image and video compression standards like JPEG, MPEG1, MPEG2 and MPEG4.The transformation simplicity and explicit separation of luminance and chrominance components makes YCbCr color space [3]. In this format, luminance information is stored as a single component (Y), and chrominance information is stored as two color-difference components (Cb and Cr). Cb represents the difference between the blue component and reference value. Cr represents the difference between the red component and a reference value. YCbCr values can be obtained from RGB color space according to eq. 4 to eq. 6. [7][8][4] Uses YCbCr space for skin detection.

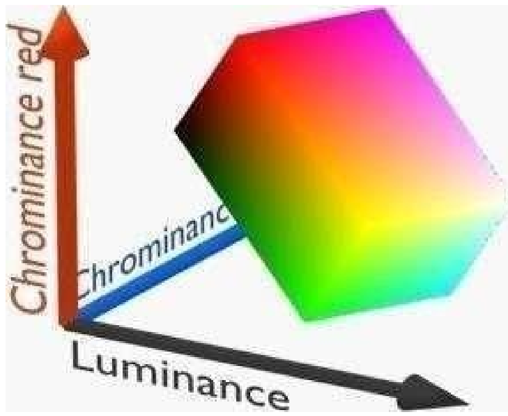

Fig - YCbCr Color Model

III. PROPOSED SYSTEM

Our proposed framework, explained in the following sections, includes face illumination assessment, and using the properly illuminated face, for beauty product recommendation.

A. Face Illumination Assessment

Our face illumination assessment workflow is illustrated in Fig. 2. At the first step, a 3D modelling software is used to produce models of different skin tone and illumination patterns, which are labeled grounded on their quality for the downstream tasks similar as rooting face features. The skin tones, light patterns and their associated markers are accordingly transferred to an in- house dataset of 1000 anterior faces, substantially under neutral illumination. Eventually a MobileNet- v2 is trained.

Generating synthetic exemplifications of skin tones and illumination patterns. We used a 3D modelling software to induce models of light and dark skin tones as well as 200 illumination patterns, labeled grounded on their quality. The skin tones and patterns are all transferred to the in- house dataset of 1000 faces. The markers for the constructed dataset directly come from the pattern markers, which means that the only primer labeling needed for this study was to label the 200 light patterns generated by a 3D modelling software

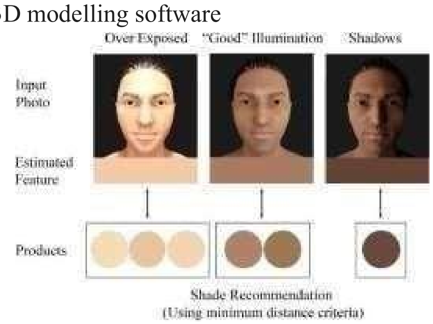

Fig. 3 illustrates some examples for both light and dark skin tones. The light patterns were generated by moving two spot lightsources among the grid of match values relative to a model of mortal

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Figure 1 Effect of using prints under different illumination conditions on shade recommendation for foundation and robe products. Only well- illuminated face print (middle) results in recommending medium range tones as intended. The same stoner is given disagreeing recommendations in the other two cases. Synthetic face images are used because of sequestration reasonsand having further control over illumination/ skin tone variations.

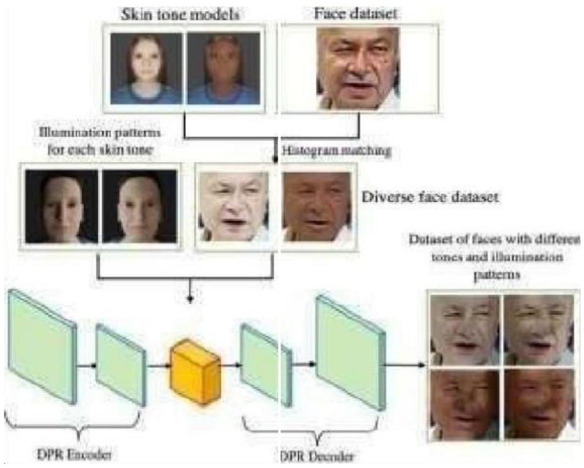

Figure 2 Proposed frame. Light and dark skin tones are transferred to detected faces, followed by applying different illumination patterns. Original face print from (4), used for illustration purposes only.

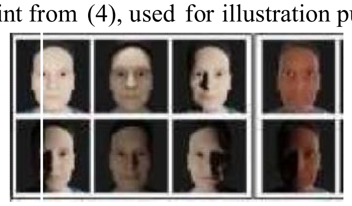

Figure 3 exemplifications of light and dark skin tone images with different illumination patterns.

Bear further picture time and computational coffers, are limited to a many hundreds mortal models, and acquiring their high quality models is precious.

Color matching to pretend skin tones. To transfer skin tone from a source to a target image, we first segmented the skin area of the face, using the BiSeNet model introduced in Reference (4). BiSeNet is a real time semantic segmentation armature with two branches, the first of which captures low- position details, and the alternate captures high- position environment. Segmenting the face skin area is followed by a histogram matching fashion (8, 17). To perform histogram matching, first the accretive color histogram of the source and reference images, denoted by Cs and Cs are calculated, Where source and reference relate to the face image and the skin tone model, independently. Having the accretive histogram functions, the affair image Is for pixel p is deduced from the input image I.

Parameters are also used (SH) lighting as the target illumination, and a portrayal image as the source image. Accordingly the target lighting is applied to the source image to induce the affair. Besides the affair image, DPR also generates the SH lighting parameters of the input portrayal. Since in this study we didn't have the SH lighting of the reference illumination patterns, we first fed all the reference images to DPR as target illumination to be applied to all the source images. One limitation of the DPR model is that it cannot fully disentangle lighting and skin tone, as in general what we see from a face image is told by both the essential skin tone as well as terrain illumination and it's delicate to disentangle the two. In other words, using a light tone reference for a dark tone source image results in anon- realistic face. To attack this, for light skin tone faces, illumination patterns are transferred from the light skin model, and for dark skin faces, patterns are converted from the dark skin model. Media Pipe face discovery and MobileNet- v2. In this study, we've used MediaPipe(2) result for face discovery, in order to forget inapplicable background information. MediaPipe face discovery is erected upon BlazeFace(3) which is a light- weight face discovery armature. Eventually, the constructed dataset is fed to a MobileNet- v2 model to classify faces as good or bad illuminated. This armature is

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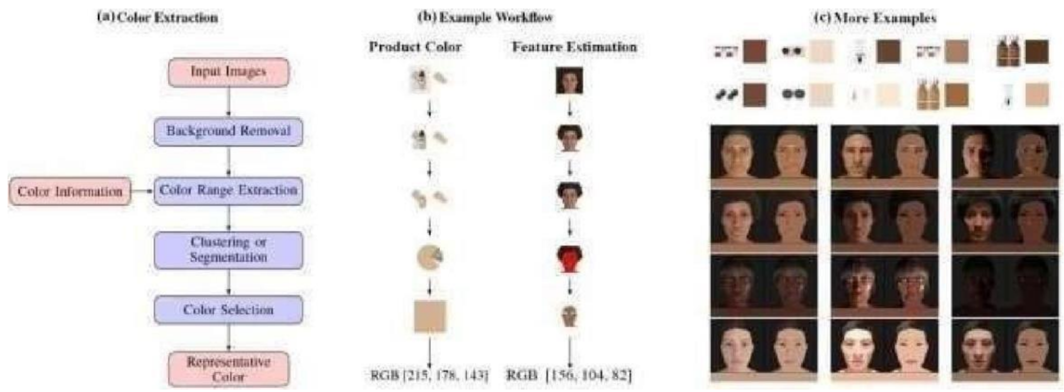
named for its effectiveness run on edge bias. To handle class imbalanced cause by further to badillumination patterns than good bones,more weight is given to error.

It is also worth noting that the 3D modelling software used in this study generates mostly unrealistic cartoon images as shown in Fig. 3. Therefore, these images cannot be directly used for training, and the consequent color matching and light transfer toa real face dataset is necessary. There are 3D modelling software available that can generate more realisti c face images. Those software, however, where C^{-1} acts as a reverse lookup on the histogram, V is the- togram bin width, and function v is defined as:

$$v(i) = \min(\mathbf{I}) + (i - 1)V. \quad (2)$$

Using Face Photos for Beauty Product Recommendation



While some beauty product recommendation does not require knowing facial features such as skin tone, it is difficult to recommend base makeup products Similar as foundation and concealers without knowing similar features. Foundation products in particular have a trait called shade which denotes the color of the product. A foundation product is offered in multiple tones, and shade recommendation comprises of opting the shade that stylish matches a client's need. See Figure 1. For illustration, some guests may prefer a shade that's closest to their skin tone, while others prefer a shade that's either lighter darker or warmer cooler than their skin tone. Anyhow of different preferences, the color difference between each shade and the client's skin tone needs to be assessed in order to do with the shade recommendation. Numerous guests feel overwhelmed in opting the shade that matches their preference, especially if they've to shop online. In this section, we will first describe how we assign an RGBvalue for each foundation shade, and how we cipher estimated skin tone from face prints. Incipiently, we will introduce how we compare the shade color with the estimated skin tone. In Section3.2, we will show how our illumination assessment improves the quality of the shade recommendation.

Product Color and Facial point Estimation. Historically, foundation shade range has not been adequately reflecting skin tone diversity and only in recent times, this issue has been ac- tively corrected by the assiduity (1, 6, and 3). This also means that the shade distribution tends to be heavy on the lighter color spectrum, and a color Conclusion model trained on unmitigated training dataset can be prone to bias. Thus, we applied the product color birth frame shown in Fig. 4 using an unsupervised ap- proach for each element. Specifically, we applied threshold grounded background junking, and excerpt colors in certain fixed range, and applied K- means to prize the most prominent brown color shown in the foundation product images. Using this approach, we attained about 2000 tons of foundation products. Any error cases were examined and removed from the dataset. An analogous color birth frame was acclimated for face images in estimating skin tones. That is, we remove the background.

Applicable member of the print, as shown in Fig. 4. We call this resulting color value estimated skin tone. It's important to note that we don't claim that the estimated skin tone is the person's factual skin tone. We only infer the skin tone as they're representedas RGB values in the prints in order to compare it with the product colors to produce a meaningful shade recommendation. Poor illumination conditions similar as partial murk can affect the value of estimated skin tone, and different prints might indeed point to a wide range of estimated skin tone. Illumination assessment addresses this issue by guiding the stoner towardtaking a print under optimal illumination. In Section3.2, we will show how the shade recommendation improves with our illumination assessment.

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Color Comparison Using CIEDE2000 distance. To comshear the RGB value representation of a foundation shade with esti- slept skin tone, CIEDE2000 color difference was used(2). This number assigns a distance between two colors in the scale of 0 to 100 and was developed to capture the perceptual color difference. CIEDE2000 had been tested via studies involving mortalspectators (1, 8). Heuristically, it's accepted that the distance lower than 2 means two colors are veritably close to each other, and between 2 and 5 means the colors are analogous, while lesser than 10 means the colors start to be relatively different to mortal eyes. We'll use this metric to estimate the color friction among the estimated skin tone from the set of all images and compare that with the friction among the images that the model classifies as good illuminated. Since the foundation shade range (brown tinge) tends to gauge a small color space, the increase in variation results in recommendation that isn't specific and mayindeed be worse than an arbitrary conjecture. The details will be given in Section3.2. EXPERIMENTS In this section, we first analyze the performance of the face illumination assessment model. Then, in Section 3.2, we show how it improves the accuracy of beauty product recommendation. Section 3.3 is dedicated to investigate impact of this study on customers.

IV. COLOUR ANALYSIS FOR BEAUTY RECOMMENDATION

In this section, we present two different color analyses to access significance of using well-illuminated photos. Variation among Estimated Skin Tones.

We computed estimated skin tone for 6 different synthetically generated models representing different parts of Monk Skin Tone scale [3]. Then the distance between the estimated skin tone of the best illuminated photo and the rest was computed. This computation is to measure how much the colors deviates from the color extracted from the ideal illumination condition. Table 2 summarizes the finding. The average distance is smaller if we only use the set of well illuminated photos for all 6 models. The average color difference was greater than 10 for 5 out of 6 models if we only use the ill-illuminated images, which implies that the estimated skin tone from these have perceptually noticeable difference to the color estimated from the best illuminatedphoto. The examples in Figure 1 and 4(c) verifies this: A same model can have significantly different estimated skin tones. The difference being smaller for the well-illuminated photos show that there are many ways for the illumination condition to be bad, while good illumination tend to introduce similar color patterns.

Shade Recommendation Using Face prints.

In this trial, we cipher the distance between the shade and the esti- slept skin tone to pretend shade recommendation. The shade range varies by the product, and there's no assiduity standard on the shade range or the number of tones being offered. Thus, we named three products that represent different shade distributions. Product A has 39 tons of varying lightness with numerousmedium range tones, Product B focuses on 12 deeper tones, and Product C focuses on 17 light to medium tones. To pretend theshade recommendation, we assumed that the stoner preference is to find the shade that's the closest to their skin tone, i.e. the color distance is minimized. Table 3 shows the number of tones within the distance threshold of 2 or 5. We observed that usingill illuminated prints impacts the shade recommendation in number of ways. First, the number of tones being recommended can drastically change. For Model 4, there's no shade within distance 5 for Product B if we only use the good images. Still, 11 out of 12 tones are lower than distance 5 if we use the bad illuminated images for the point estimation. Recom- mending 11 out of 12 tones would not give any discrimination Power, and may not be any better than aimlessly recommending one. In addition, if the thing is to recommend a product that has the model's shade, ill- illuminated prints may recommend products that aren't intended for the the model's skin tone(Figure 5(a)). Next, there's a disagreement between the shade recommended by the well- conditioned vs. ill-illuminated images. For Model 3, good images induce 3 distance< 5 matches for Product A while the bad images induce 4 similar. Still, only 1 shade overlaps between these, meaning the stoner may admit a disagreeing recommendation depending on the illumination condition (Figure 5(b)). This implies that in the absence of illumination assessment- the input face print can be moreover well or ill- illuminated- the variability in shade recommendation will be widened. This is reflected in the larger figures for" All prints" column in Table 3. It's also important to note that the product images tend to be taken beneath well- illuminated terrain. Thus, comparing the product color with the skin tone estimated from an ill- illuminated photo may lead to an incorrect shade recommendation altogether. Lastly, illumination condition impacts the number of distance < 2 matches. In Table 3, we see there are more number of matches if we use

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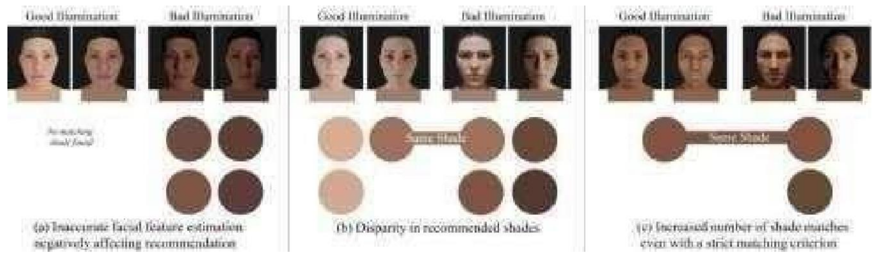
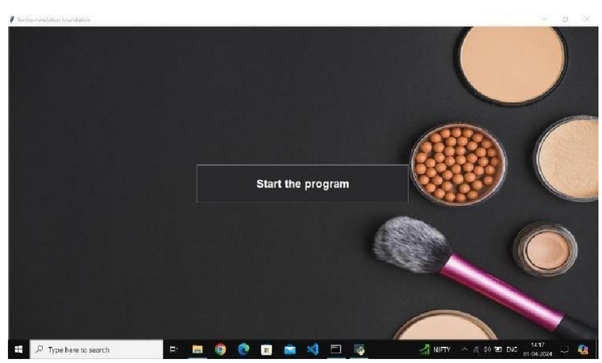
bad illuminated images. This is another reflection of different color variation patterns introduced by varying light conditions, while color variation is more confined for the good illuminated images (Figure 5(c)). Note that this may not be true if we relax the distance threshold to 5. That is, the ill illuminated photos do not always increase the shade matches and may even decrease it as the threshold increases. This is due to over or under exposed pictures producing very light or dark browns and the shadows can lower the color saturation. A typical foundation shade ranges may not cover these ranges.



V. CUSTOMER PROBLEM STATEMENT

The beauty e-commerce industry is witnessing a growing trend of applications that provide customers with personalized recommendations based on their face features. Given the diversity in mobile devices and customer skin tones and the variability of light conditions, the models using the photos may behave unexpectedly. The models are often trained under the assumption that the input data is a faithful representation of the customer's face and does not factor possible ill- illuminated environments. Reduced performance of the model that is a part of a recommendation framework can decrease customer satisfaction. A user guidance module can solve this prob lem by encouraging the users to take photos under a good lighting environment. In this work, we propose a framework that can detect the quality of the illumination in face photos. We ensure the good performance of the model across various skin tones which is often neglected in previous studies. In our experiments, we have found that ourproposed framework has a higher probability of producing successful outcomes compared to its counterparts. This indicates that the application using the face images will be more satisfactory if they leverage our approach. For example, our approach may be used to reject poorly illuminated input photos, so the customers can continue taking photos until a good illumination isdetected. The customer may also upload a photo, and our model informs them of any possible issue of bad illumination. The customer then may decide if they still want to proceed or upload a new one

VI. RESULTS



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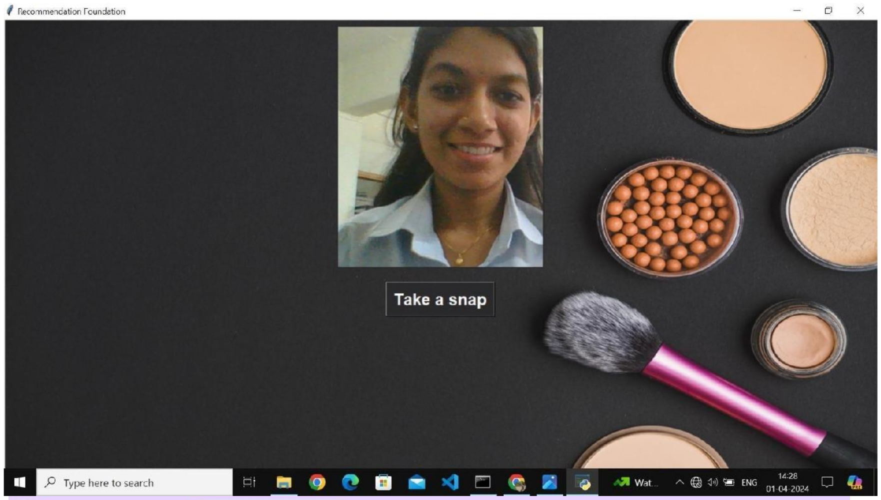

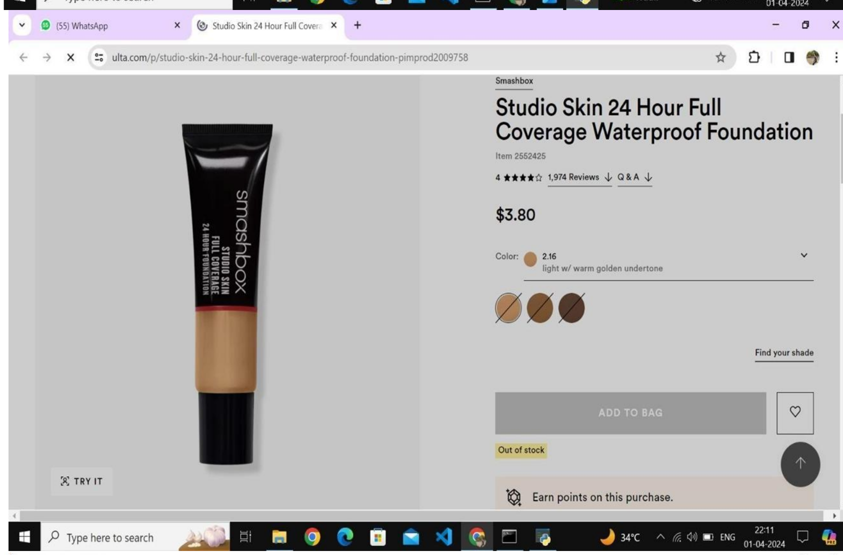

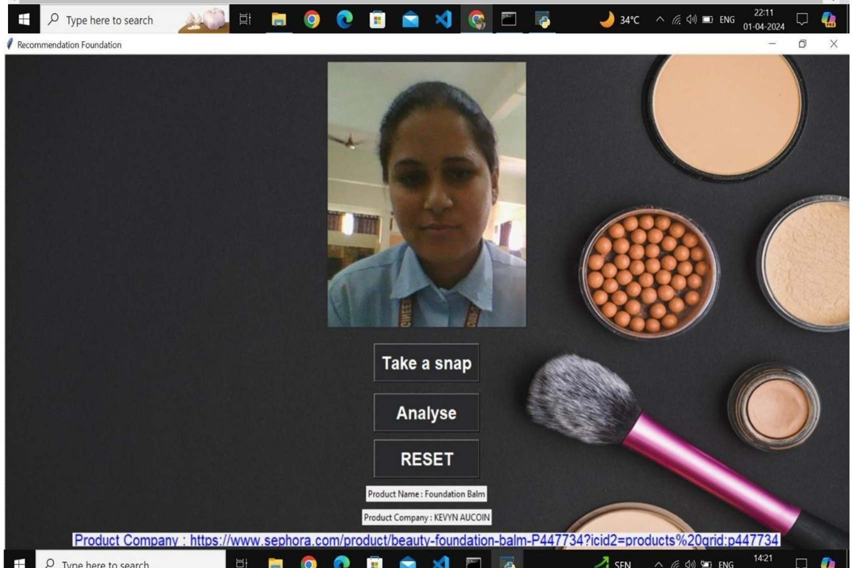

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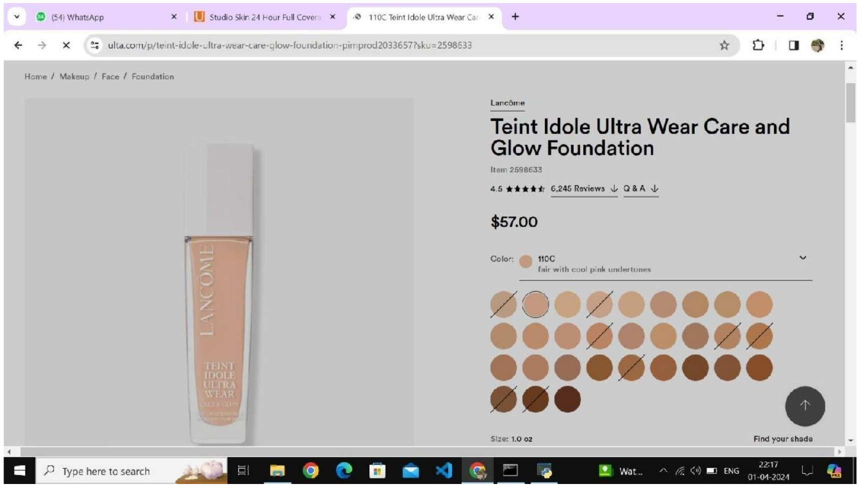

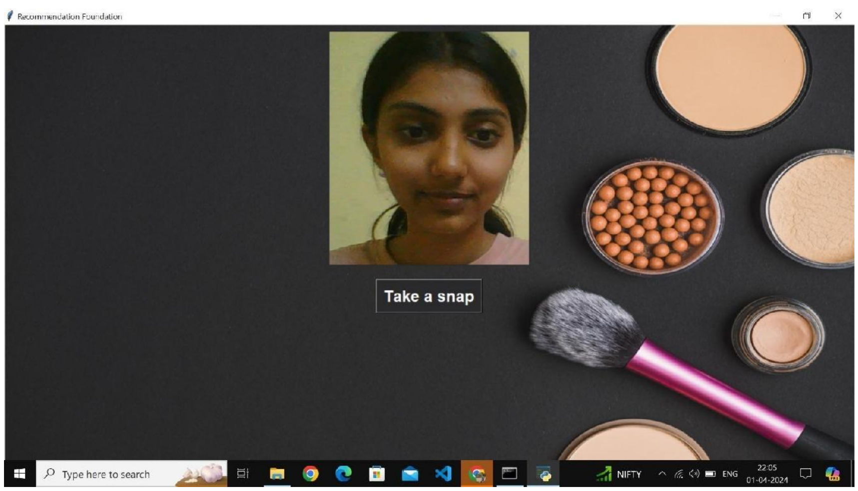

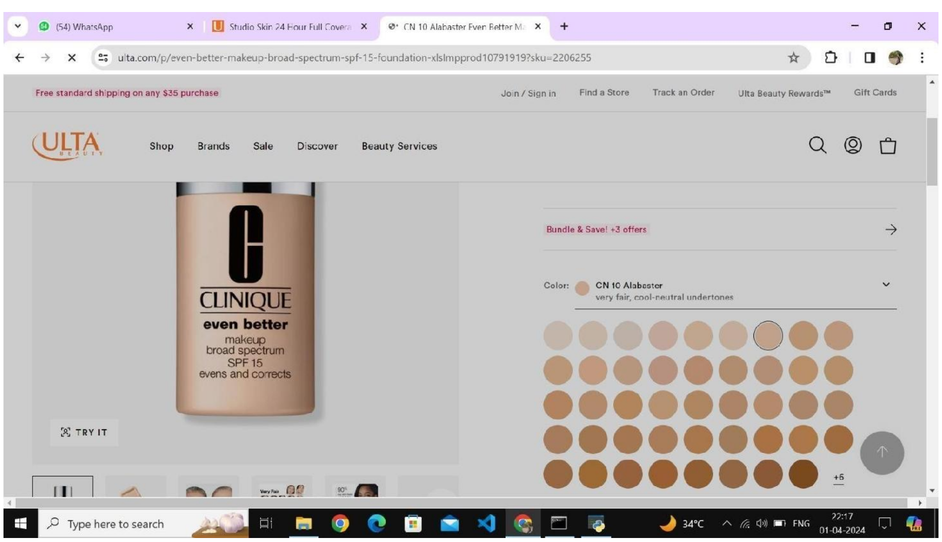

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VII. CONCLUSION

In this work, we approached fair and responsible beauty product recommendation by proposing a light assessment model that classifiers input face images as well or ill-illuminated. The motivation behind developing such model and tool is beauty product recommendations often requiring the input face photo to have good lighting. The pivotal piece in enhancing the model was to develop synthetic dataset with a wide range of skin tones and illumination patterns. This dataset synthesis also meant only 1,000 real face images were needed for our method, which Provides the benefit of minimizing the manual data collection and labeling effort which can be expensive and time consuming. The synthetic dataset was used to train a MobileNet-v2 for the final illumination condition classification. Our experiments evaluated on a real dataset show that the proposed approach outperforms its counterparts. It also improves the quality of the shade recommendation and eliminates the need to correct colors which can be have biased performance and the result unexplainable to the user. The live feedback and the interactivity of our tool may provide more trustworthy experience for the users.

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