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RESEARCH ARTICLE

Pigment-Aware: Understanding Skin Tone Variations in Digital Image Analysis

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ABSTRACT Optical sensors, such as the RGB cameras embedded in smartphones, often fail to accurately capture the full spectrum of skin tones. As a result, individuals with darker skin may experience reduced performance in machine vision-based security systems. Insufficient attention to human diversity, including variations in skin tone, can contribute to biased training data and, subsequently, to disparities in AI systems, especially in biometric recognition. This paper highlights the need for more consistent and objective approaches to assessing skin tone, which are often treated subjectively or applied inconsistently. We address this issue by analyzing RGB finger photo data using colorimetric techniques to support the development of more inclusive machine vision systems.

INDEX TERMS Biometrics, cybersecurity, digital devices, individual typology angle, reflectance, skin tone.

I. INTRODUCTION

Technology-driven discrimination occurs when AI-powered optical sensors fail to accurately capture key human characteristics, resulting in biased outcomes that disproportionately affect certain populations [1]. These disparities raise critical concerns about equity, systemic bias, and the broader consequences of deploying such technologies at scale. Current optical sensors (e.g., smartphone RGB cameras) are limited in their ability to interpret variations in skin tone features, primarily due to light absorption, which reduces the reflectance signal required for image formation. This limitation is linked to the optical properties of the human skin, which influence how light is absorbed, reflected, and transmitted through the tissue. These properties can vary widely based on factors such as ethnicity, chromophore concentration, age, gender, body size, skin conditions, and sun exposure, making it challenging to achieve consistent and equitable skin tone representation in imaging systems [2]. Despite advances in smartphone camera technology aimed at better capturing darker skin tones [3], [4], significant challenges remain. Some contactless biometric systems—though deployed in high-security applications—have not been thoroughly evaluated for skin tone bias and often exhibit reduced accuracy for individuals with darker skin. These limitations can result in disproportionate error rates, raising concerns about fairness and reliability.

In the domain of contactless fingertip-based biometrics, there remains a lack of systematic evaluation concerning the influence of skin tone on image quality and algorithmic performance [5], [6]. This gap is particularly significant given that fingertip coloration varies considerably across individuals due to physiological and environmental factors, including ethnicity, melanin concentration, blood perfusion, skin thickness, temperature, and exposure to external conditions. Fingertip pulse oximeters, although widely used and cost-effective, often exhibit unregulated performance, particularly for darker skin tones, which affects diagnostic accuracy [7]. AI models that do not account for this variability risk biased performance, particularly in applications such as contactless palm or finger imaging.

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This highlights the need to investigate the underexplored impact of skin tone in RGB-based finger photo analysis and emphasizes the importance of designing inclusive identity verification systems that perform equitably across all demographics [8].

In the visible range, the primary absorbing molecule is melanin, located in the superficial layers of the skin, which determines an individual's skin tone and the amount of hemoglobin in the blood. Melanin absorption is higher in the visible range, resulting in a lower reflectance intensity for skin with a higher melanin concentration. In the near-infrared region, water absorption becomes significant near 970 nm [9]. The concentrations of these absorbing molecules vary across different body regions, influencing light absorption and reflection. These characteristics impact the imaging systems. Several early vision systems assume homogeneous skin reflectance in RGB fingertip images, overlooking variability from differing melanin levels. This can bias feature extraction and reduce recognition accuracy, particularly for darker skin tones [10].

Increasing evidence suggests that noninvasive assessment tools, such as pulse oximeters, temperature probes, and AI dermatology benchmarks, can exhibit reduced accuracy when used on individuals with darker skin tones [11]. Although the Food and Drug Administration (FDA) is exploring strategies to improve device performance in diverse skin tones by incorporating skin tone criteria, there is still no consensus on standardized methods to assess skin tone bias in prospective studies [12]. Available tools, including visual scales (e.g., Fitzpatrick Skin Type, Monk Skin Tone) and color measurement instruments (e.g., colorimeters, spectrophotometers, cameras), have yet to be consistently validated across various domains, such as medical. *Inconsistent skin tone measurement*, affected by lighting and individual conditions, complicates accurate device performance assessments, particularly in AI dermatology, security, and non-invasive diagnostics. The *subjectivity* inherent in traditional skin tone evaluation, shaped by personal biases and environmental factors, introduces significant bias, especially in skin lesion segmentation models, which underperform in individuals with darker skin tones. While *subjective* estimation of skin tone, often based on human perception or non-standardized visual assessments influenced by lighting, cultural biases, camera settings, and environmental factors, can be inconsistent or inaccurate, more *objective* approaches using digital color analysis and spectrophotometry can be explored to quantify skin tone using measurable properties such as reflectance spectra.

To address the research question—*"Can we minimize subjectivity in evaluating skin tone using objective colorimetric analysis?"*—this paper emphasizes the urgent need for standardized data-driven techniques in dermatological imaging to reduce bias and improve consistency. A key parameter for objectively assessing human skin color is the Individual Typology Angle (ITA). ITA is a quantitative measure used to classify skin tone through colorimetric analysis. This spectroscopic method correlates directly with skin pigmentation and is linearly proportional to melanin concentrations [13]. The ITA has not been widely adopted in AI security [14]. Originating from dermatology and cosmetic science, ITA is a quantitative and objective metric derived from the CIE Lab* color space, commonly used for skin phototype classification. In AI fairness research, skin tone is typically categorized using subjective scales, such as Fitzpatrick or basic RGB groupings, which lack the precision of ITA. While some recent work has explored colorimetric approaches for skin tone assessment, ITA remains absent mainly from standard biometric benchmarking protocols [14]. This article advocates for the adoption of standardized evaluation methods to reduce inconsistencies and enhance the reliability of skin tone assessments in imaging through colorimetric analysis, an objective approach. Experiments are conducted on finger photo RGB data to address the complex variations in individual skin tones.

The paper is structured as follows: Section II reviews the literature on AI fairness, focusing on variations in skin tone in security. Section III outlines the proposed colorimetric analysis method. Section IV discusses experimental results. Section V concludes with findings and future research directions.

II. LITERATURE REVIEW

A. HUMAN SKIN MODELS

Researchers have previously studied the interaction of light with human tissue to understand tissue spectral properties and how skin color is influenced by both environmental factors and genetics [15], [16], [17], [18]. The epidermal and dermal layers of human skin form a scattering medium that contains several pigments, including melanin, hemoglobin, bilirubin, and beta-carotene. Small changes in the distribution of these pigments induce significant changes in the skin's spectral reflectance [19], [20], [21], [22]. Melanin is a key factor in determining skin color in individuals with darker skin, providing pigmentation and influencing tonal qualities such as lightness and yellowness. Variations in melanin levels lead to a diverse spectrum of skin tones within populations with darker skin [9]. In contrast, lighter-skinned individuals often have skin tones influenced more by hemoglobin, which circulates in blood vessels and is associated with reddish undertones. In 2018, Howard et al. explored the effects of relative skin reflectance on biometric performance by spending efforts to measure its impact on recognition [23]. Relative skin reflectance was expressed in terms of RGB color values. Subjects belonging to the African-American subset were found to be inversely associated with skin reflectance values. Lower reflectance was found for people who self-identified as African American compared to those who self-identified as white, while it was higher in women than in men. This trend was also confirmed in later studies [24].

B. SKIN TONE BIAS IN AI

Recent research has examined demographic differences in biometric systems [7], with a primary focus on gender, age, and ethnicity. However, the role of skin tone in AI-driven security applications remains underexplored [4], [25]. Krishnapriya et al. investigate how variations in skin tone influence the accuracy and fairness of face recognition algorithms, revealing that darker-skinned individuals experience higher False Match Rates (FMR) and False Non-Match Rates (FNMR) when categorized using the Fitzpatrick scale [26], [27]. Using datasets annotated with skin tone measures, including the ITA [28], their findings underscore improved dataset diversity, algorithmic refinements, and fairness-aware training strategies to reduce bias in biometric security [29], [30], [31], [32]. A recent study examines biases in AI models related to skin tone, particularly in facial recognition and image classification systems. It highlights how current methods, especially in albedo estimation for virtual facial avatars, tend to favor lighter skin tones due to biased priors and unresolved ambiguities between albedo and lighting. The study proposes a solution through the FAIR dataset, which balances skin tones, and the TRUST algorithm, which addresses these biases by leveraging facial and surrounding lighting information. This work is connected to broader research on the impact of skin tone in AI, to reduce biases in image classification and improve fairness in AI applications in diverse populations [33].

Understanding human attributes, particularly skin tone, is crucial for enhancing the accuracy across various AI systems, ranging from computer vision to multimodal models. Skin tone annotation is subjective and influenced by technical factors, such as lighting, and social factors shaped by an annotator's background. This study examines the subjectivity of skin tone annotation using the Monk Skin Tone (MST) scale and introduces the Monk Skin Tone Examples (MSTE) dataset to improve training for annotators. The findings show that, while annotators can reliably annotate skin tone, regional differences in interpretation lead to systematic variations. These results highlight the importance of using diverse annotators and multiple replications in skin tone annotation, underscoring the need for fairness in AI systems, where biased skin tone data can affect the precision and inclusivity of image classification models [34]. In a 2024 study, Marin Benčević and colleagues explored skin tone bias in deep learning-based skin lesion segmentation. The research aimed to investigate the impact of skin tone on the accuracy and fairness of deep neural network models used in dermatology. Through extensive analysis, the study found significant performance discrepancies between lighter and darker skin tones, with models showing a consistent bias towards lighter skin. The findings underscore the importance of considering skin tone during dataset collection and model training to ensure equitable healthcare outcomes. The study also highlighted the limitations of current bias mitigation techniques, urging further improvements in dataset diversity and model development to address these disparities [35].

A recent study by Overbye-Thompson et al. examines the impact of skin tone bias in image recognition algorithms on user adoption and usage [1]. The study, conducted in two investigations, found that people with darker skin tones, despite facing more bias in these technologies, used them more frequently than those with lighter skin tones. The researchers applied a diffusion of innovations framework to explore perceptions of compatibility, complexity, observability, relative advantage, and reinvention. The findings indicated that darker-skinned individuals perceived image recognition algorithms as more compatible and advantageous, engaging in higher levels of reinvention to adapt to algorithmic biases. Although allowing better usage, this adaptation process highlights the disproportionate burden on users with darker skin and underscores the need for more equitable AI technologies [1].

C. SKIN TONE MODELING

In most cases, racial bias in biometric systems has been primarily attributed to the underrepresentation of black individuals in training datasets, which is a correct statement. While increasing dataset diversity is necessary, it is not a sufficient solution, so a more nuanced understanding of the sources of error is essential. One major flaw lies in the oversimplified classification of individuals based solely on ethnic or racial groups. Although grouping individuals by ethnicity may appear valid—since people within a group may share similar phenotypic traits—this method fails to account for the rich genetic and phenotypic diversity within populations [36]. For example, Brazil's population is characterized by a high degree of admixture between African and European ancestry (primarily Portuguese). Still, there are also Asian (notably Japanese), indigenous peoples, and immigrants from all over the globe. In a globalized world, categorizing individuals strictly by ethnicity is increasingly inadequate. Furthermore, from a photometric perspective, skin reflectance properties (i.e., light absorption and scattering) are determined by melanin concentration and are not influenced by geographic or cultural origin.

Another commonly used classification system is the Fitzpatrick skin type scale, initially developed in dermatology to assess susceptibility to UV-induced skin damage [26]. While it categorizes skin tones into six types (I to VI), its application in biometric research presents challenges. The scale is subjective and often relies on visual assessment or self-reported questionnaires [37]. Although dermatologists may achieve high inter-rater reliability, this accuracy is not easily replicable by non-experts [38], [39]. Moreover, each Fitzpatrick type encompasses a wide range of skin tones, leading to coarse and sometimes misleading classifications. A more objective and reproducible

alternative is the use of spectrophotometric techniques, particularly those based on the CIELAB color space [40]. This color model accounts for human visual perception, allowing for a more precise quantification of skin tone. From CIELAB values, the ITA can be calculated, a parameter shown to strongly correlate with melanin concentration [9], [13], [41], [42], [43]. The ITA thus provides a reproducible biological metric for skin tone classification.

Despite its advantages, spectrophotometry also has limitations — the most notable is the need for calibrated light sources and access to specialized equipment. One approach could be converting RGB images into the CIELAB color space to estimate ITA, enabling real-time, objective skin tone classification using consumer-grade devices. This could help identify where and how biometric systems fail, particularly for darker skin tones. However, no previous colorimetric analysis has been conducted on finger photo data, as the ITA primarily focuses on the palm region. This gap highlights the need for further exploration of colorimetric methods in the context of finger-based biometric data. Through intricate physical modeling of light propagation and reflectance in skin tissues, a deeper understanding and resolution of the reduced sensitivity of image biometric systems for darker skin can be achieved [44]. By accounting for melanin's absorptive properties and the complexities of light scattering, such models enable a quantitative assessment of the reflected light captured by sensors. This analytical framework can strategically inform the design of advanced acquisition devices and adaptive algorithms, ultimately guaranteeing equitable performance across all skin tones and promoting meaningful social inclusion in the deployment of biometric technologies.

In biometric research, variability in lighting and device-specific sensor characteristics can introduce uncontrolled bias in skin tone estimation [45]. To assess the reliability of *image-based skin tone* metrics, recent studies have analyzed Face Area Lightness Measures (FALMs)—automated lightness estimates derived from facial images—and compared them against ground-truth skin color readings obtained with calibrated colorimeters [45]. The results revealed substantial variability in FALMs across multiple images of the *same individual*, even under similar conditions, underscoring the sensitivity of these measures to acquisition parameters. In particular, only standardized image capture settings—such as fixed cameras, consistent lighting, and neutral backgrounds—reduced this variability [45]. Furthermore, ground-truth FALMs showed minimal differentiation across FST categories and correlated more closely with self-reported race than with actual skin pigmentation. These findings highlight the limitations of FST as a reliable proxy for skin tone in computer vision and reinforce the need for calibrated, device-independent colorimetric approaches in biometric applications.

III. COLORIMETRIC ANALYSIS OF RGB BIOMETRIC DATA

A. PRELIMINARIES

Biological tissues, such as skin, muscles, and tendons, exhibit anisotropic properties, i.e., their optical characteristics depend on the direction of incident light and its interaction with the medium. The propagation of light in the tissue can be modeled using the *Radiative Transport Equation (RTE)*, as expressed in Eqn.1 [46].

$$\frac{dL(r,\hat{s})}{ds} = -\mu_t L(r,\hat{s}) + \mu_s \int p(s,\hat{s}) L(r,\hat{s}) d\omega' \quad (1)$$

In Eqn.1, $L(r,\hat{s})$ is the light radiance (quantity used to describe the propagation of photon energy in a medium), $p(s,\hat{s})$ is the scattering phase function, and $d\omega'$ is the infinitesimal solid angle in the $\hat{s}$ light propagation direction. By definition,

$$\mu_t = \mu_a + \mu_s \quad (2)$$

The *transport* coefficient is the sum of the *absorption* coefficient μ_a and the *scattering* coefficient μ_s. In biological tissue, light propagation occurs in a forward direction, but this direction is strongly dependent on the scattering patterns. A measure of the degree of anisotropy in scattering is the anisotropy factor g, which represents the average of the scattering angle θ. If only forward scattering occurs, $g = 1$, the total backward scattering corresponds to $g = -1$, and an isotropic medium has $g = 0$ (it scatters the light equally in any direction). For reference, on human skin, $g = 0.90$ on average, which means that light propagates mainly in the direction of the depth of the skin. Mathematically, g is defined according to Eqn.3.

$$g = \frac{\int p(s,\hat{s})(\hat{s}\cdot\hat{s}')d\omega}{\int p(s,\hat{s}')d\omega} = \langle\cos(\theta)\rangle \quad (3)$$

The Henvey-Greenstein equation is typically used to estimate the scattering direction, as shown in Eq.4.

$$p(s,\hat{s}) = \frac{1}{4\pi}\frac{1-g^2}{\left(1-2g\cos\theta+g^2\right)^{3/2}} \quad (4)$$

B. SKIN TONE AND LIGHT REFLECTANCE

When light interacts with the skin, there are two main light attenuations: absorption and scattering. Melanin and hemoglobin are the main chromophores (molecules that absorb light at a particular wavelength and reflect color). People with dark skin tones typically have higher concentrations of melanin, which significantly increases light absorption and reduces the response of the optical sensor [41], [43], [47]. Melanin absorption occurs across the visible spectrum, with its effect being more pronounced at lower wavelengths. Hemoglobin has two main absorption patterns: when bound to oxygen in the blood (Oxy-hemoglobin, HbO_2), with two leading bands in the visible light spectrum, the first at 534 nm and the second at 575 nm. On the other hand, deoxyhemoglobin (Hb) exhibits a single band

centered at 540 nm. The absorption band shift is often used to estimate blood oxygen saturation (SpO_2) by using isosbestic points. When light interacts with biological tissues, part of it is absorbed, part is scattered (either forward or backward), transmitted, and a fraction is reflected (remission). The remitted light can be detected by optical devices, such as cameras or detectors. In this sense, studying the reflected light allows for a better understanding of the characteristics, composition, and structure of the tissue. A mathematical model that describes light reflection in diffuse media is given by R_d [46], [48], which represents the amount of light reflected on the tissue surface, given by Eqn 5.

$$R_d = \frac{\alpha'}{1 + 2k(1-\alpha') + (1+\frac{2k}{3})(\sqrt{3(1-\alpha')})} \quad (5)$$

were, α' is the reduced albedo given by $\alpha' = \frac{\mu_s'}{\mu_s' + \mu_a}$, and $k = \frac{1+r_{id}}{1-r_{id}}$ is the partial reflection on the interface of the air-tissue which,

$$r_{id} = -1.440\, n_{rel}^{-2} + 0.710\, n_{rel}^{-1} + 0.668 + 0.0636\, n_{rel} \quad (6)$$

and $n_{rel} = \frac{n_{air}}{n_{tissue}}$ is the relative refractive index between the air-to-tissue interface. The diffuse reflectance is given in [W].

The light source is a core in image acquisition and directly influences the accuracy and reproduction of color measurements. Factors such as the spectral distribution, intensity, directionality, and polarization state of the illumination affect how light interacts with the skin and how the imaging system captures it. For instance, broad-spectrum or natural daylight sources provide more uniform spectral coverage, reducing color bias, while narrowband or artificial sources may introduce spectral distortions. Uncontrolled lighting conditions can cause variations in shading, highlights, and specular reflections, which can alter perceived skin tone and interfere with quantitative color analysis. The absence of standardized lighting also hinders reproducibility across datasets. In this study, image acquisition was performed under ambient lighting conditions, without polarization or spectral calibration. Although this reflects real-world usage scenarios, it also introduces limitations in terms of precision.

Most of the light reflected from a turbid medium is the result of light scattering, providing valuable information about the composition of the tissue. When light interacts with the tissue, part of the incident photons are absorbed at specific wavelengths, influenced by chromophores within the analyzed region. For a more precise measurement of a person's skin tone, it is recommended to use reflectance spectroscopy methods, which consider the amount of light reflected after interaction with the tissue, rather than relying solely on visual inspection and classification into groups, as proposed by the Fitzpatrick scale. In this context, color scales such as RGB and CIELAB are highly relevant for classifying skin tones. The CIELAB scale, in particular, takes into account the human eye's perception when classifying colors, serving as a correction factor for light reflection from various objects. It categorizes colors in three dimensions (axis): L^*: Lightness (or brightness), ranging from 0 (black) to 100 (white). a^*: Variations between green (−128) and red (+128). b^*: Variations between blue (−128) and yellow (+128). Recent colorimetric studies have established a correlation between tristimulus values and the main chromophores present in the skin [40]. The L and b* components are primarily associated with overall melanin concentration and light attenuation, which include both eumelanin and pheomelanin, and therefore are relevant for the evaluation of skin pigmentation. In contrast, the a* axis is mainly influenced by hemoglobin content and vascularization; however, pheomelanin can also enhance the reflectance in the red spectrum.

Using the L and b* CIELAB parameters, usually measured with a colorimeter, the ITA can be calculated through Eqn 7, which establishes a numerical correlation between skin tone and its light reflection response.

$$ITA = \frac{180}{\pi} \cdot \arctan\left(\frac{L^* - 50}{b^*}\right) \quad (7)$$

The ITA categorization of the skin follows the sequence: very light > 55° > light > 41° > intermediate > 28° > tan > 10° > brown > −30° > dark [41]. Although this categorization does not directly enhance recognition accuracy, it approximates the melanin concentration, which is known to affect the optical system response.

C. CORRECTION FOR INSTRUMENTAL LIGHT EFFECTS

In biometric image processing, the light source signal is often considered insignificant and not considered [49], [50]. However, a white reference, or color checker, plays a crucial role in colorimetry measurements as it carries the light source signal necessary for spectral correction [51]. Spectral correction refers to the adjustment of recorded data to compensate for distortions caused by the measurement system, including variations in light source, sensor characteristics, and background noise interference. By incorporating knowledge of the light source and prior information about the imaging system, environmental conditions, and material properties, spectral correction improves the precision of RGB biometric data [52]. This process minimizes distortions that could compromise data reliability by accounting for factors such as illumination variations, sensor-specific spectral sensitivity, and the inherent reflectance properties of biometric traits. For instance, the spectral distribution of a given light source influences how a sensor perceives colors and materials. Spectral correction compensates for these variations, producing more accurate and consistent results. Normalization must be applied pixel-by-pixel to account for spatial variations in light distribution and enhance precision. Eqn. 8 describes the processing step that enables the signal to become independent of the light source, thus improving the consistency between measurements.

$$\text{Reflectance}(\lambda) = \frac{R_{\text{Sample}}(\lambda)}{R_{\text{Reference}}(\lambda)} \quad (8)$$

However, for accurate results, the integration time must be identical for both images; if this condition is not met, an additional correction is necessary. A reference material, such as a spectrum, is commonly employed to capture the reflection spectrum of the light source or ambient illumination, as it reflects all wavelengths in the visible spectrum, facilitating precise recovery of the source spectrum.

D. COLORIMETRY: CONVERTING RGB TO CIELAB

This study used the XYZ conversion matrix to estimate the L*, a*, and b* of the CIELAB color space from the RGB images. Eqn. 9 presents the conversion matrix from RGB to XYZ color space, which is used to compute the corresponding values of L, a*, and b* through Eqn. 10 to Eqn. 12. This matrix is based on the standard D65 illuminant [53], [54], and the values adhere to the definitions provided by the OpenCV library for this illuminant.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.212671 & 0.019334 \\ 0.357580 & 0.180423 & 0.715160 \\ 0.072169 & 0.119193 & 0.950227 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{9}$$

$$L^* = \begin{cases} 116 \cdot Y^{1/3} - 16, & \text{for } Y > 0.008856 \\ 903.3 \cdot Y, & \text{for } Y \leq 0.008856 \end{cases} \tag{10}$$

$$a^* = 500 \cdot (f(X) - f(Y)) \tag{11}$$

$$b^* = 200 \cdot (f(Y) - f(Z)) \tag{12}$$

where

$$f(t) = \begin{cases} t^{1/3}, & \text{for } t > 0.008856 \\ 7.787 \cdot t + 16/116, & \text{for } t \leq 0.008856 \end{cases} \tag{13}$$

and

$$\delta = \begin{cases} 128, & \text{for 8-bit images} \\ 0, & \text{for floating-point images} \end{cases} \tag{14}$$

with $X \leftarrow \frac{X}{X_n}$, where $X_n = 0.950456$ and $Z \leftarrow \frac{Z}{Z_n}$, where $Z_n = 1.088754$. The ITA was calculated using L^* and b^* from the converted images and then applied to Eqn 7.

Device-specific spectral sensitivity introduces substantial variability in RGB values, even for identical scenes. Consumer-grade cameras, including smartphones, utilize CMOS or CCD sensors with proprietary Bayer filters and processing pipelines, resulting in inconsistent RGB outputs across devices [55], [56], [57]. Accurate conversion to device-independent color spaces (CIEXYZ, then CIELAB) requires camera-specific calibration. Without it, colorimetric estimates, such as ITA, become unreliable [51], [53]. Uncalibrated RGB-to-CIELAB conversions have been shown to cause significant color estimation errors, particularly under variable lighting [58]. Therefore, smartphone-based ITA estimation should be interpreted with caution. Future work must incorporate device calibration and standardized imaging protocols to improve consistency in skin tone analysis.

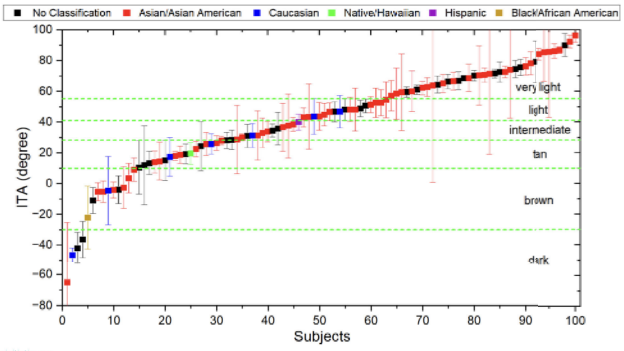

FIGURE 1. ITA of the fingertips from Mason data, categorized by their typology.

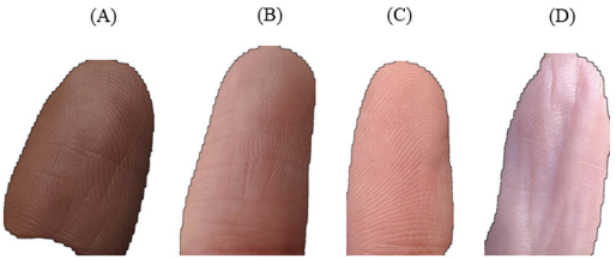

FIGURE 2. Asian and Asian American groups ITA gradients, in (A) ITA = −65°, (B) ITA = 11°, (C) ITA = 48°, and (D) ITA = 90°.

IV. EXPERIMENTAL RESULTS

The dataset used in the experiments was collected at George Mason University and consists of finger photo RGB images of 100 subjects. These images were captured with an iPhone 13 Pro under various indoor and outdoor lighting conditions to ensure variability and robustness in the analysis [59]. Initially, the data was converted from the RGB color space to the CIELAB color space using the equations described in the previous section. Fig. 1 shows the distribution of the ITA, in degrees, for 100 individuals classified by ethnic group. On the x-axis, individuals are arranged in ascending order of ITA. The data show that individuals classified as Asian or Asian American exhibit a wide range of ITA values, from very light to dark skin tones. This broad variation highlights the considerable diversity in skin pigmentation within a single ethnic group, as illustrated in Fig. 2.

Although ethnicity categorization is not the primary focus of this analysis, we include it to provide context and highlight that ethnicity does not reliably predict skin tone. Our findings indicate that ethnic demographic labels alone are insufficient; accurate skin tone measurement is crucial to conduct meaningful and equitable analysis.

Using Equation (5), with reference data set of absorption coefficient and scattering coefficient [9], it is possible to estimate the skin reflectance on a camera sensor under different conditions. Fig. 3 shows the reflectance of a light skin (ITA = 32.7), and brown skin (ITA = -13.6^{o}) under normal, higher, and poor illumination;

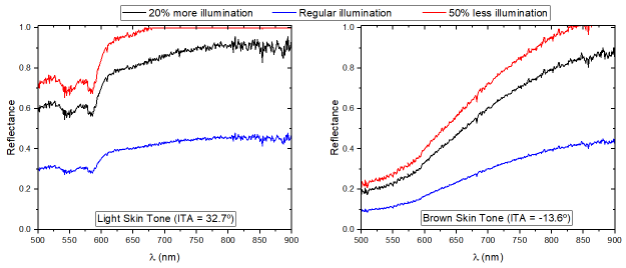

FIGURE 3. (Left) Light skin tone, ITA = 32.7º, and (right) brown skin tone, ITA = 13.6º. In black is the sample's reflectance under standard illumination, red is the same sample under high illumination (20% more), and blue is a poor illumination condition (50% less), simulating a digital camera sensor under different conditions.

As shown in Fig. 3, with higher illumination, a light skin may saturate the sensor in some spectral regions, whereas a brown skin would have reflectance similar to that of a light skin. However, poor illumination can hinder the skin's tone, and light skin may appear darker. Both conditions may lead to an incorrect classification by several methods.

ITA values typically do not exceed 80 degrees, which may indicate a saturation effect in some images within the dataset. Saturation can occur due to automatic camera adjustments, excessive lighting, or limitations in converting RGB to the CIELAB color space. When lighting is too intense, pixels may reach their maximum brightness limit, leading to artificially high ITA values. This issue underscores the importance of strict standardization in image acquisition conditions to avoid artifacts that could distort the analysis. Conversely, extremely low ITA values are often more related to shadows in the images than actual skin pigmentation. Inadequate lighting reduces the intensity of reflected light, resulting in inaccurate color measurements that tend to skew toward darker tones. Shadows may result from the positioning of the light source, nearby objects, or the finger's positioning during image capture. This highlights the critical need for rigorous lighting control to ensure precise and reliable colorimetric measurements. The scientific literature suggests that palms tend to be naturally lighter in color than other areas of the skin due to the presence of DKK1 (Dickkopf-related protein 1). This molecule inhibits melanocyte growth in the palmar epidermis [60]. This biological factor explains why palms generally exhibit higher ITA values, even in individuals with darker non-palmar skin. Consequently, very low ITA values in palm images may suggest experimental errors during image acquisition, such as improper lighting or incorrect camera settings.

The standard deviation observed in Fig. 1 reflects the color variation within the same Region of Interest (ROI). High deviations may be caused by factors such as dirt, cream residues, skin oiliness, and variations in surface texture. These irregularities disrupt the uniformity of the color and can compromise the accuracy of ITA measurements. Similar effects can be observed in images of very light skin, where subtle lighting differences can result in significant variations in color measurement. Errors in skin color measurement can directly impact biometric acquisition, reducing the quality of captured images and complicating the processing of recognition algorithms. Image-based biometrics are based on well-defined visual characteristics, and artificial variations in skin color can interfere with segmentation, contour detection, and pattern extraction. Inconsistent lighting, dirt, and unwanted reflections can cause recognition system failures, leading to higher error rates. Therefore, a standardized capture environment and control of the experimental conditions are essential to ensure the robustness and reliability of biometric analysis.

Genetic Variations in melanin expression contribute significantly to the diversity observed in human pigmentation [61]. Research has identified multiple genes that influence skin, hair, and eye color, with distinct alleles prevalent in different populations due to evolutionary pressures. These genetic differences, shaped by natural selection, account for the range of pigmentation observed between human groups. As a result, ethnicity-based classification may not be the most accurate approach to represent the skin color distribution; therefore, quantitative measurements, such as ITA, could be a more reliable alternative.

The Equipment used for image capture can introduce inherent inaccuracies due to the technical limitations of the sensors, improper calibration, or degradation of components over time. These inaccuracies can lead to variations in the recorded colorimetric values, compromising the reliability of the results. Different camera models can further exacerbate inconsistencies, as each sensor has unique characteristics for color capture, white balance, and spectral response. These differences make it difficult to compare images taken directly with different devices.

The Distance between the finger and the camera lens can also impact color capture due to optical effects such as perspective distortion and light dispersion. Variations in lighting conditions, such as differences in color temperature, shadows, and reflections, can significantly affect the characterization of skin color. Therefore, standardizing lighting is crucial to minimize bias in the data collection process. Without a reference device, such as a colorimeter, image calibration becomes challenging, which can lead to deviations in the obtained color values. Utilizing established color standards can help mitigate this issue, thereby improving the reliability of results. Additionally, residues of dirt, oil, or products on the skin can alter light reflectance and absorption, interfering with the accuracy of color and biometrics capture. To avoid such variations, standardizing hand cleaning before image capture is essential. The small number of volunteers from groups Native/Hawaiian, Hispanic, and Back/African American in the study can reduce the representativeness of the results, limiting the generalizability of the conclusions. Small datasets are more prone to statistical bias and may lack robustness in analyzing variations in skin color. Finally, categorizing individuals based on ethnicity rather than skin melanin

concentration can lead to inappropriate generalizations and introduce bias into the results, as presented in the enormous diversity of skin tones in the Asian/Asian American group.

A. LIMITATIONS

Colorimetric analysis and ITA are widely used to assess skin tones, but they face limitations, particularly concerning variability in lighting conditions and skin tone diversity [62]. Research highlights the inconsistencies introduced by different light sources in skin tone estimation, emphasizing the need for standardized lighting during measurement. Similarly, studies indicate that ITA classifications may not effectively differentiate between melanin and hemoglobin influences, thereby limiting their accuracy in capturing the diverse range of skin tones. Bias in measurement has also been observed, where colorimetric methods show reduced accuracy for darker skin tones, resulting in disparities in applications such as skin lesion detection. Environmental and physiological factors make skin tone assessment more challenging, as sun exposure can cause slight changes in skin color. Findings reveal that skin tone affects light reflectance, influencing the accuracy of optical measurements. These challenges underscore the need for enhanced methodologies that account for lighting variations, diverse pigmentation, and external factors to ensure more accurate and equitable skin tone assessments [63]. Furthermore, converting images from RGB to CIELAB can introduce errors due to differences between color models. While RGB is device-dependent and influenced by lighting, CIELAB is designed to reflect human visual perception and depends on illumination.

B. ENABLING FAIRNESS-ORIENTED GUIDELINES

Our empirical evaluation of ITA in biometric systems lays a critical foundation for fairness-centered research and system design. By objectively quantifying skin tone, ITA provides a more robust alternative to subjective proxies, such as FST or self-reported race, enabling precise bias analysis across true skin tone groups. Our findings reveal significant variability in image-derived ITA values due to lighting, sensor inconsistencies, and acquisition settings—underscoring the need for standardized capture protocols and device calibration. This work positions ITA as a diagnostic tool and fairness metric, guiding future efforts in lighting control, color calibration, and balanced dataset development across biometric modalities and operational contexts. It also supports the integration of ITA-based validation steps in algorithm development pipelines to detect and mitigate disparities early. In ongoing work, we aim to translate these insights into practical design guidelines, standard procedures, and deployment checklists aligned with fairness and regulatory goals. Using ITA as a measurable way to capture skin tone helps identify and reduce bias, turning fairness goals into real system improvements.

V. CONCLUSION AND FUTURE DIRECTIONS

This work highlights the need for additional research on how skin tone affects the performance of biometric systems based on RGB-acquired data. It also highlights the importance of developing effective mitigation strategies to address potential biases or disparities in biometric recognition, ultimately promoting fairness and accuracy across diverse populations. This research contributes to advancing ethical and responsible AI cybersecurity, with a focus on enhancing inclusion without compromising security. Although various models are being explored to reduce bias in training processes, incorporating the biological response of light tissue could provide deeper insights into the limitations of these systems.

Our ongoing work leverages ITA as an objective metric to assess and quantify skin tone in deep learning-based Presentation Attack Detection (PAD) algorithms for biometric systems. We are developing a novel framework that integrates multiple color spaces to address disparities identified through ITA measures. In parallel, we are extending this research into the hyperspectral domain, covering both the visible and Near-Infrared (NIR) spectra—a direction that offers richer spectral information and the potential to overcome current limitations, beginning at the instrumentation level. Further research is needed to expand these methods and address skin tone variability, which differs even within ethnic groups. Objective metrics like ITA offer more accurate evaluation than categorical labels. Biometric systems using RGB data should be assessed for skin tone bias, and deep learning models retrained with diverse color spaces to better capture features like tone, texture, and ridge detail.

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