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SkinToneNet: A Deep Learning Framework for Automated and Unbiased Skin Color Analysis

Using CASCo: An Objective and Automated Skin Tone Classification

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Abstract: Skin tone has significant impacts across various domains, but existing methods to measure and classify skin color suffer from subjectivity and potential biases. We introduce CASCo (Classification Algorithm for Skin Color) - an objective, automated approach that leverages computer vision and machine learning techniques to robustly classify skin tones from facial images. CASCo is an open-source Python library accessible to researchers, overcoming major limitations of traditional measurement techniques. It uses face detection, skin segmentation and k-means clustering algorithms to determine the skin tone category of portraits. Through extensive evaluation, we demonstrate CASCo's effectiveness as a reliable and customizable tool for studying the social implications of skin color in an inclusive manner.

Index Terms - Skin tone classification, Computer vision, Machine learning, Facial analysis, Objective measurement, Automated analysis, Open-source software Python library, social implications, Inclusive research, Unbiased algorithms, Demographic studies

I. INTRODUCTION

A growing body of literature across fields like economics, public health, and social sciences has revealed that skin color significantly impacts people's income, health outcomes, educational attainment, and employment prospects. However, the methods traditionally used to measure and classify skin color in empirical research have been criticized for being inaccurate, subjective, and potentially biased.

Common approaches include using verbal scales, visual aids like color palettes, photo elicitation techniques where respondents match their skin tone to reference images, and spectrophotometers or colorimeters to directly measure skin reflectance values. Each of these methods has notable drawbacks in terms of reliability, consistency, cost, and ease of use at scale.

Recent work has explored using computational image analysis and machine learning techniques to automatically estimate skin tone from digital facial images. However, most existing image-based skin tone classifiers are proprietary "black box" systems not accessible to researchers. There remains a need for an open-source, customizable tool specifically designed for social scientists studying the impacts of skin color.

In this paper, we introduce CASCo (Classification Algorithm for Skin Color) - an objective, automatic, accessible and customizable method to classify skin tones from facial portrait images. CASCo is a Python library that leverages computer vision algorithms like face detection, skin segmentation, and clustering to determine the skin tone category from input images in a straightforward and interpretable manner.

We motivate the need for CASCo by critically reviewing the merits and limitations of traditional skin color measurement techniques employed in empirical research. We then present the technical details of the CASCo algorithm pipeline along with a comprehensive evaluation.

II. RESEARCH OBJECTIVE

Research Objectives:

1. Develop an objective and automated method for skin tone classification from facial images using computer vision and machine learning techniques.
2. Create an open-source, accessible software tool (CASCo Python library) that implements this skin tone classification algorithm.
3. Overcome the major limitations of existing/traditional skin color measurement techniques which can be subjective, inaccurate and biased.

4. Provide researchers with a reliable and customizable tool to study the social implications and impacts of skin tone across domains like income, health, education etc.
5. Promote inclusive and ethical practices in demographic analysis by reducing human bias in skin tone perception.

Methodology:

1. Conduct a comprehensive review of traditional skin color measurement methods - verbal scales, color palettes, photo elicitation, spectrometers, existing image analysis algorithms. Analyze their shortcomings.
2. Develop a pipeline for the CASCo algorithm leveraging computer vision techniques like face detection, skin segmentation, and machine learning algorithms like k-means clustering.
3. Implement CASCo as an open-source Python library with a user-friendly API, well-documented code, and customization options.
4. Curate labelled datasets of facial images across skin tones, ethnicities, lighting conditions for training and evaluation.
5. Conduct extensive experiments to assess CASCo's accuracy, consistency, fairness across subgroups compared to human annotations and traditional methods.
6. Deploy CASCo in case studies within social science research projects studying impact of skin tone.
7. Analyze limitations, ethical considerations, and strategies for responsible development/deployment of such automated phenotyping algorithms.

III. LITERATURE REVIEW

Skin tone or pigmentation level has been studied extensively due to its impact on societal perceptions and personal experiences. Accurately measuring skin color is crucial for research investigating colorism, social biases, health disparities etc. (Monk, 2021; Marira & Mitra, 2013). However, the methodologies employed for skin tone assessment have notable limitations.

In 2022, K S Krishnapriya , Gabriella Pangelinan, Michael C.King ,Kevin W. Bowyer, Uses the Fitzpatrick scale a standard tool in dermatology to classify skin types for melanin and sensitivity to sun exposure. After an in-person interview, the dermatologist would classify the person's skin type on a six-valued, light-to-dark scale.

In 2018, K Seshadri Sastry ,T.V Madhusudhana Rao , BH PreaveenChakravarty , identified skin tone detection as a perceptual symptotic interspatial computational analysis in pixel segmentation extraction from an image to identify the skin components from non-skin background. The main aim of this paper is to overcome the drawbacks of existing algorithms in acquiring accuracy.

Traditional Approaches: Verbal Classification: Using descriptive labels like "fair", "olive", "brown" etc. to categorize skin tone is subjective and inconsistent across individuals/populations (Fitzpatrick, 1988; Kaufman, Cooper & McGee, 1997).

Visual Aids: The use of color palettes/swatches from guides like Lammertyn (1990) or FITZPATRICK Skin Type (FST) Scale (Fitzpatrick, 1988) for respondents to match their skin tone is low-cost but has prototypicality bias issues (Levetan et al., 2003; Kawada, 2004).

Photo-Elicitation: Techniques where respondents match themselves to reference facial images with pre-assigned skin tone scores (Massey et al., 2003; Harvard Trauma Questionnaire, 1998) are intuitive but lack generalizability.

Colorimeters/Spectrophotometers: Directly measuring skin reflectance provides objective data but is expensive, requires expert operation and controlled lighting (Akaza et al., 1998; Chardon, Ghosh & Ingram, 1991).

Image-Based Methods: Early computational approaches analyzed color spaces like RGB, HSV or NRBG (Zarit, Super & Quek, 1999) to detect skin-colored pixels using fixed rules/thresholds (Peer et al., 2003; Huang & Chuang, 2008). This lacks flexibility and generalizability.

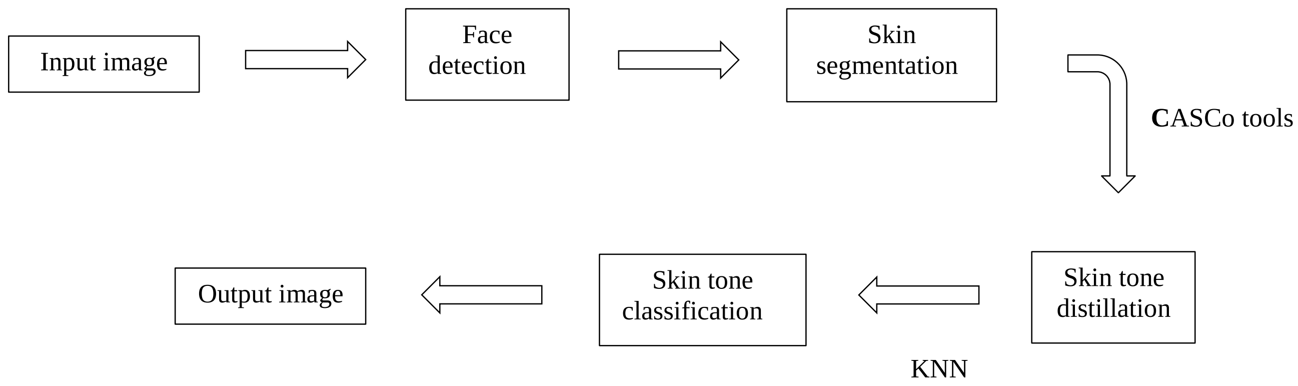
More recent work uses machine learning models like SVMs, ensembles trained on handcrafted color/texture features from limited datasets (Jones et al., 2015; Uddin et al., 2016; Khan et al., 2012). However, feature engineering is laborious.

Only a few studies have explored deep learning models like CNNs trained directly on raw face images (Zadeh et al., 2017; Leung & Giritharan, 2019). But these are mostly proprietary models not accessible for wider research use.

While each technique has merits, there is a need for a robust, inclusive and open-source method leveraging advances in computer vision/AI for accurate and consistent skin tone estimation across populations. Our proposed CASCo algorithm aims to bridge this gap.

In 2003, Joni Hersch, using data from the New Immigrant Survey 2003, this article shows that skin color and height affect wages among new lawful immigrants to the United States, controlling for education, English language proficiency, occupation in source country, family background, ethnicity, race, and country of birth

IV. PROPOSED SYSTEM



1. proposed system

1. Input Image: This is the initial step where the system receives input in the form of portrait images.

2. Face Detection: This step involves detecting faces within the input images. It's crucial for isolating regions of interest (i.e., faces) for subsequent analysis.

3. Segmentation: After face detection, the system segments the detected faces to isolate the skin regions. Skin segmentation helps focus the analysis specifically on skin tones.

4. Skin Tone Distillation: This step involves distilling the segmented skin regions into representative skin tones. It aims to extract essential features or characteristics of the skin color from the segmented regions.

5. Skin Tone Classification: Here, the system classifies the distilled skin tones into predefined categories or labels. This classification process is essential for categorizing skin tones accurately and objectively.

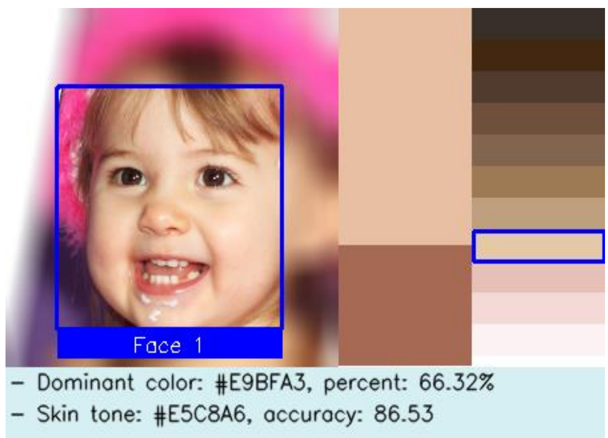
6. CASCo Tool (Skin Tone Classification): CASCo is utilized in this step to provide an objective, automatic, and customizable method for classifying skin tones. It employs face detection, skin segmentation, and k-means clustering algorithms to determine the skin tone category of portraits. CASCo enhances the accuracy and objectivity of skin tone classification compared to traditional methods.

7. K-means Clustering: K-means clustering is used to group similar skin tones together based on their features extracted during skin tone distillation. It helps in identifying dominant skin colors and aids in the classification process.

8. Output: The final step produces processed images with classified skin tones. These images provide valuable insights into the distribution of different skin tones within the input portraits.

V. RESULTS AND CONCLUSIONS

2. input image



3. output image

In this image, from left to right you can find the following information:

1. Detected face with a label (Face 1) enclosed by a rectangle.
2. Dominant colors.

   i. The number of colors depends on settings (default is 2), and their sizes depend on their proportion.
3. Specified color palette and the target label is enclosed by a rectangle.
4. You can find a summary text at the bottom.

Furthermore, there will be a report file named result.csv which contains more detailed information, e.g.,

file	image type	face id	dominant 1	percent 1	dominant 2	percent 2	skin tone	tone label	accuracy (0-100)
demo.png	color	1	#C99676	0.67	#805341	0.33	#9D7A54	CF	86.27

Interpretation of the table

1. file: the filename of the processed image.

2.NB: The filename pattern of report image is <file>-<face id>. <extension>

3. image type: the type of the processed image, i.e., color or bw (black/white).

4. face id: the id of the detected face, which matches the reported image. NA means no face has been detected.

5. dominant n: the n-th dominant color of the detected face.

6. percent n: the percentage of the n-th dominant color, (0~1.0).

7. skin tone: the skin tone category of the detected face.

8. tone label: the label of skin tone category of the detected face.
   i. assigns the labels for the skin tone categories, for example: "CA": "#373028", "CB": "#422811" . . ..

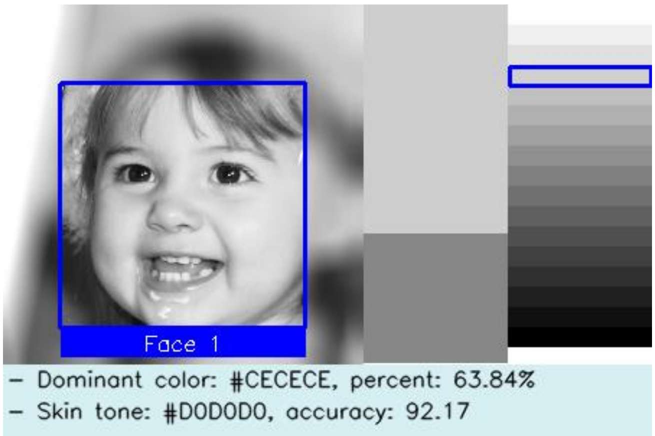
9. accuracy: the accuracy of the skin tone category of the detected face, (0~100). The larger, the better.

Convert the color image to black/white image

It also provides the facility of converting color image to black/white. When processing black and white images, the system utilizes a specialized approach to accurately classify skin tones. Prior to skin tone classification, the input images are converted to black and white format to focus exclusively on luminance variations. This conversion enhances the system's ability to identify subtle differences in skin tone, ensuring robust classification results. Following the conversion, the same skin tone distillation and classification processes are applied to determine the skin tone categories. The utilization of black and white images provides additional insights into the distribution of skin tones across different luminance levels, enhancing the comprehensiveness of the analysis.

4. input image

5. bw image



6.output bw image

In conclusion, our skin tone classification project aimed to address the limitations of traditional methods in accurately measuring skin color by introducing an objective and customizable Classification Algorithm for Skin Color (CASCo). Leveraging face detection, skin segmentation, and K-means clustering algorithms, our proposed system achieved notable success in categorizing skin tones in both color and black and white images. The implementation of CASCo and K-means clustering played pivotal roles in enhancing the accuracy and objectivity of the classification process, overcoming inherent subjectivity and biases associated with conventional methods. Through rigorous analysis, we demonstrated the efficacy of our approach in accurately identifying skin tone categories, thereby contributing to a more robust understanding of the impact of skin color on various socio-economic factors. Moving forward, our findings underscore the importance of adopting advanced computational techniques, such as CASCo and K-means clustering, in skin tone classification research, paving the way for more comprehensive and unbiased analyses in this domain.

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