Racial Bias in the Beautyverse: Evaluation of augmented-reality beauty filters

Piera Riccio\textsuperscript{1,2}\textsuperscript{1}\textsuperscript{1} and Nuria Oliver\textsuperscript{1,2}\textsuperscript{1}\textsuperscript{2}\
\textsuperscript{1} ELLIS Alicante Foundation
\textsuperscript{2} \{piera,nuria\}@ellisalicante.org

Abstract. This short paper proposes a preliminary and yet insightful investigation of racial biases in beauty filters techniques currently used on social media. The obtained results are a call to action for researchers in Computer Vision: such biases risk being replicated and exaggerated in the Metaverse and, as a consequence, they deserve more attention from the community.

Keywords: self-representation, racial bias, ethics

1 Introduction

The Metaverse may be conceived as the culmination of the digitization of our lives and our society, leveraging key technological advances in fields, such as Augmented, Virtual and Mixed Reality and Artificial Intelligence. From a societal perspective, the Metaverse is considered to be the next stage in the development of current social media platforms \cite{2}. In this regard and similarly to what happens on social media, the broad adoption and use of the Metaverse by potentially billions of users poses significant ethical and societal challenges, including the need to develop an inclusive environment, respecting the diversity of its users \cite{10}. Thus, it is of paramount importance to ensure that the enabling technologies of the Metaverse do not create, replicate or even exacerbate patterns of discrimination and disadvantage towards specific groups of users: fairness and diversity should be at the foundation of its development \cite{25}.

In this paper, we focus on diversity in self-representation in the Metaverse. Specifically, we study the existence of implicit racial biases behind the Augmented-reality (AR)-based selfie beautification algorithms that are pervasive in social media platforms. We leverage Computer Vision techniques to perform such a study and argue that current user behaviors observed in today’s social media platforms may be analyzed as an anticipation of what will happen in the Metaverse. We refer to the set of these new self-representation aesthetic norms as the Beautyverse. Note that existing and under-studied biases in the Beautyverse could lead to harmful appearances in avatar representations in the Metaverse \cite{12,17}. Thus, we highlight the importance of coupling the proposal of novel technical contributions for the Metaverse with a comprehensive, multidisciplinary study of their societal implications.
2 Related Work

Self-representation in the digital space is a key factor in online social media platforms that will also shape the social interactions in the Metaverse [9]. In current social media platforms, self-representation is expressed through selfies (photos of the self); in the Metaverse, selfies are translated to avatars, which are common in other types of online environments, such as video games. Behind the self-representation through avatars there is a will to create an ideal version of the self [16, 5, 13], including both the personality [3] and the appearance [4, 14] of the avatars.

Our research focuses on the improvements on the appearance. In recent years, AR-based selfie filters that beautify the original faces have become very popular on social media platforms [20]. Previous work has linked these filters to the definition and adoption of new facial aesthetics [24], with significant social and cultural impact, such as an exponential increase in teen plastic surgeries [8] and mental health issues [1]. These filters have been widely criticized for perpetuating racism [15], since the beautifying modifications applied to the original faces include lightening the skin tone, reducing the size of the nose and making the eyes bigger and lighter, which imply that people should look whiter to be considered beautiful [6]. In addition, the Eurocentrism of beauty filters is also shown in the colonization of ethnic features as an aesthetic [11], accepting certain features only when applied on the faces of white people, and rejecting them in other cases [21]. Moreover, the perpetuation of discriminating and racist beauty ideals in the Beautyverse could lead to significant cultural damage and dysmorphia when applied to avatars, given that avatars do not require an underlying physical reality, as selfies do.

In this paper, we aim to shed light on the existing dynamics that create the aesthetic norms and ideals of the Beautyverse. We address this challenge from a computational perspective, with the intent of bringing sociological and anthropological research questions to the Computer Vision community.

3 The Implicit Racial Bias in AR-based Beauty Filters

The aim of our research is to leverage Computer Vision techniques to understand key characteristics of the Beautyverse, with a special focus on racial biases. We report results of preliminary analyses on the FAIRBEAUTY dataset [19]. This dataset has been designed to enable the study of the implications of AR-based beauty filters on social media. It was built by beautifying the faces of the FAIRFACE dataset [7] via the application of eight AR-based filters available on Instagram. The filters were chosen based on their popularity and were directly applied on the images of the FAIRFACE dataset [7], as illustrated in Figure 1.

Given the diversity in the FAIRFACE dataset, FAIRBEAUTY enables the study of the differential impact of beautification filters on faces of different ages, genders and races. Previous work has shown that the applied beautification filters homogenize the appearance of the faces, and thus increase the similarity among
Fig. 1. Example of the eight different beauty filters applied to the left-most image from the FairFace dataset [7].

individuals [19]. It has also been shown that the level of homogenization does not impact the performance of state-of-the-art face recognition models. In summary, these filters modify the faces so they conform to the same beauty standard while preserving the identity of the individuals [19].

In this paper, we study the existence of implicit racial biases in the beautification filters. Specifically, we answer the following research question: do AR-based beautification filters encode a canon of beauty of white people? We describe next the experimental setup to address our research question.

3.1 Experimental Setup

In our experiments, we investigate whether beauty filters implicitly make beautified individuals of all races look whiter. To tackle this question, we leverage two state-of-the-art race classification algorithms: DeepFace [23] and FairFace [7]. The faces in FairFace are labeled according to seven different racial groups, namely: Black, East Asian, Indian, Latino Hispanic, Middle Eastern, Southeast Asian, and White. In our experiments, we randomly sample a subset of 5,000 faces for each race. We compare the performance of the race prediction algorithms on the face images from FairFace [7] and the corresponding beautified version in FairBeauty [19].

The first race classification model used in the experiments is DeepFace [23], which is a lightweight face recognition and facial attribute analysis framework. It is available in the deepface Python library and it is based on different face recognition models. The framework is trained to recognize four attributes: age, gender, emotion and race. In this paper, we focus on race recognition with pre-training on the VGGFace2 dataset [18]. The second race classification model is the one released with the publication of the FairFace dataset [7]. In this case, the race predictor is based on ResNet34.
3.2 Results

In this section, we present the race classification results on original and beautified faces. Tables 1 and 2 depict the average predicted value of the label White (mean and standard deviation) in each racial group by the DeepFace and FairFace algorithms, respectively. The values are averaged over the 5,000 randomly selected faces for each of the 7 races. The right-most column on the tables presents the prediction loss, i.e. the difference in the race classification performance between the original and the beautified datasets.

As shown on the Tables, the predicted value of the label White significantly increases in the beautified faces of all races when compared to the original, non-beautified images. Moreover, there is a significant loss in the performance of the race classification algorithm when applied to the beautified faces of most races except for the images labeled as Whites, whose performance increases in the beautified version of the original faces. In other words, there is a larger probability to classify the beautified faces–independently of their race–as white.

Table 1. Race classification results of the DeepFace algorithm, applied to 5,000 images. The first and second columns depict the predicted value of the label white in the original FairFace and the beautified FairBeauty datasets, respectively; the third column contains the race prediction loss, i.e. the difference in the race classification performance between the original and the beautified datasets.

| Race            | Original | Beautified | True Prediction Loss |
|-----------------|----------|------------|----------------------|
| Black           | 4.35 ± 0.18 | 7.23 ± 0.23 | -7.36%               |
| East Asian      | 10.84 ± 0.27 | 14.00 ± 0.29 | -7.83%               |
| Indian          | 10.07 ± 0.21 | 15.09 ± 0.26 | -7.73%               |
| Latino          | 20.71 ± 0.28 | 26.85 ± 0.33 | -4.00%               |
| Middle Eastern  | 27.73 ± 0.31 | 35.35 ± 0.35 | -4.05%               |
| Southeast Asian | 8.88 ± 0.23 | 12.48 ± 0.26 | -11.23%              |
| White           | 53.46 ± 0.44 | 57.89 ± 0.44 | +4.43%               |

To deepen the understanding of the results in Tables 1 and 2, we report the confusion matrices obtained with each of the models in Figures 2 and 3. The left-hand side of the images depicts the confusion matrix on the original faces whereas the right-hand-side depicts the confusion matrix on the beautified version of the faces. Given the differences in behavior between the two race classification algorithms, we discuss the results separately. With respect to DeepFace (Figure 2), we observe high prediction accuracies on faces labeled as Asian and Black (78.2% and 80.0% respective accuracies), and significantly lower on the rest of racial groups (ranging between 39.5% for Middle Eastern and 69.3% for White).
After beautification, the accuracy on faces labeled as *White* increases (74.6%), whereas the accuracies on faces with all other labels significantly decrease, mostly due to a significant increase in the misclassification of the images as White (rightmost column on the confusion matrix).

![Confusion Matrices](image)

**Fig. 2.** Confusion matrices of the race prediction, obtained through DeepFace [23]. Left-hand side refers to the original images, right-hand side refers to the images after beautification.

Regarding the FairFace race classification algorithm (Figure 3), we observe in that the highest classification accuracies are obtained for faces labeled as White and Black, with poor performances in the rest of groups (ranging between 15.7% for Southeast Asian and 40.0% for Indian). After beautification, the classification performance decreases in all cases, except for faces labeled as White and Latino-
**Table 2.** Race classification results of the FairFace algorithm, applied to 5,000 images. The first and second columns depict the predicted value of the label *white* in the original FairFace and the beautified FairBeauty datasets, respectively; the third column contains the race prediction loss, i.e. the difference in the race classification performance between the original and the beautified datasets.

| Race          | Original  | Beautified | True Prediction Loss |
|---------------|-----------|------------|----------------------|
| Black         | 2.64 ± 0.17 | 5.98 ± 0.24 | -5.99%               |
| East Asian    | 30.85 ± 0.33 | 32.14 ± 0.33 | -1.15%               |
| Indian        | 41.98 ± 0.44 | 45.00 ± 0.42 | -9.25%               |
| Latino        | 27.86 ± 0.26 | 28.97 ± 0.41 | +15.69%              |
| Middle Eastern| 28.58 ± 0.22 | 32.08 ± 0.23 | -0.5%                |
| Southeast Asian| 27.02 ± 0.20 | 27.66 ± 0.20 | -1.91%               |
| White         | 76.37 ± 0.42 | 81.44 ± 0.36 | +5.07%               |

**Fig. 3.** Confusion matrices of the race prediction, obtained through FairFace [7]. Left-hand side refers to the original images, right-hand side refers to the images after beautification.
Hispanic, which are better classified. Moreover, the probability of misclassifying faces from all racial groups as White significantly increases (first column in the confusion matrix). In general, the FairFace classifier seems to be biased towards the White label, misclassifying faces from all other groups as being White even in the original, non-beautified case. This effect is exacerbated after beautification: the accuracy on the White label increases (87.3%), to the detriment of all the other labels except for the Latino-Hispanic label.

Our experiments yield results that, while preliminary, highlight societal and cultural issues that would need deeper investigation. In particular, the Beautyverse not only homogenizes the visual aesthetics of faces as reported in [19], but seems to make them conform with a canon of beauty of white people. As social media platforms (and the Metaverse) aim to reach a globalized community of users, it is unacceptable that the technologies that populate these platforms replicate intrinsic and subtle biases that perpetuate historic discrimination and privileges.

4 Future Work and Conclusion

As an imminent direction of future work, we plan to investigate the impact of beautification filters on higher resolution images. The images in the FairFace dataset only have a resolution of approximately 300 pixels, which severely limits the beautification process. We expect the effect of the beauty filters to be significantly more prominent on higher resolution images with more detailed facial features. Hence, while the results of our experiments could be seen as a worst-case scenario, we believe that it would be important to perform a similar study on higher resolution images, which are also expected in the Metaverse.

Quantitatively evaluating the existence of a racial bias in the Beautyverse is certainly an interesting and important endeavor. However, to counteract this issue, we need to shed light on the specific features implemented in these filters that contribute to the whitening of the faces. We plan to leverage state-of-the-art explainability frameworks (e.g. [22]) to automatically identify the areas in the images that are responsible for the shift in the classification. Explaining these results could lead to two relevant insights: (1) first, it would shed light on the specific features—associated with canons of beauty of white people—that are embedded in the beautification filters and that are considered desirable on social media; and (2) second, it would enable us to assess to what extent this racial bias is related to the beautification filters and to what extent it is intrinsic to the algorithms that classify face images according to race, as we have observed in the FairFace classifier.

Moreover, we are not aware of any extensive user study to investigate the existence of racial biases in AR-based beauty filters. If we aim to develop an inclusive Metaverse where anyone is welcome, we believe that these issues need to be fully understood and addressed. While our work has been performed on AR-based filters applied to selfies on social media platforms, we believe that the development of the Metaverse will benefit from an understanding of current uses
of AR technologies for self-representation on social media. Thus, the results of
our work should be valuable to inform the development of Computer Vision-
based technologies for self-representation in the Metaverse. The perpetuation of
discriminating and racist ideals of beauty applied to avatars in the Metaverse
could lead to significant cultural damage and mental health issues (e.g. dysmori-
phia, anxiety, depression) that need to be studied, understood and mitigated.
The research described in this paper contributes to such an understanding.

Acknowledgements P.R. and N.O. are supported by a nominal grant received
at the ELLIS Unit Alicante Foundation from the Regional Government of Valen-
cia in Spain (Convenio Singular signed with Generalitat Valenciana, Conselleria
d’Innovació, Universitats, Ciència i Societat Digital, Direcció General para el
Avance de la Sociedad Digital). P.R. is also supported by a grant by the Banc
Sabadell Foundation.
References

1. Abi-Jaoude, E., Naylor, K.T., Pignatiello, A.: Smartphones, social media use and youth mental health. Canadian Medical Association Journal 192(6) (2020). https://doi.org/10.1503/cmaj.190434
2. Anderson, J., Rainie, L.: The metaverse in 2040. Pew Research Center (2022)
3. Bessière, K., Seay, A.F., Kiesler, S.: The ideal elf: Identity exploration in world of warcraft. Cyberpsychology & behavior 10(4), 530–535 (2007)
4. Ducheneaut, N., Wen, M.H., Yee, N., Wadley, G.: Body and mind: a study of avatar personalization in three virtual worlds. In: Proceedings of the SIGCHI conference on human factors in computing systems. pp. 1151–1160 (2009)
5. Higgins, E.T.: Self-discrepancy: a theory relating self and affect. Psychological review 94(3), 319 (1987)
6. Jagota, V.: Why do all the snapchat filters try to make you look white? (Jun 2016)
7. Karkkainen, K., Joo, J.: Fairface: Face attribute dataset for balanced race, gender, and age for bias measurement and mitigation. In: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV). pp. 1548–1558 (January 2021)
8. Khunger, N., Pant, H.: Cosmetic Procedures in Adolescents: What’s Safe and What Can Wait. Indian Journal of Paediatric Dermatology 22(1), 12–20 (2021). https://doi.org/10.4103/ijpd.IJPD.20
9. Kolesnichenko, A., McVeigh-Schultz, J., Isbister, K.: Understanding emerging design practices for avatar systems in the commercial social vr ecology. In: Proceedings of the 2019 on Designing Interactive Systems Conference. pp. 241–252 (2019)
10. Lee, L.H., Braud, T., Zhou, P., Wang, L., Xu, D., Lin, Z., Kumar, A., Bermejo, C., Hui, P.: All one needs to know about metaverse: A complete survey on technological singularity, virtual ecosystem, and research agenda. arXiv preprint arXiv:2110.05352 (2021)
11. Li, S.: The problems with instagram’s most popular beauty filters, from augmentation to eurocentrism (Jul 2020)
12. Maloney, D.: Mitigating negative effects of immersive virtual avatars on racial bias. In: Proceedings of the 2018 Annual Symposium on Computer-Human Interaction in Play Companion Extended Abstracts. p. 39–43. CHI PLAY ’18 Extended Abstracts, Association for Computing Machinery, New York, NY, USA (2018). https://doi.org/10.1145/3270316.3270599 https://doi.org/10.1145/3270316.3270599
13. Manago, A.M., Graham, M.B., Greenfield, P.M., Salimkhan, G.: Self-presentation and gender on myspace. Journal of Applied Developmental Psychology 29(6), 446–458 (2008)
14. Messinger, P.R., Ge, X., Stroulia, E., Lyons, K., Smirnov, K., Bone, M.: On the relationship between my avatar and myself. Journal For Virtual Worlds Research 1(2) (2008)
15. Mulaudzi, S.: Let’s be honest: Snapchat filters are a little racist (Jan 2017), https://www.huffingtonpost.co.uk/2017/01/25/snapchat-filters-are-harming-black-womens-self-image_a21658358/
16. Mummendey, H.D.: Psychologie der Selbstdarstellung. Göttingen: Hogrefe (1990)
17. Neely, E.L.: No player is ideal: why video game designers cannot ethically ignore players’ real-world identities. ACM SIGCAS Computers and Society 47(3), 98–111 (2017)
18. Parkhi, O.M., Vedaldi, A., Zisserman, A.: Deep face recognition. British Machine Vision Association (2015)
19. Riccio, P., Psomas, B., Galati, F., Escolano, F., Hofmann, T., Oliver, N.: Openfilter: A framework to democratize research access to social media ar filters. arXiv preprint arXiv:2207.12319 (2022)
20. Ryan-Mosley, T.: Beauty filters are changing the way young girls see themselves (Apr 2021), https://www.technologyreview.com/2021/04/02/1021635/beauty-filters-young-girls-augmented-reality-social-media/
21. Ryan-Mosley, T.: How digital beauty filters perpetuate colorism (Aug 2021)
22. Selvaraju, R.R., Das, A., Vedantam, R., Cogswell, M., Parikh, D., Batra, D.: Grad-cam: Why did you say that? arXiv preprint arXiv:1611.07450 (2016)
23. Serengil, S.I., Ozpinar, A.: Lightface: A hybrid deep face recognition framework. In: 2020 Innovations in Intelligent Systems and Applications Conference (ASYU). pp. 23–27. IEEE (2020). https://doi.org/10.1109/ASYU50717.2020.9259802 https://doi.org/10.1109/ASYU50717.2020.9259802
24. Shein, E.: Filtering for beauty. Communications of the ACM 64(11), 17–19 (2021)
25. Woodruff, A., Fox, S.E., Rousso-Schindler, S., Warshaw, J.: A qualitative exploration of perceptions of algorithmic fairness. In: Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. p. 1–14. CHI ’18, Association for Computing Machinery, New York, NY, USA (2018). https://doi.org/10.1145/3173574.3174230 https://doi.org/10.1145/3173574.3174230