A Comprehensive Study on Face Recognition Biases Beyond Demographics

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Abstract—Face recognition (FR) systems have a growing effect on critical decision-making processes. Recent works have shown that FR solutions show strong performance differences based on the user’s demographics. However, to enable a trustworthy FR technology, it is essential to know the influence of an extended range of facial attributes on FR beyond demographics. Therefore, in this work, we analyse FR bias over a wide range of attributes. We investigate the influence of 47 attributes on the verification performance of two popular FR models. The experiments were performed on the publicly available MAADFace attribute database with over 120M high-quality attribute annotations. To prevent misleading statements about biased performances, we introduced control group based validity values to decide if unbalanced test data causes the performance differences. The results demonstrate that also many non-demographic attributes strongly affect the recognition performance, such as accessories, hair-styles and colors, face shapes, or facial anomalies. The observations of this work show the strong need for further advances in making FR system more robust, explainable, and fair. Moreover, our findings might help to a better understanding of how FR networks work, to enhance the robustness of these networks, and to develop more generalized bias-mitigating face recognition solutions.

Index Terms—Face recognition, Biometrics, Bias, Fairness, Performance differences, Bias estimation, Soft-Biometrics

I. INTRODUCTION

Large-scale face recognition systems are spreading worldwide [13]. These systems have a growing effect on the daily life [25] and are increasingly involved in critical decision-making processes, such as in forensics and law enforcement. However, recent works [47], [4], [23], [51], [4], [24], [60] showed that current face recognition solutions possess biases leading to discriminatory performance differences [56] based on the user’s demographics [64], [71].

From a legal perspective, there are several regulations to prevent such discrimination, for instance, Article 7 of the Universal Declaration on Human Rights, Article 14 of the European Convention of Human Rights, or Article 71 of the General Data Protection Regulation (GDPR) [74]. Driven by (a) these legal efforts to guarantee fairness and (b) the findings that the performance of current face recognition solutions depends on the user’s demographics, several approaches were proposed to mitigate demographic-bias in face recognition technologies. This was achieved through adversarial learning [26], [41], [46], [45], margin-based approaches [76], [34], data augmentation [77], [59], [78], metric-learning [70], or score normalization [69]. However, the research focus on demographic-bias does only tackle a minor proportion of all possible discriminatory effects. Knowing the influence of an extended set of facial attributes on the face recognition performance will enable the development of accurate and less discriminatory face recognition systems.

In this work, we aim at investigating the face recognition bias based on a wide range of attributes beyond demographics. These biases might affect the fairness [56] but also the security of face recognition systems [31]. Biases can be identified as learning weaknesses to be exploited by users with malicious intentions (i.e. vulnerability attacks [50]). To be precise, we analyse the differential outcome as defined by Howard et al. [33] of two popular face recognition models (FaceNet [55] and ArcFace [17]) with regard to 47 attributes. The experiments are conducted on the recently published and publicly available MAAD-Face annotation database [66] based on VGGFace2 [8]. It consists of over 120M high-quality attribute annotations for 3.3M face images. For the experiments, several decision thresholds are taken into account to cover a wide range of applications. To prevent misinterpretations of the results origin from testing data with (a) unbalanced label distributions or (b) attribute correlations, we (a) introduce control groups to derive a validity value for the recognition performance in the presence of a specific attribute and (b) analyse the pairwise correlations of the attribute annotations. While (a) allows us to quantify results that arise from unbalanced testing data and prevent falsified statements about the attribute-related bias, (b) emphasize if an attribute bias might originate from a different (correlated) attribute. Besides a detailed analysis, we present a visual summary that states the performance difference between samples with and without a specific attribute over the validity of the results. This aims to present the results in a compact and simply understandable manner.

The results support the findings of previous works stating that face recognition systems have to deal with demographic-biases [57]. We differentiate between explicit demographic attributes such as gender, age or ethnicity and non-explicit demographic attributes such as accessories, hairstyles and colors, face shapes, or facial anomalies. However, we have to consider that some of the non-explicit demographic attributes might be affected by implicit demographic covariates. For example, the hairstyle is highly affected by gender or eth-

https://github.com/pterhoer/MAAD-Face
The results demonstrate that also many of the non-demographic attributes strongly affect the recognition performance. Investigating two face recognition models that differ only in the loss function used during training, we showed the effect of the underlying training principles on recognition. While the triplet-loss based FaceNet model showed attribute-related differential outcomes that are relatively constant on several decision thresholds, the angular margin based ArcFace model showed differential outcomes that are often dependent on the used decision threshold. Many performance differences affected by attributes could be explained through the attribute’s relation to the visibility of a face, the temporal variability, and the degree of abnormality. However, our experiment also reveals many unconventional results that future work have to address. Our findings strongly motivate further advances in making recognition systems more robust against covariates and open-sources face recognition algorithms. Studies analysing the impact of age demonstrated a face recognition error that increases when facing the same biased race, gender, and age user demographics on face recognition. These studies showed that the often-cited evidence regarding biometric equitability has thus, might have an unfair impact, e.g. on specific subgroups of the population. Howard et al. introduced the terms differential performance and outcome for classifying biometric performance differentials that separately considers the effect of false positive and false negative outcomes. They show that the often-cited evidence regarding biometric equitability has focused primarily on false-negatives.

Previous works on bias in face recognition mainly focused on the influence of demographics. However, Terhörst et al. demonstrated recently that more (non-demographic) characteristics are stored in face templates that might have an impact on the face recognition performance. In the following, we will shortly discuss related works on estimating and mitigating bias in face biometrics. For a more complete overview, we refer to.

### A. Estimating Bias in Face Recognition

In recent years, several works have been published that demonstrated the influence of demographics on commercial and open-sources face recognition algorithms. Studies analysing the impact of age demonstrated a lower biometric performance on faces of children. Studies analysing the effect of gender on face recognition showed that the recognition performance of females is weaker than the performance on male faces. Experiments without unbalanced data distributions and with an unbalanced towards female faces resulted in similar results. In experiments with a PCA-decomposition that females faces are intrinsically more similar than male ones. Research analysing the impact of the user’s ethnicity showed faces of ethnicities which were under-represented in the training process perform significantly weaker. The same was found for darker-skinned cohorts in general.

More recent studies focused on jointly investigating the effects of user demographics on face recognition. These studies showed that the effects lead to an exponential face recognition error increase when facing the same biased race, gender, and age factors. Particular attention deserves the Face Recognition Vendor Test (FRVT), a large-scale benchmark of commercial algorithms analysing the face recognition performance with regards to demographics. They consistently elevated false positives for female subjects and subjects at the outer ends of the age spectrum. An overview of bias estimation in face recognition is shown in Table I.

### B. Mitigating Bias in Face Recognition

The findings summarized in Section A motivated research towards mitigating demographic-bias in face recognition approaches. An early approach was presented by Zhang and Zhou who formulated the face verification problem as a multiclass cost-sensitive learning task and demonstrated that this approach can reduce different kinds of faulty decisions of the system. In 2017, range loss was proposed to learn robust face representations that can deal with long-tailed

| Work | Identities | Images | Attributes (number classes) |
|------|------------|--------|-----------------------------|
| Ricanek et al. | 0.7k | 8.0k | Age (2) |
| Deb et al. | 0.9k | 3.7k | Age (cont.) |
| Srinivas et al. | 1.7k | 9.2k | Age (2) |
| Michalski et al. | - | 4.7k | Age (cont.) |
| Albiero et al. | 26.9k | 151.6k | Gender (2) |
| Albiero et al. | 15.9k | 101.3k | Gender (2) |
| Vera-Rodríguez et al. | 0.5k | 169.4k | Gender (2) |
| Cavazos et al. | 0.4k | 1.1k | Ethnicity (2) |
| Krishnapriya et al. | 22.7k | 3.3k | Gender (2), Ethnicity (2) |
| Serna et al. | 55k | 1.4M | Gender (2), Ethnicity (4) |
| Acien et al. | 1.7k | 13k | Gender (2), Ethnicity (3) |
| Hupont et al. | 0.6k | 10.8k | Gender, Ethnicity (3) |
| Robinson et al. | 0.8k | 2.0k | Gender (2), Ethnicity (4) |
| Srinivas et al. | 0.7k | 8.0k | Age (cont.), Gender (2) |
| Klare et al. | 52.3k | 102.9k | Age (5), Gender (2), Ethnicity (3) |
| Howard et al. | 1.1k | 2.7k | Age (cont.), Gender (2), Ethnicity (2) |
| Grother et al. | 8.0M | 18.0M | Age (5), Gender (2), Ethnicity (4) |
| Georgopoulos et al | 1.0k | 41.0k | Age (5), Gender (2), Kinship (5) |
| Balakrishnan et al. | 1.3k | 1.3k | Gender (2), Hair (cont.), Ethnicity (cont.) |
| Cook et al. | 1.1k | 2.7k | Age (cont.), Gender (2), Ethnicity (4), Eyewear (2) |
| Lu et al. | 5.4k | 162.5k | Demographics (3), Non-demographics (4) |

This work | 9.1k | 3.3M | Demographics (8), Non-demographics (40) |
training data. It is designed to reduce overall intrapersonal variations while enlarging interpersonal differences simultaneously. Recent works aimed at mitigating demographic-bias in face recognition focused on demographic factors such as age, gender, and race. However, to achieve a generally accurate and fair face recognition model, it is necessary to know all potential origins of differential outcome. Therefore, this work aims at closing this knowledge gap by analysing the differential outcome on a much wider attribute range than previous works (see Table I). More precisely, this work investigates the influence of 47 attributes on the face recognition performance of two popular face embeddings. The 47 attributes represent a step forward in the literature in comparison with previous analyses focused on no more than seven attributes [43].

III. EXPERIMENTS ON MEASURING DIFFERENTIAL OUTCOME

A. Database and Considered Attributes

To get reliable statements on the effect of different attributes on face recognition, we need a database that (a) provides a high number of face images with (b) many attribute annotations of (c) high quality. For the experiments, we choose the publicly available MAAD-Face[2] annotation database [69] based on the images of VGGFace2 [8] since this database fulfills our experimental requirements. MAAD-Face provides over 120M high-quality attribute annotations of 3.3M face images of over 9k individuals. It provides annotations for 47 distinct attributes of various kinds such as demographics, skin types, hair-styles and -colors, face geometry, annotations for the periocular, mouth, and nose area, as well as annotations for accessories. An exact list of the MAAD-Face annotation attributes can be seen in Table I and II. These attribute annotations proved to have a higher quality than comparable face annotation databases [66].

B. Face Recognition Models

For the experiments, we use two popular face recognition models, FaceNet [55] and ArcFace [17]. To create a face embedding for a given face image, the image has to be aligned, scaled, and cropped. Then, the preprocessed image is passed to a face recognition model to extract the embeddings. For FaceNet, the preprocessing is done as described in [57]. To extract the embeddings, a pretrained model [5] was used. For ArcFace, the image preprocessing was done as described in [29] and a pretrained model [2] is used, which is provided by the authors of ArcFace. Both models use a ResNet-100 architecture and were trained on the MS1M database [30]. The identity verification is done by comparing two embeddings with the widely-used cosine-similarity.

C. Evaluation Metrics

The face verification performance is reported in terms of (a) false non-match rates (FNMR) at a fixed false match rate (FMR) and (b) equal error rates (EER). The EER equals the FMR at the threshold where FMR = FNMR and is well known as a single-value indicator of the verification performance. The used error rates are specified for biometric verification evaluation in the international standard [36]. In the experiments, the face verification performance is reported on three operating points to cover a wide range of potential applications. This includes EER, as well as, the FNMR at $10^{-3}$ and $10^{-2}$ FMR as recommended by the best practice guidelines for automated border control of the European Boarder Guard Agency Frontex [22]. For each operating point and attribute, the verification performance is computed on all samples with positive and all samples with negative annotations. This will allow to compare the performance differences of face embeddings regarding binary attributes, such as bald vs non-bald faces.

D. Control Groups

During the experiments, the number of testing samples with positive and negative labels might be significantly different. To prevent misleading conclusions from such unbalanced annotation distributions, we introduce positive and negative control groups for each attribute. For each attribute, six positive and six negative control groups are created by randomly selecting samples from the database. This control group creation is done such that the synthetic control groups have the same number of samples as their positive and negative counterparts.

Comparing the verification performance of the positive and negative control groups allow us to state the validity of the (real) attribute-based verification performance. If the performances of the negative and positive control groups is very similar, the (real) attribute recognition performance is treated as valid. In this case, the unbalanced testing data distribution shows no effect on the performance. If the relative performance of the control groups differ strongly, the recognition performance might be significantly affected from the unbalanced distribution of the positively and negatively annotated samples. In this case, the (real) attribute recognition performance might be affected as well. Consequently, statements about the influence of this attribute on the recognition performance are of low validity. In the experiments, the validity $\text{val}$ of an attribute $a$

$$\text{val}(a) = 1 - \frac{err_{control}^{(+)}(a)}{err_{control}^{(-)}(a)},$$  

(1)

is defined over the relative performance differences between the control groups. The terms $err_{control}^{(+)}(a)$ and $err_{control}^{(-)}(a)$ represent the recognition errors of the positive ($+$) and the negative ($-$) control groups of attribute $a$. For the experiments, we consider attributes with a validity of $< 0.9$ as not valid. However, we will also present the performance differences...
with the corresponding validity values so that the operators are able to choose more suitable validity threshold for their applications.

E. Investigations

To analyse the influence of different attributes on the recognition performance of two face recognition models, the investigations are divided into several parts.

1) To emphasize if an attribute bias might originate from correlated attribute annotations, we analyse the correlation between the attribute annotations.

2) For each attribute, the recognition performance of its positively- and negatively-labelled attribute groups are compared to investigate the influence of this attribute on the recognition performance. The results are discussed in the context of the corresponding validity values to avoid misinterpretations occurring from unbalanced testing data.

3) A visual summary is provided to relate the impact of the attributes on the face recognition systems to the validity of the results. This aims at providing a compact and easily-understandable overview of the findings of this work.

4) We provide possible explanations causing the differential outcome and discuss these differences between both face recognition systems.

5) Lastly, we use the observations to derive future research directions for face recognition systems.

IV. RESULTS

A. Investigating the Correlation of Facial Attributes

To understand the quality of the used labels and potential biases in the attribute space, Figure 1 shows a selection of specific attribute-label correlations. The attributes are chosen to show the 15 most positive and negative pairwise correlations. It can be seen that Wearing Lipstick, Wearing Earrings, Heavy Makeup, Young, and Attractive correlate highly positively with Arched Eyebrows, Wavy Hair, and Rosy Cheeks. In contrast, these attributes correlate negatively with Square Face, Male, and Bags Under Eyes. These correlations have to be considered when comparing the differential outcome for the different attributes. However, the correlation matrix also approves the quality of some labels that semantically excludes each other. For instance, 5 o’Clock Shadow negatively correlates with No Beard and Eyeglasses negatively correlates with No Eyewear.

B. The Impact of Facial Attributes on Recognition

The main contribution of this work is an analysis of the effect of 47 distinct attributes on two popular face recognition models. This aims at investigating model biases. For each attribute, the face verification performance is calculated on positively-labelled samples, as well as on negatively-labelled samples. This is done on three operating points as explained in Section III-C. The relative performance between the positive and negative groups allows to investigate potential biases of the face recognition model towards the analysed attribute. To determine if differential outcome results from unbalanced data distributions we introduced control groups as explained in Section III-D.

In Tables I, II, IV, and V the performance of the positive and negative class is shown for each attribute. The performance of the annotated data is referred as Real while the performance of the control groups is referred as Control. The relative performance (Rel. Perf.) shows the relative performance difference between the positive and negative attribute classes. If the relative performances between the control classes are below 10% (val $\leq 0.9$), the result is considered as valid (green highlighting). Otherwise, the result is considered as not valid indicated by a grey highlighting. Positive values for the relative performance of an attribute represents a positive effect of the attribute on the face recognition performance. Negative values indicate a negative influence of the attribute on the recognition performance. In the following, we present the results of our study on bias on FaceNet and ArcFace embeddings.

1) Biases in FaceNet Embeddings: The results of our attribute-related study on differential outcome of the FaceNet model are shown in Table I and III.

Previous works focused on differential outcome affected by the user’s demographics. The results on FaceNet confirms the observations of these works. Demographics strongly affect the recognition performance. One of the strongest impacts on FaceNet is observed for ethnicities. For the investigated FaceNet model, Asian and Black faces lead to significantly lower recognition rates than White faces. Also Young ones perform significantly weaker than Middle-aged faces. Concerning gender, we observe that Male face perform better then Female ones. These finding are intensively discussed in previous works [2], [3]. However, the experimental results show that there are many more aspects that strongly affect the recognition performance.

One factor leading to differential outcome is the user’s hair.
While Bald faces and Receding Hairlines lead to a improved recognition performance, Wavy Hair styles or Bangs are observed to degrade the performance. This can be explained by the visibility of the face. In general, Wavy Hair and Bangs are more likely to cover parts of the face while Bald faces or faces with Receding Hairlines do not occlude part of the faces.

A contradictory observation can be made for facial hair. Faces with No-Beard perform worse than faces with a beard, such as a 5 o Clock Shadow. A reason for this can be that people might keep their beards over a long period of time and thus, the training and testing data might be biased such that the recognition networks consider the beards for recognition.

Also the color of the hair has an impact on the FaceNet embeddings. While Blond Hair shows a strongly degraded face recognition performance, Gray Hair leads to the strongest performances.

The results indicate that the shape of a face only have a minor impact on the face recognition performance. For Oval Faces, no significant differences to non-oval faces could be observed. Although, a positive effect on the recognition performance is shown for Square Faces, in Section IV-A, a strong correlation between Square Face and Male was shown. This might explain the behaviour.

Faces with High Cheekbones, Double Chins, and Chubby faces also perform better for FaceNet features than the inverted counterparts. Probably because these properties provide additional information that can be used for recognition. In contrast to this, an Obstructed Forehead strongly degrades the recognition performance while a Fully Visible Forehead provides additional (uncovered) information that supports the recognition process.

Anomalous properties in the periorcular area, such as Bags Under Eyes, Bushy Eyebrows, or Arched Eyebrows, lead to better recognition rates compared to face images without these attributes. The same goes for Big Nose and Pointy Nose.

The reason that Smiling and a Mouth Closed lead to a stronger recognition performances than non-neutral expressions might be explainable through the used face databases that mainly contain of face with these expression. In [14], the opposite effect was already shown by demonstrating that crazy faces result in low comparison scores. However, this considered extreme expressions aim at avoiding identification.

Interestingly, accessories have a strong influence on the recognition performance of FaceNet. Wearing Hat, Wearing Earrings, or Eyeglasses degrade the face recognition performance significantly and might be explained by the fact that these accessories cover parts of the face.

2) Biases in ArcFace Embeddings: The results of our attribute-related study on differential outcome of the ArcFace model are shown in Table IV and V.

Similar to FaceNet, the results on ArcFace confirms the observed demographic performance differences shown by previous works. For the investigated ArcFace model, Young faces perform weaker than Middle-aged or Senior faces. Interestingly, the intensively discussed gender bias is strongly dependent on the used decision threshold. Especially for lower FMRs the differential outcome between Male and Female increases. Concerning the ethnic-bias on the ArcFace model, we are not able to confirm the observations from previous works. For White faces, the performance is significantly higher than for non-white faces. For Asian and Black faces, a strong degradation in the recognition performance can be observed. However, we have to consider this results as not valid, since we can observe strong performance differences on the control groups. This indicates that these results are strongly influenced by the unbalanced testing data.

Similar to FaceNet, the user’s hair shows to have a significant impact on the face recognition performance. While, Receding Hairlines, Wavy Hair and Sideburns supports the recognition process, faces with Bangs show a strong degradation. Again, the performance differences on ArcFace show to be threshold-dependent. For Wavy Hair, the positive effect on face recognition vanishes for lower FMRs, and for Bangs, the negative effect increases drastically for lower FMRs.

Also the color of the user’s hair have an impact on the recognition performance. Gray Hair performs significantly above average, while Black Hair performs significantly below average. Blond Hair and Brown Hair lead to differential outcome depending on the decision threshold. For high FMRs, Blond Hair improves the recognition performance, while for lower FMRs, the recognition performance changes to below-average. For faces with Brown Hair, the positive effect on recognition vanishes for lower FMRs.

The effect of wearing a beard on the performance of ArcFace is similar to FaceNet. Having No Beard decreases the recognition performance and having a beard, such as a 5 o Clock Shadow, enhances the recognition. These effects are clearer for lower FMRs.

On contrast to FaceNet, the face shape effects the recognition performance of ArcFace. Both, Oval Faces and Square Faces have positive effect on the recognition performance, which is dependent on the utilized decision threshold. Round Faces show a strongly degraded recognition. However, a large fraction of this performance differences can be explained by the unbalanced data distribution and thus, we have to neglect the results for Round Faces.

Similar to FaceNet, High Cheekbones, Double Chin, Chubby, and a Fully Visible Forehead lead to improved face recognition performances. While a Fully Visible Forehead refers to no partial occlusions of the face that might negatively infer, the other attributes provide anomalous characteristics that might help for recognition.

Surprisingly, faces with Brown Eyes perform drastically weaker than faces with non-brown eyes. For Bags Under Eyes, Bushy Eyebrows, and Arched Eyebrows, an improved face recognition performance can be observed. These attributes can be treated as anomalies and thus, can support the recognition process. The same goes for Big Nose and Pointy Nose.

Similar to FaceNet, accessories have a strong impact on the differential outcome of ArcFace. While having Heavy Makeup, such as Wearing Lipstick, improves the recognition, faces with Eyeglasses or Wearing Hat lead to strong degradations in the face recognition performance. A reason for this might be that people using Heavy Makeup frequently. Consequently, a person in the training data might either have no or only Heavy
Oval Faces for performance unlike previously reported in [52]. The same goes for the use of area. 

The red area indicates that the recognition performance of the positive attribute class over the negative class, such as for accessories, a degraded face recognition performance can be observed. This includes Wearing Hat, Wearing Earrings, Wearing Lipstick, and Eyeglasses.Beside a partial-occlusion of small parts of the face, these attributes are non-permanent and can quickly change the appearance of the face.

C. Performance Analysis

To provide an overview of the findings, Figure 2 shows the relative performance differences on FaceNet and ArcFace features based on the investigated attributes. The shown relative performance is based on the FMR at $10^{-3}$ FNMR as recommended by the European Boarder Guard Agency Frontex [22]. The validity describes the performance difference between the positive and negative attribute-related control groups as shown in Equation 1. An attribute performance with a validity of less than 90% is considered as not valid (grey area) since the unbalanced data annotations might affect the reported performance. The red area indicates that the recognition performance of the positive attribute class is significantly weaker than the performance of the negative class. In contrast, the green area indicates a significant improvement of recognition performance of the positive attribute class over the negative class. If an attribute has only a minor effect on the recognition performance, the relative performance is close to 0% (yellow area).

1) FaceNet vs ArcFace: The main difference between FaceNet and ArcFace are the underlying training-principles. FaceNet uses triplet-loss learning [52] that aims solely at minimizing the intra-class variations while maximizing the inter-class variations. In contrast, ArcFace introduces an angular large-margin principle [17] that additionally aims at enhancing the robustness of recognition model. The utilized training principle together with the used network structure and the training data determines the recognition behaviour. This includes the effect of differential outcome appearing when certain attributes of the face are present. Since the used FaceNet and ArcFace models share the same network structure and training data, the observed differential outcome might arise from the training principles.

2) The Effect of Attributes on Recognition: It turns out that the majority of the investigated attributes strongly affect the recognition performance of both, FaceNet and ArcFace. For FaceNet, many faces that are perceived as Attractive or make use of Heavy Makeup do not show to alter the recognition performance unlike previously reported in [52]. The same goes for Oval Faces and faces with Sideburns. For ArcFace, Blond Hair, Big Nose, Big Lips, Wearing Earrings, and Young faces show only a minor effect on the recognition performance. For both recognition models, the majority of the investigated attributes strongly affect the recognition performance. Some of the observations might be explainable.

- **Demographics:** Recent works [33], [54], [28], [6] extensively discussed the impact of demographic attributes on face recognition. Our results support the findings from previous works. We observe an improved recognition performance for the attributes Middle Aged, Senior, White, and Male. Contrarily, a degraded recognition performance is observed for Young, Asian, Black, and Female faces. For FaceNet, the observed differential outcome are stronger than for ArcFace. Moreover, we could not show that Asian or Black faces perform weaker than White faces on ArcFace, since the data unbalance lead to a low validity for our results.

- **Visibility-related attributes:** We observe that attributes that indicate a fully visible face lead to an improved face recognition performance. This includes the attributes Fully Visible Forehead, Receding Hairline, No Eyewear, and Bald. In contrast, attributes that might lead to small partial occlusions of the face lead to significantly degraded recognition performances [72]. For FaceNet, this includes faces with an Obstructed Forehead, Bangs, and Wavy Hair. For ArcFace, this includes samples with Eyeglasses or Bangs.

- **Temporary attributes:** For faces with temporary attributes, such as for accessories, a degraded face recognition performance can be observed. This includes Wearing Hat, Wearing Earrings, Wearing Lipstick, and Eyeglasses. Beside a partial-occlusion of small parts of the face, these attributes are non-permanent and can quickly change the appearance of the face.

- **Anomalous characteristics:** It turns out that conspicuous characteristics that is only possessed by a small proportion of the population lead to strongly enhanced recognition performances. This includes Arched Eyebrows, Big Nose, Pointy Nose, Bushy Eyebrows, Double Chin, and High Cheekbones [66].

While these attribute-dependent differential outcome might be explainable, the reason for the impact of other attributes on recognition is currently unclear.

- **Colors:** The results demonstrate strong differential outcome based on the user’s hair- and eyecolor. For FaceNet, faces with Blond Hair, Black Hair, and Brown Hair show strongly degraded recognition performances. In contrast, faces with Gray Hair lead to an improved recognition. For ArcFace, Gray Hair also strongly improves the recognition performance while Black Hair decreases it. The differential outcome for Blond Hair and Brown Hair strongly varies dependent on the used decision threshold. For instance, for high FMRs, Blond Hair has a positive effect on recognition, for a lower FMR (e.g. $10^{-4}$) the same attribute changes to a negative effect. The same can be observed for eyecolors. Faces with Brown Eyes perform weaker than faces from the opposite group. The differential outcome of these attributes does not reflect the distribution of the training data and thus, might arise from a different origin.

- **Beard:** As we discussed before, attributes that might induce a partially occluded face lead to a degraded
| Category       | Attribute       | Class   | EER  | FNMR@FMR=10⁻³ | FNMR@FMR=10⁻⁴ |
|----------------|----------------|---------|------|---------------|---------------|
| Demographics   | Male           | Positive| 6.64%| 6.49%         | 32.28%         |
|                |                | Negative| 7.87%| 6.46%         | 32.40%         |
|                |                | Rel. Perf.| 15.56%| -0.42%         | 21.63%         |
|                | Young          | Positive| 6.91%| 6.46%         | 39.39%         |
|                |                | Negative| 5.73%| 6.47%         | 28.93%         |
|                |                | Rel. Perf.| -20.58%| 0.12%         | -36.19%         |
|                | Middle_Aged    | Positive| 5.41%| 6.33%         | 28.77%         |
|                |                | Negative| 6.96%| 6.48%         | 36.72%         |
|                |                | Rel. Perf.| 22.29%| 2.33%         | 21.74%         |
|                | Senior         | Positive| 6.01%| 6.23%         | 30.26%         |
|                |                | Negative| 6.69%| 6.49%         | 34.19%         |
|                | Asian          | Positive| 11.16%| 5.91%         | 69.46%         |
|                |                | Negative| 6.33%| 6.49%         | 31.91%         |
|                |                | Rel. Perf.| -76.30%| 8.88%         | -117.66%        |
|                | White          | Positive| 5.97%| 6.48%         | 31.28%         |
|                |                | Negative| 7.51%| 6.44%         | 46.82%         |
|                | Black          | Positive| 8.85%| 6.02%         | 52.50%         |
|                |                | Negative| 3.48%| 6.49%         | 33.47%         |
|                |                | Rel. Perf.| 20.54%| -0.56%         | 33.18%         |
|                | Skin           | Roxy_Cheeks| Positive| 1.29%| 5.46%         | 3.76%           |
|                |                | Negative| 7.36%| 6.48%         | 37.03%         |
|                |                | Rel. Perf.| 82.42%| 15.80%         | 89.86%         |
|                | Shiny_Skin     | Positive| 6.08%| 6.41%         | 36.43%         |
|                |                | Negative| 7.90%| 6.47%         | 41.33%         |
|                |                | Rel. Perf.| 23.06%| 0.85%         | 11.86%         |
|                | Hair           | Bald     | Positive| 5.10%| 6.13%         | 30.52%         |
|                |                | Negative| 6.70%| 6.49%         | 34.13%         |
|                |                | Rel. Perf.| 23.89%| 5.55%         | 10.59%         |
|                |                | Receding_Hairline| Positive| 4.93%| 6.43%         | 26.02%         |
|                |                | Negative| 7.35%| 6.47%         | 39.92%         |
|                |                | Rel. Perf.| 32.90%| 0.74%         | 34.82%         |
|                |                | Bangs     | Positive| 6.82%| 6.34%         | 45.53%         |
|                |                | Negative| 6.43%| 6.49%         | 32.02%         |
|                |                | Rel. Perf.| -5.99%| 2.25%         | 42.17%         |
|                |                | Sideburns| Positive| 6.68%| 6.46%         | 34.33%         |
|                |                | Negative| 6.75%| 6.49%         | 35.47%         |
|                |                | Rel. Perf.| 1.04%| 0.43%         | 3.24%           |
|                |                | Black_Hair| Positive| 7.13%| 6.42%         | 42.35%         |
|                |                | Negative| 6.48%| 32.49%         | 32.49%         |
|                |                | Rel. Perf.| -15.04%| 1.02%         | -30.74%         |
|                |                | Blond_Hair| Positive| 9.63%| 6.34%         | 52.00%         |
|                |                | Negative| 6.45%| 6.48%         | 32.63%         |
|                |                | Rel. Perf.| -49.35%| 2.17%         | -59.37%         |
|                |                | Brown_Hair| Positive| 7.40%| 6.45%         | 39.73%         |
|                |                | Negative| 6.21%| 32.41%         | 32.41%         |
|                |                | Rel. Perf.| -19.52%| 0.26%         | -13.08%         |
|                |                | Gray_Hair| Positive| 5.32%| 6.29%         | 26.00%         |
|                |                | Negative| 6.72%| 6.49%         | 34.60%         |
|                |                | Rel. Perf.| 20.83%| 3.05%         | 24.83%         |
|                | Beard          | No_Beard | Positive| 7.20%| 6.48%         | 37.97%         |
|                |                | Negative| 6.16%| 6.40%         | 31.07%         |
|                |                | Rel. Perf.| -17.83%| 1.38%         | -22.20%         |
|                |                | Mustache | Positive| 6.45%| 4.93%         | 50.77%         |
|                |                | Negative| 6.90%| 6.48%         | 35.54%         |
|                |                | Rel. Perf.| 6.41%| 23.94%         | -42.88%         |
|                |                | 5-o_Clock_Shadow| Positive| 6.16%| 6.38%         | 30.98%         |
|                |                | Negative| 7.49%| 6.48%         | 39.91%         |
|                |                | Rel. Perf.| 17.78%| 1.54%         | 22.37%         |
|                |                | Goatee   | Positive| 2.59%| 4.69%         | 18.78%         |
|                |                | Negative| 6.92%| 6.49%         | 35.49%         |
|                |                | Rel. Perf.| 62.59%| 27.63%         | 47.09%         |
| Category          | Attribute        | Class    | EER   | FNMR@FMR=10^{-3} | FNMR@FMR=10^{-4} |
|-------------------|------------------|----------|-------|------------------|------------------|
| Face Geometry     | Oval_Face        | Positive | 8.14% | 6.40%            | 45.16%            |
|                   |                  | Negative | 8.26% | 6.46%            | 45.11%            |
|                   |                  | Rel. Perf. | 1.45% | 6.84%            | 1.01%            |
|                   | Square_Face      | Positive | 6.32% | 6.48%            | 31.37%            |
|                   |                  | Negative | 7.81% | 6.47%            | 41.51%            |
|                   |                  | Rel. Perf. | 19.13% | -0.12%       | 24.42%            |
|                   | Round_Face       | Positive | 16.53% | 5.2%         | 88.11%            |
|                   |                  | Negative | 5.31% | 6.49%            | 27.06%            |
|                   |                  | Rel. Perf. | -21.11% | 107.17%     | -20.65%           |
|                   | Double_Chen      | Positive | 5.45% | 6.44%            | 26.28%            |
|                   |                  | Negative | 7.09% | 6.48%            | 38.20%            |
|                   |                  | Rel. Perf. | 23.05% | 0.71%       | 31.20%            |
|                   | High_Chekbones   | Positive | 5.99% | 6.46%            | 33.69%            |
|                   |                  | Negative | 8.10% | 6.47%            | 41.66%            |
|                   |                  | Rel. Perf. | 28.51% | 0.20%       | 19.13%            |
|                   | Chubby           | Positive | 5.11% | 6.38%            | 26.98%            |
|                   |                  | Negative | 6.85% | 6.49%            | 36.65%            |
|                   |                  | Rel. Perf. | 25.35% | 1.62%       | 26.38%            |
|                   | Obstructed_Forehead | Positive | 8.85% | 6.11%            | 60.01%            |
|                   |                  | Negative | 6.02% | 6.49%            | 31.14%            |
|                   |                  | Rel. Perf. | -39.28% | 5.69%       | -92.69%           |
|                   | Fully_Visible_Forehead | Positive | 5.47% | 6.48%            | 28.25%            |
|                   |                  | Negative | 7.82% | 6.45%            | 44.34%            |
|                   |                  | Rel. Perf. | 30.01% | -0.43%      | 36.29%            |
|                   | Periocular       | Positive | 7.54% | 6.48%            | 42.04%            |
|                   | Brown_Eyes       | Negative | 6.12% | 6.36%            | 33.59%            |
|                   |                  | Rel. Perf. | -22.58% | -1.81%      | -25.15%           |
|                   | Bags_Under_Eyes  | Positive | 5.90% | 6.45%            | 31.51%            |
|                   |                  | Negative | 8.03% | 6.47%            | 42.47%            |
|                   |                  | Rel. Perf. | 26.47% | 0.36%       | 25.79%            |
|                   | Bushy_Eyebrows   | Positive | 5.66% | 6.47%            | 29.86%            |
|                   |                  | Negative | 7.26% | 6.48%            | 37.79%            |
|                   |                  | Rel. Perf. | 4.29% | 0.23%            | 21.00%            |
|                   | Arched_Eyebrows  | Positive | 5.99% | 6.46%            | 33.71%            |
|                   |                  | Negative | 7.59% | 6.48%            | 38.64%            |
|                   |                  | Rel. Perf. | 21.10% | 0.37%       | 12.75%            |
|                   | Mouth_Closed     | Positive | 5.25% | 5.99%            | 27.84%            |
|                   |                  | Negative | 7.05% | 6.41%            | 46.08%            |
|                   |                  | Rel. Perf. | 25.49% | 6.53%       | 39.60%            |
|                   | Smiling          | Positive | 6.04% | 6.44%            | 34.06%            |
|                   |                  | Negative | 8.67% | 6.46%            | 47.88%            |
|                   |                  | Rel. Perf. | 29.86% | 0.28%       | 28.87%            |
|                   | Big_Lips         | Positive | 6.79% | 6.45%            | 39.95%            |
|                   |                  | Negative | 6.97% | 6.47%            | 34.09%            |
|                   |                  | Rel. Perf. | 2.38% | 0.32%            | -17.20%           |
|                   | Nose             | Big_Nose | Positive | 6.28% | 6.42%            | 36.68%            |
|                   |                  | Negative | 8.40% | 6.48%            | 46.15%            |
|                   |                  | Rel. Perf. | 25.23% | 0.90%       | 20.52%            |
|                   | Pointy_Nose      | Positive | 6.04% | 6.48%            | 32.67%            |
|                   |                  | Negative | 7.80% | 6.46%            | 43.90%            |
|                   |                  | Rel. Perf. | 23.56% | -0.33%      | 23.57%            |
|                   | Accessories      | Heavy_Makeup | Positive | 6.25% | 6.46%            | 35.96%            |
|                   |                  | Negative | 7.08% | 6.49%            | 34.76%            |
|                   |                  | Rel. Perf. | 11.70% | 0.46%       | -3.44%            |
|                   | Wearing_Hat      | Positive | 9.01% | 6.24%            | 55.58%            |
|                   |                  | Negative | 6.05% | 6.49%            | 30.40%            |
|                   |                  | Rel. Perf. | -48.74% | 3.78%       | -82.84%           |
|                   | Wearing_Earrings | Positive | 7.54% | 6.46%            | 41.92%            |
|                   |                  | Negative | 6.78% | 6.48%            | 33.84%            |
|                   |                  | Rel. Perf. | -11.15% | 0.25%       | -23.89%           |
|                   | Wearing_Necktie  | Positive | 3.99% | 6.36%            | 19.72%            |
|                   |                  | Negative | 7.53% | 6.48%            | 41.03%            |
|                   |                  | Rel. Perf. | 47.05% | 1.88%       | 51.93%            |
|                   | Wearing_Lipstick | Positive | 6.74% | 6.48%            | 38.36%            |
|                   |                  | Negative | 7.01% | 6.49%            | 34.54%            |
|                   |                  | Rel. Perf. | 3.91% | 0.39%            | -11.05%           |
|                   | No_Eyewear       | Positive | 5.77% | 6.48%            | 29.39%            |
|                   |                  | Negative | 6.64% | 6.11%            | 37.21%            |
|                   |                  | Rel. Perf. | 13.10% | -0.99%      | 21.03%            |
|                   | Eye_glasses      | Positive | 7.59% | 6.35%            | 43.15%            |
|                   |                  | Negative | 5.70% | 6.49%            | 29.16%            |
|                   |                  | Rel. Perf. | -36.65% | 2.51%       | -47.99%           |
|                   | Attractive       | Positive | 6.27% | 6.45%            | 36.28%            |
|                   |                  | Negative | 7.05% | 6.49%            | 34.77%            |
|                   |                  | Rel. Perf. | 11.16% | 0.51%       | -4.35%            |
| Category          | Attribute          | Class       | EER | FNMR@FMR=10^{-4} | FNMR@FMR=10^{-4} |
|-------------------|--------------------|-------------|-----|-------------------|-------------------|
| Demographics      | Male               | Positive    | 3.98% | 3.98%              | 7.07%              |
|                   |                    | Negative    | 3.82% | 3.96%              | 7.99%              |
|                   |                    | Rel. Perf.  | -4.35% | -0.38%              | 11.54%             |
|                   | Young              | Positive    | 3.74% | 3.97%              | 7.30%              |
|                   |                    | Negative    | 3.70% | 3.95%              | 6.32%              |
|                   |                    | Rel. Perf.  | -0.86% | -0.46%              | -15.42%             |
|                   | Middle_Aged        | Positive    | 3.01% | 3.81%              | 5.05%              |
|                   |                    | Negative    | 4.07% | 3.98%              | 7.79%              |
|                   |                    | Rel. Perf.  | 26.14% | 4.05%              | 35.20%             |
|                   | Senior             | Positive    | 2.95% | 3.62%              | 4.52%              |
|                   |                    | Negative    | 4.02% | 3.98%              | 7.47%              |
|                   |                    | Rel. Perf.  | 26.60% | 9.02%              | 39.44%             |
|                   | Asian              | Positive    | 7.99% | 3.29%              | 16.68%             |
|                   |                    | Negative    | 7.33% | 3.98%              | 6.75%              |
|                   |                    | Rel. Perf.  | -48.63% | 14.53%              | -54.43%             |
|                   | White              | Positive    | 0.98% | 2.91%              | 1.17%              |
|                   |                    | Negative    | 4.39% | 3.98%              | 8.33%              |
|                   |                    | Rel. Perf.  | 77.61% | 26.88%              | 85.99%             |
|                   | Black              | Positive    | 5.72% | 3.46%              | 10.90%             |
|                   |                    | Negative    | 3.85% | 3.98%              | 7.06%              |
|                   |                    | Rel. Perf.  | -48.63% | 14.53%              | -54.43%             |
|                   | Skin               | Rosy_Cheeks | Positive | 0.98%    | 2.91%      |
|                   |                    | Negative    | 4.39% | 3.98%              | 8.33%              |
|                   |                    | Rel. Perf.  | 77.61% | 26.88%              | 85.99%             |
|                   | Shiny_Skin         | Positive    | 3.50% | 3.93%              | 6.33%              |
|                   |                    | Negative    | 4.17% | 3.96%              | 8.13%              |
|                   |                    | Rel. Perf.  | 16.14% | 0.61%              | 22.13%             |
|                   | Hair               | Bald       | Positive    | 2.79%    | 3.50%  |
|                   |                    | Negative    | 4.01% | 3.98%              | 7.43%              |
|                   |                    | Rel. Perf.  | 30.40% | 12.13%              | 39.77%             |
|                   |                    | Wavy_Hair   | Positive    | 3.03%    | 3.95%  |
|                   |                    | Negative    | 4.35% | 3.97%              | 7.92%              |
|                   |                    | Rel. Perf.  | 30.46% | 0.73%              | 19.95%             |
|                   |                    | Receding_Hairline | Positive | 3.03%       | 3.92%  |
|                   |                    | Negative    | 4.10% | 3.97%              | 8.20%              |
|                   |                    | Rel. Perf.  | 26.21% | 1.18%              | 42.90%             |
|                   |                    | Bangs      | Positive    | 4.03%    | 3.86%  |
|                   |                    | Negative    | 3.83% | 3.98%              | 6.77%              |
|                   |                    | Rel. Perf.  | -5.11% | 4.43%              | -29.80%            |
|                   |                    | Sideburns  | Positive    | 3.72%    | 3.97%  |
|                   |                    | Negative    | 3.98% | 3.97%              | 7.62%              |
|                   |                    | Rel. Perf.  | 6.58% | 0.08%              | 14.56%             |
|                   |                    | Black_Hair | Positive    | 5.12%    | 3.92%  |
|                   |                    | Negative    | 7.23% | 3.84%              | 6.36%              |
|                   |                    | Rel. Perf.  | -47.25% | 1.28%              | -58.86%            |
|                   |                    | Blond_Hair | Positive    | 3.09%    | 3.81%  |
|                   |                    | Negative    | 4.09% | 3.98%              | 7.34%              |
|                   |                    | Rel. Perf.  | 24.53% | 4.22%              | -0.57%             |
|                   |                    | Brown_Hair | Positive    | 3.24%    | 3.96%  |
|                   |                    | Negative    | 4.12% | 3.97%              | 7.59%              |
|                   |                    | Rel. Perf.  | 21.36% | 0.35%              | 14.93%             |
|                   |                    | Gray_Hair  | Positive    | 2.68%    | 3.76%  |
|                   |                    | Negative    | 4.07% | 3.98%              | 7.57%              |
|                   |                    | Rel. Perf.  | 34.09% | 5.58%              | 47.01%             |
|                   |                    | Beard      | No Beard | Positive    | 4.13%    |
|                   |                    | Negative    | 3.31% | 3.89%              | 5.61%              |
|                   |                    | Rel. Perf.  | -23.05% | -2.23%              | -44.32%            |
|                   |                    | Mustache   | Positive    | 4.89%    | 2.63%  |
|                   |                    | Negative    | 4.06% | 3.98%              | 7.62%              |
|                   |                    | Rel. Perf.  | -20.46% | 33.85%              | -26.25%            |
|                   |                    | 5_o_Clock_Shadow | Positive | 2.96%       | 3.90%  |
|                   |                    | Negative    | 4.24% | 3.96%              | 8.55%              |
|                   |                    | Rel. Perf.  | 30.18% | 1.74%              | 42.22%             |
|                   |                    | Goatee     | Positive    | 1.18%    | 2.46%  |
|                   |                    | Negative    | 4.08% | 3.98%              | 7.67%              |
|                   |                    | Rel. Perf.  | 71.16% | 38.16%              | 78.13%             |

TABLE IV: ArcFace - Part 1/2. Face recognition performance based on several attributes.
| Category         | Attribute      | Class   | EER | FNMR@FMR=10<sup>-3</sup> | FNMR@FMR=10<sup>-4</sup> |
|------------------|----------------|---------|-----|---------------------------|---------------------------|
| Face Geometry    | Oval_Face      | Positive| 2.73%| 3.90%                     | 5.69%                     |
|                  |                | Negative| 5.40%| 3.96%                     | 11.10%                    |
|                  |                | Rel. Perf.| 49.55%| 1.59%                     | 48.72%                    |
|                  | Square_Face    | Positive| 3.73%| 3.97%                     | 6.37%                     |
|                  |                | Negative| 4.13%| 3.97%                     | 8.61%                     |
|                  |                | Rel. Perf.| 9.65%| 0.03%                     | 25.96%                    |
|                  | Round_Face     | Positive| 7.04%| 2.30%                     | 22.68%                    |
|                  |                | Negative| 3.17%| 3.98%                     | 5.30%                     |
|                  |                | Rel. Perf.| -122.66%| 42.18%              | -320.09%                  |
|                  | Double_Chin    | Positive| 3.34%| 3.93%                     | 5.32%                     |
|                  |                | Negative| 4.08%| 3.98%                     | 7.84%                     |
|                  |                | Rel. Perf.| 18.22%| 1.23%                     | 32.24%                    |
|                  | High_Cheekbones| Positive| 3.34%| 3.95%                     | 5.96%                     |
|                  |                | Negative| 4.28%| 3.97%                     | 8.60%                     |
|                  |                | Rel. Perf.| 22.07%| 0.48%                     | 30.76%                    |
|                  | Chubby         | Positive| 3.70%| 3.87%                     | 6.11%                     |
|                  |                | Negative| 3.90%| 3.97%                     | 7.37%                     |
|                  |                | Rel. Perf.| 5.21%| 2.62%                     | 17.14%                    |
|                  | Obstructed_Forehead| Positive| 5.48%| 3.51%                     | 13.03%                    |
|                  |                | Negative| 5.32%| 3.97%                     | 6.10%                     |
|                  |                | Rel. Perf.| -5.28%| 11.62%              | -113.74%                  |
|                  | Fully_Visible_Forehead| Positive| 3.30%| 3.97%                     | 5.47%                     |
|                  |                | Negative| 4.64%| 3.95%                     | 9.98%                     |
|                  |                | Rel. Perf.| 28.85%| -0.46%                    | 45.15%                    |
|                  | Periocular     | Brown_Eyes| Positive| 4.69%| 3.97%                     | 9.13%                     |
|                  |                | Negative| 2.63%| 3.85%                     | 5.36%                     |
|                  |                | Rel. Perf.| -78.04%| 2.96%              | -70.17%                    |
|                  | Bags_Under_Eyes| Positive| 3.78%| 3.96%                     | 6.37%                     |
|                  |                | Negative| 3.87%| 3.96%                     | 8.17%                     |
|                  |                | Rel. Perf.| 2.20%| 0.13%                     | 22.05%                    |
|                  | Bushy_Eyebrows | Positive| 3.51%| 3.96%                     | 6.05%                     |
|                  |                | Negative| 4.00%| 3.97%                     | 7.81%                     |
|                  |                | Rel. Perf.| -12.35%| 0.20%              | 22.58%                    |
|                  | Arched_Eyebrows| Positive| 3.21%| 3.94%                     | 6.08%                     |
|                  |                | Negative| 4.42%| 3.97%                     | 8.38%                     |
|                  |                | Rel. Perf.| 27.52%| 0.81%                     | 27.46%                    |
|                  | Mouth_Closed   | Positive| 3.06%| 3.37%                     | 5.40%                     |
|                  |                | Negative| 3.88%| 3.90%                     | 7.79%                     |
|                  |                | Rel. Perf.| 21.21%| 13.69%              | 30.62%                    |
|                  | Smiling        | Positive| 3.35%| 3.94%                     | 5.93%                     |
|                  |                | Negative| 4.62%| 3.96%                     | 9.65%                     |
|                  |                | Rel. Perf.| 27.32%| 0.56%                     | 38.59%                    |
|                  | Big_Lips       | Positive| 4.15%| 3.94%                     | 8.12%                     |
|                  |                | Negative| 3.88%| 3.97%                     | 7.00%                     |
|                  |                | Rel. Perf.| -6.93%| 0.78%              | -16.08%                   |
|                  | Big_Nose       | Positive| 4.33%| 3.90%                     | 7.89%                     |
|                  |                | Negative| 3.90%| 3.95%                     | 8.62%                     |
|                  |                | Rel. Perf.| -12.67%| 1.49%              | 8.52%                     |
|                  | Pointy_Nose    | Positive| 3.15%| 3.97%                     | 5.84%                     |
|                  |                | Negative| 5.28%| 3.96%                     | 10.46%                    |
|                  |                | Rel. Perf.| 40.44%| -0.43%             | 44.19%                    |
|                  | Accessories    | Heavy_Makeup| Positive| 3.08%| 3.96%                     | 5.79%                     |
|                  |                | Negative| 4.32%| 3.97%                     | 8.02%                     |
|                  |                | Rel. Perf.| 28.75%| 0.18%                     | 27.75%                    |
|                  | Wearing_Hat    | Positive| 5.51%| 3.66%                     | 12.28%                    |
|                  |                | Negative| 3.71%| 3.98%                     | 6.53%                     |
|                  |                | Rel. Perf.| -48.79%| 8.09%              | -88.01%                   |
|                  | Wearing_Earrings| Positive| 3.25%| 3.95%                     | 6.64%                     |
|                  |                | Negative| 4.08%| 3.98%                     | 7.33%                     |
|                  |                | Rel. Perf.| 20.23%| 0.83%                     | 9.44%                     |
|                  | Wearing_Necktie| Positive| 2.72%| 3.82%                     | 3.84%                     |
|                  |                | Negative| 4.25%| 3.97%                     | 8.52%                     |
|                  |                | Rel. Perf.| 35.95%| 4.00%                     | 54.94%                    |
|                  | Wearing_Lipstick| Positive| 3.28%| 3.93%                     | 6.38%                     |
|                  |                | Negative| 4.27%| 3.98%                     | 7.85%                     |
|                  |                | Rel. Perf.| 23.21%| 0.40%                     | 17.84%                    |
|                  | No_Eyewear     | Positive| 3.64%| 3.98%                     | 6.39%                     |
|                  |                | Negative| 3.86%| 3.50%                     | 6.62%                     |
|                  |                | Rel. Perf.| 5.75%| -13.57%              | -3.42%                    |
|                  | Eyeglasses     | Positive| 4.60%| 3.79%                     | 9.13%                     |
|                  |                | Negative| 3.68%| 3.98%                     | 6.45%                     |
|                  |                | Rel. Perf.| -25.08%| 4.88%              | -41.53%                   |
|                  | Other          | Attractive| Positive| 2.95%| 3.96%                     | 5.49%                     |
|                  |                | Negative| 4.30%| 3.97%                     | 8.02%                     |
|                  |                | Rel. Perf.| 31.44%| 0.20%                     | 31.57%                    |
Face recognition performance. Although, beards can cover parts of the face, the results demonstrate the faces with No Beard perform below-average, while faces with e.g. a 5 o Clock Shadow achieve much higher recognition rates.

- **Wearing Necktie:** Unlike other accessories, Wearing Necktie improved the face recognition performance drastically. We assume that this might result from a data collection bias induced by the correlation with hidden factors, such as environment. Persons who present themselves in public (e.g. celebrities) might often wear a necktie and thus, photos are often taken with frontal poses and full lightning. However, the high validity and the strong differential outcome makes it hard to argue in this direction.

- **Antagonistic Behaviour:** Some attributes might result in differential outcome of the opposite direction depending on the used training-principle (triplet vs angular margin loss). For instance, faces with Wavy Hair lead to a negative performance on FaceNet and to positive performance on ArcFace. Also the attributes Attractiveness, Heavy Makeup, and Oval Faces negatively affect the recognition performance on FaceNet, but show some strong positive impacts on the recognition performance of ArcFace.

As mentioned earlier, the resulting performance of a face recognition model is mainly determined by its loss-function, its network architecture, and the utilized training data. Since both investigated models have the last two points in common, the observed differences in the performance might arise from...
the underlying training principles. Generally, we observe that the large angular margin loss from ArcFace leads to a significantly stronger overall recognition performance compared to FaceNet. The loss aiming to enhance the model robustness also shows a clearly visible effect on the attribute-related differential outcome. On ArcFace, slightly less attributes negatively affect the recognition performance than on FaceNet. However, the differential outcome that origins from the affected (biased) attributes are still of high impact. A remarkable observation is the fact that the differential outcome remain relatively constant over several decision thresholds for FaceNet, while for ArcFace the differential outcome often significantly vary for different decision thresholds. This can be observed for instance for faces with Bangs, Blond Hair, or a Double Chin.

3) Future challenges for face recognition: The observations of the experiment point out some critical issues of current face recognition solutions in terms of robustness, fairness, and explainability.

- **Need for robustness**: Face recognition systems need to become more robust against partial occlusions (from accessories or hair) [72], facial expressions (beyond neutral and smiling faces) [50], and temporary attributes that might change the daily appearance of a face [54]. [71]. This can greatly enhance the applicability in more real-life scenarios.

- **Need for fairness**: Face recognition systems need to enhance the user-fairness. We observed differential outcome based on the user-demographics (demographics-bias), anomalous characteristics (such as pointy noses, bushy eyebrows, and high cheekbones), beard types, and accessories. This can lead to discriminative decisions [56] of face recognition systems that several political regulation, such as the GDPR [74], try to prevent.

- **Need for explainability**: Face recognition models need to explain themselves. Why do colors/face shapes/beards/accessories lead to differential outcome? Why can we observe an antagonistic behaviour between the two different learning principles for some attributes? In order to enhance the model transparency and to enable efficient model-debugging, future work have to elaborate on the explainability [5], [49] of face recognition models.

- **Need for comprehensive approaches and transfer learning**: The previous areas related to robustness, fairness, and explainability will significantly benefit from more comprehensive approaches that consider simultaneously all the elements and attributes in place [59], [20], exploiting at the same time previous or general knowledge of the problem at hand [21], [61]. Most of the research so far in biometrics bias, especially around face biometrics, has been mainly oriented to studying individual elements (e.g., gender or ethnicity) not exploiting previous models or evidence. There is a need for more comprehensive approaches like the one presented here (incorporating simultaneously 47 relevant attributes) and new schemes to easily exploit the generated knowledge.

**V. Conclusion**

The growing effect of face recognition systems on the daily life, including critical decision-making processes, shows the need of non-discriminative face recognition solutions. Previous works focused on estimating and mitigating demographic-bias. However, to deploy non-discriminative face recognition systems, it is necessary to know which differential outcome appear in the presences of certain facial attributes beyond demographics. Driven by this need, we analysed the performance differences on two popular face recognition models concerning 47 different attributes. The experiment was conducted on the publicly available MAAD-Face database, a large-scale dataset with over 120M attribute annotations of high-quality. To prevent misleading statements of attribute biases, we consider attribute correlations and minimize the effect of unbalanced testing data via control group based validity values. We investigated the effect of two different learning-principles on the differential outcome originating from facial attributes. The results show that, besides demographics, many attributes strongly affect the recognition performance of both investigated face recognition models, FaceNet and ArcFace. While for FaceNet the observed differential outcome originated by several attributes remain relatively constant, these differences strongly depend on the used decision threshold for ArcFace. We provided explanations for many observed performance differences. However, the reason for some observations remain unclear and have to be addressed by future work. The findings of this work strongly demonstrate the need for further advances in making face recognition systems more robust, explainable, and fair. We hope these findings lead to the development of more robust and unbiased face recognition solutions.

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**References**

[1] A. Acien, A. Morales, R. Vera-Rodríguez, I. Bartolome, and J. Fierrez. Measuring the gender and ethnicity bias in deep models for face recognition. In IAPR Iberoamerican Congress on Pattern Recognition (CIARP), volume 11401 of LNCS, pages 584–593. Springer, November 2018.

[2] V. Albiero and K. W. Bowyer. Is face recognition sexist? no, gendered hairstyles and biology are. CoRR, abs/2008.06989, 2020.

[3] V. Albiero, K. Zhang, and K. W. Bowyer. How does gender balance in training data affect face recognition accuracy? CoRR, abs/2002.02934, 2020.

[4] M. S. Alvi, A. Zisserman, and C. Nelläker. Turning a blind eye: Explicit removal of biases and variation from deep neural network embeddings. In L. Leal-Taixé and S. Roth, editors, *Computer Vision - ECCV 2018 Workshops - Munich, Germany, September 8-14, 2018, Proceedings, Part I*, volume 11129 of Lecture Notes in Computer Science, pages 556–572. Springer, 2018.

[5] A. B. Arrieta, N. D. Rodriguez, J. D. Ser, A. Bennetot, S. Tabik, A. Barbadillo, S. García, S. Gil-Lopez, D. Molina, R. Benjamins, R. Chatila, and F. Herrera. Explainable artificial intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI. *Inf. Fusion*, 58:82–115, 2020.
M. Fang, N. Damer, F. Kirchbuchner, and A. Kuijper. Demographic bias in biometrics: A survey on an emerging challenge. IEEE Journal of Information Forensics and Security, pages 77–91, New York, NY, USA, 23–24 Feb 2018. PMLR.

Q. Cao, L. Shen, W. Xie, O. M. Parkhi, and A. Zisserman. VGGFace2: A dataset for recognising faces across pose and age. In International Conference on Machine Learning Research, pages 77–87, 2019.

J. Deng, J. Guo, N. Xue, and S. Zafeiriou. Face recognition vendor test part 3: Demographic effects. NIST Interagency/Internal Report (NISTIR) 8209, 2019.

J. Guo, J. Deng, N. Xue, and S. Zafeiriou. Stacked dense u-nets with dual transformers for robust face alignment. In British Machine Vision Conference. BMVC 2015. Northumbria University, Newcastle, UK, September 3-6, 2018, page 44. BMVA Press, 2018.

Y. Guo, L. Zhang, Y. Hu, X. He, and J. Gao. MS-Celeb-1M: A dataset and benchmark for large-scale face recognition. In B. Leibe, J. Matas, N. Sebe, and M. Welling, editors, Computer Vision - ECCV 2016 - 14th European Conference, Amsterd, The Netherlands, October 11-14, 2016, Proceedings, Part III, volume 9907 of Lecture Notes in Computer Science, pages 87–102. Springer, 2016.

A. Hadid, N. Evans, S. Marcel, and J. Fierrez. Biometric systems under spoofing attack: an evaluation methodology and lessons learned. IEEE Signal Processing Magazine, 32(5):20–30, September 2015.

J. Fernandez-Ortega, J. Fierrez, A. Morales, and J. Galbally. Introduction to face presentation attack detection. In S. Marcel, M. Nixon, J. Fierrez, and N. Evans, editors, Handbook of Biometric Anti-Spoofing, pages 187–206. Springer, 2019.

J. J. Howard, B. S. Britin, and A. R. Vemury. The effect of broad and specific demographic homogeneity on the impostor distributions and false match rates in face recognition algorithm performance. In 10th IEEE International Conference on Biometrics Theory, Applications and Systems, BTAS 2019, Tampa, FL, USA, September 23-26, 2019, pages 1–8. IEEE, 2019.

C. Huang, Y. Li, C. C. Loy, and X. Tang. Deep imbalanced learning for face recognition and attribute prediction. CoRR, abs/1806.01994, 2018.

I. Hupont and C. F. Tena. Demogroups: Quantifying the impact of demographic imbalance in deep face recognition. In 14th IEEE International Conference on Automatic Face & Gesture Recognition, FG 2019, Lille, France, May 14-18, 2019, pages 1–7. IEEE, 2019.

ISO/IEC 19795-1:2006 Information technology — Biometric performance testing and reporting. Standard, International Organization for Standardization, 2016.

V. Kazemi and J. Sullivan. One millisecond face alignment with ensemble of regression trees. In 2014 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2014, pages 1867–1874. IEEE Computer Society, 2014.

B. F. Klare, M. J. Burge, J. C. Klontz, R. W. Vorder Bruegge, and A. K. Jain. Face recognition performance: Role of demographic information. IEEE Transactions on Information Forensics and Security, 7(6):1789–1801, Dec 2012.

A. Kortylewski, B. Egger, A. Schneider, T. Geric, A. Morel-Forster, and T. Vetter. Analyzing and reducing the damage of dataset bias to face recognition with synthetic data. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, June 2019.

K. S. Krishnapriya, V. Albiero, K. Kangara, M. C. King, and K. W. Bowyer. Issues related to face recognition accuracy varying based on race and skin tone. IEEE Transactions on Technology and Society, 1(1):8–20, 2020.

J. Liang, Y. Cao, C. Zhang, S. Chang, K. Bai, and Z. Xu. Additive adversarial learning for unbiased verification. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2020.

Z. Liu, P. Luo, X. Wang, and X. Tang. Deep learning face attributes in the wild. In 2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015, pages 3730–3738. IEEE Computer Society, 2015.

B. Lu, J. Chen, C. D. Castillo, and R. Chellappa. An experimental evaluation of covariates effects on unconstrained face verification. IEEE Trans. Biom. Behav. Identity Sci., 1(1):42–55, 2019.

D. Michalski, S. Y. Yiu, and C. Malec. The impact of age and threshold variation on facial recognition algorithm performance using images of children. In 2018 International Conference on Biometrics, ICB 2018, Gold Coast, Australia, February 20-23, 2018, pages 225–232. IEEE, 2018.

T. Vetter. Analyzing and reducing the damage of dataset bias to face recognition with synthetic data. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, June 2019.

K. S. Krishnapriya, V. Albiero, K. Kangara, M. C. King, and K. W. Bowyer. Issues related to face recognition accuracy varying based on race and skin tone. IEEE Transactions on Technology and Society, 1(1):8–20, 2020.

J. Liang, Y. Cao, C. Zhang, S. Chang, K. Bai, and Z. Xu. Additive adversarial learning for unbiased verification. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2020.

Z. Liu, P. Luo, X. Wang, and X. Tang. Deep learning face attributes in the wild. In 2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015, pages 3730–3738. IEEE Computer Society, 2015.

B. Lu, J. Chen, C. D. Castillo, and R. Chellappa. An experimental evaluation of covariates effects on unconstrained face verification. IEEE Trans. Biom. Behav. Identity Sci., 1(1):42–55, 2019.

D. Michalski, S. Y. Yiu, and C. Malec. The impact of age and threshold variation on facial recognition algorithm performance using images of children. In 2018 International Conference on Biometrics, ICB 2018, Gold Coast, Australia, February 20-23, 2018, pages 217–224. IEEE, 2018.

V. Mirjalili, S. Raschka, and A. Ross. PrivacyNet: Semi-adversarial networks for multi-attribute face privacy. IEEE Trans. Image Process., 29:9400–9412, 2020.

A. Morales, J. Fierrez, R. Vera-Rodriguez, and R. Tolosana. SensiNetS: Learning agnostic representations with application to face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021.

M. Orcutt. Are face recognition systems accurate? Depends on your race. MIT Technology Review, 2016.

A. Ortega, J. Fierrez, A. Morales, Z. Wang, and T. Ribeiro. Symbolic AI for XAI: Evaluating LIFT inductive programming for fair and explainable automatic recruitment. In IEEE/ACCV Winter Conf. on Applications of Computer Vision Workshops (WACVw), January 2021.
[49] A. Peña, I. Serna, A. Morales, and J. Fierrez. Bias in multimodal AI: Testbed for fair automatic research. In IEEE/CVF Conf. on Computer Vision and Pattern Recognition Workshops (CVPRw), June 2020. also presented at ICML 2020 Workshop on Human-in-the-Loop Learning.

[50] A. Peña, I. Serna, A. Morales, J. Fierrez, and A. Lapiedra. Facial expressions as a vulnerability in face recognition. CoRR, abs/2011.08809, 2020.

[51] P. J. Phillips, F. Jiang, A. Narvekar, J. Ayyad, and A. J. O'Toole. An other-face effect for face recognition algorithms. ACM Trans. Appl. Percept., 8(2):14:1–14:11, Feb. 2011.

[52] C. Rathgeb, A. Dantcheva, and C. Busch. Impact and detection of facial beautification in face recognition: An overview. IEEE Access, 7:152667–152678, 2019.

[53] K. Ricanek, S. Bhardwaj, and M. Sodomsky. A review of face recognition against longitudinal child faces. In A. Brömme, C. Busch, C. Rathgeb, and A. Uhl, editors, BIOSH 2015 - Proceedings of the 14th International Conference of the Biometrics Special Interest Group, 9–11 September 2015, Darmstadt, Germany, volume P-245 of LNI, pages 15–26. GI, 2015.

[54] J. P. Robinson, G. Livitz, Y. Henon, C. Qin, Y. Fu, and S. Timoner. Face recognition: Too bias, or not too bias? In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR Workshops 2020, Seattle, WA, USA, June 14-19, 2020, pages 1–10. IEEE, 2020.

[55] F. Schroff, D. Kalenichenko, and J. Philbin. FaceNet: A unified embedding for face recognition and clustering. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015, pages 815–823. IEEE Computer Society, 2015.

[56] I. Serna, A. Morales, J. Fierrez, M. Cebrian, N. Obradovich, and I. Rahman. Algorithmic discrimination: Formulation and exploration in deep learning-based face biometrics. In AAAI Workshop on Artificial Intelligence Safety (SafeAI), February 2020.

[57] I. Serna, A. Peña, A. Morales, and J. Fierrez. InsideBias: Measuring bias in deep networks and application to face gender biometrics. In IAPR Intl. Conf. on Pattern Recognition (ICPR), January 2021.

[58] M. Singh, R. Singh, and S. Ass. A comprehensive overview of biometric fusion. Inf. Fusion, 52:187–205, 2019.

[59] R. Singh, A. Agarwal, M. Singh, S. Nagpal, and M. Vatsa. On the robustness of face recognition algorithms against attacks and bias. In The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI, pages 13583–13589. AAAI Press, 2020.

[60] R. Singh, M. Vatsa, V. M. Patel, and N. K. Ratha, editors. Domain Adaptation for Visual Understanding. Springer, 2020.

[61] N. Srivivas, M. Hivner, K. Gay, H. Atwal, M. King, and K. Ricanek. Exploring automatic face recognition on match performance and gender bias for children. In 2019 IEEE Winter Applications of Computer Vision Workshops (WACVW), pages 107–115, 2019.

[62] N. Srivivas, K. Ricanek, D. Michalski, D. S. Bolme, and M. King. Face recognition algorithm bias: Performance differences on images of children and adults. In IEEE Conference on Computer Vision and Pattern Recognition Workshops, CVPR Workshops 2019, Long Beach, CA, USA, June 16-20, 2019, pages 2269–2277. Computer Vision Foundation / IEEE, 2019.

[63] Y. Sun, M. Zhang, Z. Sun, and T. Tan. Demographic analysis from biometric data: Achievements, challenges, and new frontiers. IEEE Trans. Pattern Anal. Mach. Intell., 40(2):332–351, 2018.

[64] P. Terhorst, D. Fährmann, N. Damer, F. Kirchbuchner, and A. Kuijper. Beyond identity: What information is stored in biometric face templates? In 2020 IEEE International Joint Conference on Biometrics, IJCB 2020, Houston, USA, Sept 28 - Oct 1, 2020. IEEE, 2020.

[65] P. Terhorst, D. Fährmann, N. Kolf, N. Damer, F. Kirchbuchner, and A. Kuijper. Maad-face: A massively annotated attribute dataset for face images. CoRR, abs/2012.01030, 2020.

[66] P. Terhorst, M. Huber, J. N. Kolf, I. Zelch, N. Damer, F. Kirchbuchner, and A. Kuijper. Reliable age and gender estimation from face images: Stating the confidence of model predictions. In 10th IEEE International Conference on Biometrics Theory, Applications and Systems, BTAS 2019, Tampa, Florida, USA, September 23-26, 2019. IEEE, 2019.

[67] P. Terhorst, J. N. Kolf, N. Damer, F. Kirchbuchner, and A. Kuijper. Face quality estimation and its correlation to demographic and non-demographic bias in face recognition. In 2020 IEEE International Joint Conference on Biometrics, IJCB 2020, Houston, USA, Sept 28 - Oct 1, 2020. IEEE, 2020.

[68] P. Terhorst, J. N. Kolf, N. Damer, F. Kirchbuchner, and A. Kuijper. Post-comparison mitigation of demographic bias in face recognition using fair score normalization. CoRR, abs/2002.03592, 2020.