Are Commercial Face Detection Models as Biased as Academic Models?

Samuel Dooley∗,†
Department of Computer Science
University of Maryland
sdooley1@cs.umd.edu

George Z. Wei∗
Manning College of Information and Computer Sciences
University of Massachusetts Amherst
gzwei@umass.edu

Tom Goldstein
Department of Computer Science
University of Maryland
tomg@cs.umd.edu

John P. Dickerson
Department of Computer Science
University of Maryland
john@cs.umd.edu

Abstract

As facial recognition systems are deployed more widely, scholars and activists have studied their biases and harms. Audits are commonly used to accomplish this and compare the algorithmic facial recognition systems’ performance against datasets with various metadata labels about the subjects of the images. Seminal works have found discrepancies in performance by gender expression, age, perceived race, skin type, etc. These studies and audits often examine algorithms which fall into two categories: academic models or commercial models. We present a detailed comparison between academic and commercial face detection systems, specifically examining robustness to noise. We find that state-of-the-art academic face detection models exhibit demographic disparities in their noise robustness, specifically by having statistically significant decreased performance on older individuals and those who present their gender in a masculine manner. When we compare the size of these disparities to that of commercial models, we conclude that commercial models — in contrast to their relatively larger development budget and industry-level fairness commitments — are always as biased or more biased than an academic model.

1 Introduction

Facial recognition systems are increasingly a ubiquitous part of daily life. Currently we see facial recognition technologies in myriad settings such as personal use for quickly locating pictures of loved ones in photo repositories [31], population monitoring and government surveillance [36], and target identification in war [55]. Additionally, facial recognition is an increasing necessity for citizens to interact with government services as well, like unemployment benefits [12] and filing taxes online [17, 45]. These services are known to have problems which affect the use of the services by various people [47], and we have known for a over a decade that facial recognition technologies have disparate performance on various demographic groups [7, 23, 43] with increasing regulatory interest only starting to be common in the US with the first county-wide ban on its use for policing [see, e.g., 27] went into effect [33].

Recently, Dooley et al. [18] performed the first benchmark of commercial face detection systems’ robustness to natural noise. They found that each of Amazon Rekognition, Microsoft Azure, and

∗Equal contribution.
†Corresponding author.

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Google Cloud Platform exhibited various forms of systematic bias. Specifically, they detail how the commercial providers are biased against older people, individuals who are masculine presenting, those of darker skin type, and people who are dimly lit. Their work focuses on outputs of models which other companies can purchase, which is very important because these models not only are used by the producing companies, but other entities use them for a variety of purposes [13, 36, 81] such as surveillance, government monitoring, and identity verification.

While auditing commercial products provides insights into models which have a vast reach, there is another set of models which also provides researchers valuable insights: academically released models. In this work, we audit leading academic models in the same way as Dooley et al. [18], and compare against those leading commercial services. By examining academic models, we can understand two important insights: (1) we can audit the use-case of a company which takes open-source models to build in-house facial recognition services, and (2) we can adjudicate corporation’s claims of caring about demographic biases in their products by measuring the extent to which their services are less biased than academic models which have no fairness considerations. As such, we endeavor to answer three research questions:

(RQ1): How robust are academic face detection models to natural types of noise?

(RQ2): Do academic face detection models have demographic disparities in their performance on natural noise robustness tasks?

(RQ3): Are the robustness disparities exhibited by commercial models more or less than the robustness disparities exhibited by academic models?

To answer these questions, we statistically analyze the performance of three state-of-the-art academic face detection models and compare their performance and demographic disparities against the commercial models whose results are presented in Dooley et al. [18].

We observe that (RQ1) the leading academic face detection models show varying degrees of robustness to natural noise, but generally perform poorly on this task. Further, we conclude that (RQ2) these academic models do have demographic disparities which are statistically significant, and show a bias against individuals who are older and people who present as masculine. Additionally, we see that (RQ3) these biases align with the commercial models, but that no commercial model has a lower level of disparity than all the academic models.

Overall, our results suggest that regardless of a commercial company’s commitments to equal treatment of different demographic groups, there are still pernicious problems with their products which treat demographic groups differently. Further, our results confirm the types of biases found by Dooley et al. [18] and indicates that the biases found in the commercial face detection systems are present in a larger class of face detection models. We see further evidence that face detection is less robust to noise on older and masculine presenting individuals, which calls for future efforts to address this systemic problem. While our work indicates that the commercial providers are no worse on this important and socially impactful task than academics, we would hope to see that the commitments made by commercial companies would have them dedicate their vast resources and access to do better than comparatively under-resourced academics and substantially improve upon the robustness of their widely-used systems.

2 Related Work

We briefly overview related work addressed by and complementary to our audit, the various debiasing strategies in face detection and recognition, the approaches commonly used in deep-learning-based face detectors, and WIDER FACE [85]—the most commonly used face detection benchmark. To our knowledge, there has not been a thorough comparison of commercial and academic facial detection and recognition systems that analyze the demographic bias in these areas besides just evaluating systems on the MALF dataset [84].

2.1 Facial Detection and Recognition Robustness

It is known that noise still degrades detection and recognition performance of commercial systems—Hosseini et al. [41] and Dooley et al. [18] demonstrates the intersection of noise with bias. We focus
on natural noise and not the recent adversarial attacks proposed that successfully break commercial face recognition systems [e.g., 9, 73]. Face detection and recognition robustness to natural noise in images has been a long studied research problem. NIST’s Facial Recognition Vendor Test (FRVT) is an example of a mature challenge that has tested for robustness since the 2000s [64]. Other challenges have targeted Pose, Illumination, and Expression (PIE) robustness in these systems [65].

2.2 Debiasing Face Detection and Recognition

The three (or arguably four [71]) approaches that have been used to debias inequitable ML systems are pre-, in-, and post-processing. Pre-processing work usually tackles the fairness issue at the dataset curation and preprocessing level [e.g., 25, 34, 42, 44, 67, 70, 78]. In-processing does so by explicitly focusing on fair representation learning [e.g., 1, 5, 14, 20, 21, 54, 79, 88] or on constraining the ML training method or optimization algorithm directly [e.g., 2, 15, 16, 30, 46, 56, 61, 78, 86, 87]. Finally, adjusting inference time decisions to follow quantitative fairness decisions lies at the heart of post-processing literature [e.g., 35, 80]. As in Dooley et al. [18], we focus on quantifying the impact of noise on the face detection task given the input’s demographic associations. We see this work as purely a benchmark that measures rather than that which rectifies the demographic inequities in a system.

2.3 Demographic Effects in Facial Detection and Recognition

What is there to debias? How does the demographic background of pictured individuals affect the detection and recognition performance of these algorithms? Multifarious studies have examined how the performance of facial detection and recognition differ at the group or subgroup level of populations. The seminal work typically referred to as “Gender Shades,” due to Buolamwini and Gebru [7], uncovers unequal performance across intersectional demographic subgroups in commercial gender classification systems and left a lasting impact in both academia and industry. Furthermore, a follow-up [68] found that the companies whose gender classification systems were scrutinized (IBM, Microsoft, Megvii) updated their APIs within a year to address the concerns that were raised, leading credence to the large influence of Buolamwini and Gebru [7]. Furthermore, the NIST FRVT update in December 2019 suggests that performance at the group and subgroup level is being focused on by commercial systems [32]. Earlier analyses of traditional face detection and recognition systems [e.g., 43, 60] as well as more recent work [e.g., 57, 74] focuses on single-demographic effects, such as race and gender. For a more thorough review of the broader fairness in machine learning literature, we direct the reader to the survey works of Chouldechova and Roth [10] and Barocas et al. [4].

2.4 Approaches in Deep Face Detection

Since 2012, neural-network-based face detectors have become ubiquitous in both industry and academia due to their comparative advantage in model capacity over traditional methods. As such, we are only going to focus on the prevailing approaches in deep face detection. According to Minaee et al. [58], there are five main categories of face detectors. Cascade-CNN Based Models generally use convolutional neural networks (CNNs) that operate at various resolutions to produce detections that are then repeatedly refined (or “cascaded”) through non-maximum suppression and bounding box regression to ultimately output final face detections [48]. R-CNN Based Models utilize a region proposal network to predict face regions and landmarks and then verify that the candidate regions are faces or not with a Regional CNN [29]. Single Shot Detector (SSD) Models discretize the output space of bounding boxes over different aspect ratios as well as scales then use the confidence scores to reshape the default boxes to better contain the detected faces by using convolutional features from different layers, usually the higher level layers [51]. Feature Pyramid Network (FPN) Based Models upsample the convolutional features of higher (semantically richer) layers, aggregates them with those calculated in the initial forward pass to create semantically rich features at all image scales, then detects faces with each of these features at each layer [49]. Transformers Based Models use the Transformer [77] (or the Vision Transformer [19]) as the backbone for face detection. The academic models evaluated in this paper fall into the FPN or SSD based detector categories.
2.5 WIDER FACE

In the face detection space, WIDER FACE [85] has become the de facto benchmark for measuring a model’s overall performance (e.g., precision, recall). WIDER FACE was first introduced as the first large scale face detection dataset that aimed to provide images that contain harder-to-detect faces due to the large scale range of included images, atypical pose of pictured subjects, varying magnitude of occlusion, and varied (and potentially cluttered) backgrounds. WIDER FACE is a strict subset of the WIDER dataset [83], which filtered out similar images in the event categories given in WIDER to maintain diverse facial appearance.

The WIDER FACE dataset consists of 32,203 images with 393,703 labeled faces with a 40%/10%/50% split for training, validation, and testing. In like manner to the KITTI [28] and MALF datasets [84], WIDER FACE defines three difficulty levels on the test split, namely ‘Easy’, ‘Medium’, and ‘Hard’. The dataset has an associated leaderboard,³ where teams can submit their model’s predictions on the non-train splits to view precision-recall curves and average precision scores across the different difficulty levels. We used this leaderboard to guide the selection of the academic models used in this analysis.

3 Methodology

In order to answer our research questions, we conduct experiments on three state-of-the-art face detection models. We then analyze their robustness to noise and compare the results from the corruption experiments on these models to the results detailed in [18] to draw conclusions. We detail overall experimental design in Section 3.1. We describe the datasets we use in Section 3.2. We outline the academic models used in our evaluation in Section 3.3, and the methodology for answering our three research questions in Section 3.4.

3.1 Overall Experimental Design

Recall that our main research question is to examine the robustness of various academic face detection models to noise. This question is motivated by the growing ubiquity of face detection and recognition in real-world, uncontrolled environments where clean and controlled images of faces are not guaranteed. In order to evaluate a model’s robustness to noise, we extend the methodology outlined in Hendrycks and Dietterich [40] to object localization problems.

Specifically, our overall experimental design is as follows: (1) we corrupt each image in our dataset according to Hendrycks and Dietterich [40], (2) we pass each clean and corrupted image through each model, (3) we treat the detections of the clean image as ground truth, and finally (4) evaluate precision and recall metrics for each corrupted image against that ground truth clean image. An overview of the pipeline is detailed in Figure 1.

We use the clean image’s detections as ground truth for two reasons. Methodologically, our first research question centers on the effect of corruptions to a face detection model. Thus, in order to isolate the effect of the corruption, we fix the detections of the clean image as ground truth. If we were to use human-provided bounding boxes as ground truth, we would introduce other cofounders into our evaluation protocol and be unable to purely answer our research question. Additionally, from a practical perspective, there is a dearth of face detection datasets with ground truth bounding boxes which additionally have demographic metadata about their subjects. Therefore, the datasets which we used (outlined below) do not have ground truth bounding boxes to use. As such, we take the principled approach of comparing detections from corrupted images to detections from the clean images.

3.2 Datasets

We use three datasets for our experiments: Adience, MIAP, and UTKFace. These datasets were also used in the similar work on commercial face detection [18]. These datasets represent the largest and most comprehensive public datasets of people with associated metadata corresponding to age.

³http://shuoyang1213.me/WIDERFACE/WiderFace_Results.html
Figure 1: An example of how the face detection methodology works. For each clean image, we corrupt it, in this example with a pixelization. Both clean and corrupted images are passed through the face detection model. The detections of the clean image are used as ground truth to measure the performance of the model under the corruption. In this example, the clean image has a face detected and the corrupted image does not. Therefore, the precision on the corrupted image is 0.

and gender presentation. We use these metadata labels to answer our research question around demographic disparities in face detection robustness.

Adience The Adience dataset [22] includes cropped images of faces from in-the-wild images collected from online sources. The cropped images include one primary face centered in the image and includes the entire head of the subject as well as minimal contextual information from the surrounding background. The dataset includes metadata labels for apparent age and gender, provided by external human evaluators. The gender presentation labels are provided in the gender binary and age labels are provided in non-uniform age ranges: 0-2; 3-7; 8-14; 15-24; 25-35; 36-45; 46-59; 60+. The data are released and used under a Creative Commons (CC) license.

MIAP The Open Images Dataset V6 – Extended; More Inclusive Annotations for People dataset [72] was recently released in 2021. These data extend the popular Open Images Dataset, licensed by Google under a CC license, and aim to improve and unify the ways in which humans are labeled in the images. To accomplish this, the MIAP dataset exhaustively annotates every human present in a selection of Open Image. Each human gets a bounding box for the entirety of their body present in the image with metadata like whether the person is occluded, is part of a group, etc. The MIAP dataset also has labels for perceived gender (Feminine/Masculine/Unknown) presentation and perceived age (Young, Middle, Old, Unknown) presentation. Additionally, every individual with a “Young” age label is automatically given an “Unknown” gender presentation label.

UTKFace The UTKFace dataset [90] is akin to the Adience dataset insofar that the images provided have one primary person in them and are cropped to include the entirety of the individual’s head and minimal associated background context. These data, released under a non-commercial license, are provided with associated metadata of perceived age (rated on a continuous scale), perceived gender (rated on the gender binary), and “ethnicity” labels (which we do not use as they are not provided within any acceptable framework of race, ethnicity, or skin type). The demographic labels were produced by a machine first and then checked by a human.
We use the same images and image counts provided by Dooley et al. [18] for consistency of comparison to commercial models. Therefore, we use a total of 45,218 clean images with 14,919 images from Adience, 8,194 images from MIAP, and 22,105 images form UTKFace. Since we corrupt each clean image 75 times, that means we process a total of 3,436,568 clean and corrupted images through each model for our analysis.

We are assured that in each image of Adience and UTKFace, there will be only one face present. However, MIAP uses images from in-the-wild sources and do not crop them to individuals. Therefore, these images include larger scenes with more context and potentially more people in them. As such, we interpret the Adience and UTKFace results according to having cropped, centered, and a singular face — which is a good proxy for images which may be prepossessed for facial recognition tasks. On the other hand, we interpret the results of MIAP as images more akin to tasks which search for faces or people in natural images.

We also note that Dooley et al. [18] includes a fourth dataset, called the Casual Conversations Dataset [37], which we omit from our experiments. We have done this due to a potential interpretation of the data use license agreement which limits modifications and could preclude corrupting the images in their dataset. This license inhibits further research on algorithmic fairness in this way, which is especially unfortunate because the dataset has actor-provided age and gender labels as well as human-reviewer-provided Fitzpatrick skin types and ambient lighting conditions. Yet, due to potential legal liability, we choose not to compare to the CCD results of Dooley et al. [18].

### 3.3 Academic Models

We chose three academic models that for analysis which have high average precision scores on the ‘Hard’ difficulty level of the test split of WIDER FACE [85]. We chose the top two performing models (MogFace and TinaFace) as well as a third model (YOLO5Face) which is still recent but represents a simpler style of face detection model which still scores in the top 6 models, and has gained popularity due in part to that simplicity. These models happen to be the three most recent publications included on the WIDER FACE leaderboard, which allows us to examine the most recent and, to the best of our knowledge, state-of-the-art academic face detection models at the time of publication. We also chose these models because they have open-source code and pre-trained model checkpoints. We will briefly overview each model.

**TinaFace**  This model was proposed to show that face detection is just a one class generic object detection problem – even “unique” characteristics of faces such as expression and makeup could correspond to distortion and color in objects [92]. At its core, TinaFace uses a ResNet-50 [39] with a Deformable Convolutional Network (DCN) [11] as the backbone and 6 level FPN [49] neck to extract the multi-scale features of the input image, an Inception block [75] to contextualize and broaden the receptive fields, a 5-layer Fully Convolutional Network (FCN) [53] classification head for classifying anchors, a 5-layer FCN regression head for bounding box regression of anchors, and a single convolutional layer that shares the first 4 convolutional layers with the regression head as the Intersection-of-Union-aware [82] (IoU-aware) head for predicting IoU of the face with the bounding box. The IoU-aware branch is particularly important for maintaining localization accuracy. Focal loss was used for classification, DiIoU loss [91] for bounding box regression, and cross-entropy loss for IoU prediction. DiIoU [91] was used for the regression loss because two thirds of WIDER FACE [85] contains small faces and DiIoU [91] aligns better with small objects. The SGD optimizer was used to train the network. The ONNX [3] file for R50-FPN-BN was used, which does not use the DCN mentioned because deformable convolution operations are not supported in the ONNX opsets.

**YOLO5Face**  Similar to TinaFace, the creators of this model treated faced detection as a generic object detection task [66]. The CSPNet used in YOLOv5 [24] in combination with the FPN [49] serves as the backbone. At the end of the backbone, a SPP block [38] block is added and smaller kernel sizes are used in comparison to YOLOv5 [24]. Also, an optional sixth PAN [50] is added to the FPN. For the neck, a Focusing Attention Network (FAN) [8] is used. More specifically, a PAN [50] to aggregate features is used in the neck. The focus layer at the input of YOLOv5 is replaced with a stem block that they proposed [66]. The model outputs a bounding box, confidence, class, and five-point face landmarks. The Wing loss [26] on the 5 facial landmarks along with the original loss function used by YOLOv5 constitute the complete loss function they use. The SGD optimizer was used to train the network. The best publicly available checkpoint on the ‘Hard’ difficulty of the
WIDER FACE test split \[85\] (\text{yolov5l}) was used in this analysis, which does not use the optional sixth PAN block mentioned.

\textbf{MogFace} \quad MogFace was created to address three research topics in face detection: label assignment, scale-level data augmentation, and reducing false positive detections \[52\]. To this end, they introduce three novel components that are used in the model – Adaptive Online Incremental Anchor Mining Strategy (Ali-AMS), Selective Scale Enhancement Strategy (SSE), and the Hierarchical Context-Aware Module (HCAM). For explanations on how each of these components work, we refer you to Liu et al. \[52\]. For the baseline model itself, a S3FD \[89\] with ResNet-50 \[39\] backbone was trained with focal loss and smooth L1 loss weighted with a 1:2 ratio and the SGD optimizer. After the baseline model is trained, a subset of the components were added to form the final models. All components were added to the baseline to form MogFace-E and only Ali-AMS and HCAM were added for MogFace. Like how the specific version of YOLO5FACE was chosen, the best publicly available checkpoint on the ‘Hard’ difficulty of the WIDER FACE test split \[85\] (MogFace) was used in this analysis.\(^4\)

3.4 Model Performance Analysis Methodology

To analyze the performance of the models, we use the precision and recall metrics defined by comparing corrupt images to their clean image’s detections as ground truth, as described above. We compute per-image precision and recall numbers and average across relevant groups.

To answer RQ1, we report overall performance (precision and recall) or the corruptions on each dataset and each model. To answer RQ2, we segment the datasets into different combinations of age and gender groups and report precision and recall metrics. In order to statistically validate results, we perform a variety of statistical analysis techniques. We draw conclusions of demographic disparity through a two step statistical process. We first perform a Kruskal-Wallis Rank Sum Test between explanatory and response variables which indicate whether two or more groups are treated equally or not, i.e. whether the model exhibits a demographic disparity. In the case where there is enough evidence to show that groups are treated differently, we then run the Pairwise Wilcoxon Rank Sum Tests to observe which groups have significantly different treatment and in which direction. All statistical tests are reported with \(\alpha = 0.05\).

To quantify the extent of the disparity between two groups, we report odds ratios and computer standard errors for such. Recall that the odds of an event with probability \(p\) is \(p/(1−p)\). The odds ratios of two events are the odds of one event divided by another event. For example, if we wanted to examine the disparity between perceived genders, we would calculate the odds of the feminine presenting individuals, \(o_f\), having precision equal to 1, and calculate the odds of the masculine presenting individuals, \(o_m\). If we look at the odds ratios of these two events \(o_f/o_m\), this odds ratio would be greater than 1 if the odds for Females were higher than males, and vice-versa. We can also compute the standard error of these odds ratios. To answer RQ3, we run a statistical test to compare where the odds ratios of a disparity in commercial models equals that of the odds ratios of a disparity in the academic model. We can also test for one-sided tails of the equivalent null hypothesis to test if the academic disparities are higher than the commercial disparities. The statistical test we will use will examine overlapping 95% confidence intervals as detailed in Vaske \[76\].

4 Results

4.1 Overall Model Performance

To answer RQ1, we examine the overall performance of each model on each dataset. We present these results in Figure 2. We see from the outset that MogFace is remarkably robust to noise. When comparing to the commercial model performance, MogFace achieves an average precision score of 92.8% and bests all three commercial providers (AWS achieves 82.5%, Azure achieves 87.6%, and GCP achieves 86.2%). On the other hand, TinaFace struggles on Adience (54.9%) and YOLO5Face achieves a middling score of 71.7%. On MIAP, the academic models all perform worse than all

\(^4\)The evaluation metrics of this particular checkpoint specifies that multi-scale testing was used. As a result of computational restraints, we used this checkpoint at inference time with single-scale testing, so the performance of the model in this analysis might not accurately reflect the reported metrics.
the commercial models with the commercial models achieving between 82% and 86% whereas the academic models achieve between 70% and 77%. Finally, on the UTKFace dataset, MogFace again outperforms all the commercial models (92.3%), TinaFace does the worst of all the models with only 63.5% average precision and YOLO5Face achieves a middling score of 81.7% (which is worse than any commercial provider).

The pattern that emerges here is that on Adience and UTKFace, the academic models have all performed in the following order of decreasing average precision: MogFace, YOLO5Face, and TinaFace, with TinaFace struggling very significantly compared to the other two. However, on MIAP, TinaFace bests YOLO5Face. We hypothesize that, since these patterns follow the patterns in the types of images in the datasets (Adience and UTKFace being frontal cropped images of faces and MIAP being whole-scene in the wild images), this might be playing an important role here.

The other impressive pattern is that MogFace beats the performance of the commercial models on our task of robustness to noise on Adience and UTKFace. We hypothesize two reasons for what might explain this. First, MogFace was published very recently (late 2021), and perhaps much more recently than the commercial models. In examining the code of Dooley et al. [18] and documentation of the commercial providers, only Azure indicates when its model was released (February 2021). The analysis of the commercial providers was also done prior to the release of MogFace. While more contemporary models do not necessarily imply better performance, this could be playing a role.

The other hypothesis for the high robustness performance of MogFace when compared to the other academic and commercial models is that they may use the Adience and UTKFace datasets during training. While their paper describes their training procedure as only using the WIDER FACE dataset (which does not include Adience and UTKFace data), the authors may have used the data during training and some memorization of these data points might have occurred. Recall that we used publicly available model checkpoints for these experiments, and thus it is not unreasonable to hypothesize that the checkpoints that were released were trained on these data.

4.2 Demographic Disparities in Noise Robustness

We now turn our attention to answer RQ2: do academic face detection models have demographic disparities in their performance on noise robustness tasks? Recall that to answer this question, we bin our datasets into groups and look at qualitative and quantitative analysis of these group’s performance.
Each dataset we analyze has both perceived gender and perceived age labels. We first search for gender disparities and then explore age disparities.

4.2.1 Gender Disparities

We begin by, first, pausing to note that the labels we have for perceived gender were in all cases provided by a third-party human reviewer, and the labels fall within the gender binary. The one exception is the MIAP dataset which reports a category of “Unknown” for times when the human reviewers were unable to reach a decision on the perceived gender of the subject. While gender is not binary and gender identity is not something which third party reviewers can assess, we use the perceived gender concept in our work to measure how model performance may differ for people who present gender differently. We note that we may shorten the description of “perceived gender” or “gender presentation” to just “gender” for brevity, but this should be understood to capture the concept of how a subject presents and not the subject’s gender identity.

We visually depict the performance of each model on each dataset in Figure 3 broken down by perceived gender. We will analyze the observed perceived gender disparities for each dataset separately, starting with Adience. We will discuss the average precision for the perceived gender groups in the different dataset and model combinations. We will look for significance of difference between the average precision following the plan outlined in Section 3.4. Statistical tests are reported in Appendix Tables 22 - 30. We also report the odds ratio of feminine presenting individuals over masculine presenting individuals. Recall, values over 1 indicate higher performance on those who are feminine presenting, and values less than 1 indicate higher performance on those who are masculine presenting.

We observe, qualitatively, that there do not appear to be a significantly large gender disparity between masculine and feminine presenting individuals for the Adience dataset across all the models. However, our statistical tests indicate that there are statistically significant, though small in magnitude differences. MogFace and TinaFace are biased against masculine presenting individuals (i.e., the models perform better on feminine presenting individuals), and YOLO5Face is biased against feminine presenting individuals. In terms of the magnitude of these disparities, they are very small. The odds ratio for MogFace is 1.05, TinaFace, 1.02, and YOLO5Face, 0.96.

On the MIAP dataset, there are larger disparities, and they always are biased against masculine presenting individuals. All statistical tests indicate significant disparities between feminine and masculine presenting individuals. MogFace has an odds ratio favoring feminine presenting individuals of 1.07, TinaFace at 1.12, and YOLO5Face at 1.15. This indicates that all models are less robust to noise on masculine presenting individuals than on feminine presenting individuals.

The MIAP dataset also has a gender presentation category of “Unknown” which allows us some insight into how models perform when the gender presentation of an individual is not able to be determined by a human. It is important to note that in this category or individuals who have the
“Young” age labels, may have been occluded, presented in an androgynous manner, etc. Qualitatively, we observe that the Unknown perceived gender category is much less robust to noise than feminine presenting individuals (odds ratios are 1.61, 1.18, and 1.69 for MogFace, TinaFace, and YOLO5Face respectively). The Unknown category also performs significantly worse than masculine presenting individuals on both MogFace and YOLO5Face, though very slightly outperforms the masculine presenting group on TinaFace.

Finally, we observe similar behavior on the UTKFace dataset as we did on the Adience dataset. MogFace and TinaFace are both ever so slightly biased against masculine presenting individuals (odds ratios of 1.12 and 1.02 respectively) and YOLO5Face is slightly biased against feminine presenting individuals (odds ratio of 0.97). These conclusions are statistically significant. One hypothesis for the mirroring of the results on Adience and UTKFace is the similarity of their dataset composition of cropped images of faces, whereas the MIAP dataset is of full-scene in-the-wild images.

Taken together, we observe that all these models have a statistically significant gender disparity favoring feminine presenting individuals (except for YOLO5Face on Adience and UTKFace). However, it is important to note that these disparities are very, very small in terms of their magnitude. Practically speaking, the models have minimal gender disparity for Adience and UTKFace and more pronounced and concerning disparities on the MIAP dataset.

4.2.2 Age Disparities

We move on to a discussion of the age disparities present in these models and datasets. We report the results of this age disparity in Figure 4. We note again, that age labels are given by perceived age of the subject in the image. Adience provides disparate age categories, MIAP provides age groupings (Young, Middle, Older, and Unknown) and UTKFace natively provides a numeric value. Since numeric age values from UTKFace are likely misspecified as it is nearly impossible to correctly predict a person’s age from a photo, we bin these numeric values into three buckets of (0-18), (19-45), (45-65) and (65+).

Qualitatively, looking at all these data, we observe that the oldest group in each dataset has the lowest performance. Quantitatively as well, we see that the oldest group is always statistically significantly the lowest performer of the groups. We note that while there may be differences in the sample sizes of these groups, the statistical tests are robust to these differences and account for sample size differences. Statistical test results for Pairwise Wilcoxon Rank Sum Tests can be found in Appendix Tables 13 - 21. We now speak to this age disparity for each dataset separately.

Starting with the Adience dataset, we observe that each model performs the worst on the oldest category (60+), though there are differing behaviors on the younger ages. MogFace and TinaFace have a bump shape which indicates the middle age groups are the most robust. YOLO5Face generally decreases in performance as the ages increase, though there are some exceptions (like the 8-14 age group). For an odds ratio comparison here, we examine the odds for a middle aged group of 25-35 compared to the oldest age group (60+). We then can report odds ratios of 1.37, 1.30, and 1.21 for MogFace, TinaFace, and YOLO5Face respectively.

For MIAP, we observe an interesting pattern for MogFace and YOLO5Face where both are the most robust on the Middle age category and significantly least robust on the Older category. Conversely, TinaFace observes a very, very slight decrease in performance as the age presentation increases. For an odds ratio comparison on MIAP, we examine the odds for the Middle group divided by the odds of the Older group, observing odds ratios of 2.85, 1.10, and 3.34 for MogFace, TinaFace, and YOLO5Face respectively. Interestingly, MIAP also reports an Unknown age category. When examining the behavior of this category, we observe that each model performs significantly better on Unknown age presenting individuals than Older age presenting people.

Finally, we also observe a bias against older individuals in the UTKFace dataset on all the models. Every model’s performance strictly decreases between the age groups 18-45 and 65+. Comparing the ratios of the odds for the age group 19-45 and the age group 65+, we see significant disparity in favor of the younger group. The odds ratio for MogFace is 1.66, 1.53 for TinaFace, and 1.10 for YOLO5Face.

Finally, there is light evidence of a trend that the youngest groups are less robust to noise than the middle aged groups in every case except for YOLO5Face on Adience and UTKFace as well as
Figure 5: Disparity odds ratios are presented for the gender presentation demographic for each dataset and with the three academic models tested in this paper and the three commercial models tested in Dooley et al. [18]. An odds ratio larger than 1 indicates a bias against masculine presenting individuals, and the closer the odds ratio is to 1 the less biased that model is.

Figure 6: Disparity odds ratios are presented for the age demographic for each dataset and with the three academic models tested in this paper and the three commercial models tested in Dooley et al. [18]. An odds ratio larger than 1 indicates a bias against older people, and the closer the odds ratio is to 1 the less biased that model is.

TinaFace on MIAP. Each instance of these differences are statistically significant, but the trend is only present in six of the nine combinations. Further exploration of this finding on more datasets and models is warranted.

4.3 Disparity Comparison to Commercial Models

Following the methodology laid out in Section 3.4, we now discuss RQ3: are the robustness disparities exhibited by commercial models more or less than the robustness disparities exhibited by academic models? Recall that to answer this, we calculate odds ratios and 95% confidence intervals for each model (both academic and commercial). Above, we have detailed the confidence intervals for the academic models, and we use the data provided by Dooley et al. [18] to compute the disparity odds ratios for the commercial models on our three datasets. We report the results in Figures 5 and 6 for the perceived gender and age demographics.

First regarding the disparities in perceived gender. We see that for Adience, the least biased model is TinaFace. This means an academic model is least biased when compared to state-of-the-art commercial models, at least on this common dataset. In fact, on Adience, every leading academic model that we tested is less biased than every commercial model. On MIAP, the least biased model is
also an academic model: MogFace. Finally in the case of UTKFace, we observe that TinaFace and AWS are the least biased with no statistically significant difference between them.

With respect to age disparities, we observe a similar pattern. On Adience, the least biased model is an academic model: YOLO5Face. On MIAP, the least biased models are TinaFace and GCP, both statistically overlapping in the confidence intervals. Finally, UTKFace sees that YOLO5Face is the least biased model of all the academic and commercial models.

We note that we do not see signs of systemic differences between academic and commercial models in terms of their demographic disparities. In only one case (perceived gender disparities on Adience) do we see that every academic model is less biased than every commercial model. It is far more common that there is not a clear ordering between academic and commercial models as a whole. However, we do see clearly that in every case, an academic model is no more biased than any other commercial model.

In reviewing these results, we see that in four of the six cases, an academic model is statistically better than all commercial models, and in the other two cases, an academic model is as biased or less biased than all commercial models. We also observe that every model (except for GCP on MIAP) is biased against older individuals. This presents a very clear picture of systemic age bias in face detection writ large. As for perceived gender bias, we see strong evidence of bias against masculine presenting individuals. Of the eighteen model and dataset combinations all but three indicate a bias against masculine presenting individuals. Again, this presents strong evidence that there is systemic perceived gender bias in face detection.

5 Discussion & A Call to action

Revisiting our research questions, we come away with rather clear answers. We see that academic face detection models:

(RQ1): show that their robustness to noise could be improved significantly;

(RQ2): have significant perceived gender and age demographic disparities in their performance on noise robustness tasks; and

(RQ3): show less demographic bias than commercial face detection models.

Additionally, we see above that for the most part, face detection systems, be they academic or commercial, show significant perceived gender and age disparities. In the case of age, we observe very strong evidence that face detection systems are biased against older individuals. In the case of perceived gender, we see evidence that face detection systems are biased against masculine presenting individuals.

We believe that these results beget three main conclusions for different audiences who are interested in face detection systems and/or algorithmic bias. Our results suggest that commercial systems generally are no less biased on noise robustness than academic systems. This is a rather striking result considering the resources large companies have at their disposal to tackle problems like demographic disparities in their products. Additionally, since demographic disparities in commercial products became a crucible following the publication of Buolamwini and Gebru [7] in 2018, these corporations have had ample time to address and work towards solutions to these issues. While these companies have to varying degrees acknowledged the need to equal out demographic disparities in their products, we cannot fully know what investment they have placed on these issues, and specifically on disparities in noise robustness. So at this time, we can merely speculate.

If these companies have committed vast resources to address the demographic disparities in their products, and specifically in noise robustness, then our results lead us to conclude that these investments have generally not paid off. We conclude this because we now know that for every commercial model, there is at least one academic model which is less biased than it is. Further, since these academic models are published publicly with full source code and training procedures, we know that these models have not included any fairness constraints or considerations. Thus, if these companies have invested heavily in this problem, then we conclude that their investments have not paid off sufficiently.
However, it is perhaps overly optimistic to think that corporations have invested in the mitigation of demographic bias in noise robustness — although we posit that this is not likely because many real-world use cases for facial analysis occur under imperfect “in-the-wild” conditions that would introduce various forms of natural noise. If in fact they have not done so, our results give a clear benchmark and goalpost for these corporations to improve. While in most cases, the commercial models are not the most biased system, we should endeavor to expect that if these corporations plan to continue to publicly sell face detection software — a very socially and ethically provocative tool — that they should be investing in mitigating these biases and be able to do better than academic models which have no fairness considerations.

Our results add to the increasing body of research which finds various pernicious forms of demographic bias in facial recognition technologies. We provided more evidence of the demographic biases present in face detection systems, doubling down on the conclusions from Dooley et al. [18] to show that face detection systems are less robust against noise on older individuals and on masculine presenting individuals. We conclude that despite all the talk and publicity about concerns of demographic disparities in commercially provide products, large technology companies are no better at eliminating bias for noise robustness than academic models. Thus, we end this work with two broad calls to action:

- **To industry:** we are, broadly, optimistic about the use of technology to reduce frictions in daily life, to connect the globe, and to enable the general advancement of the global society, indeed without relative harm to subpopulations within that society. Yet, the present work—performed at an overall cost of perhaps one to two months of a single engineer’s time—is one in a growing series of works showing the surprising gap between where a trillion-dollar company could be—by spending a vanishing fraction of their liquid capital—and where it should be—where “should” is, admittedly, a value judgment, but a bipartisan one [6], and one gaining increasing traction in those firms’ own home country [69].

Our call to action, then, is as follows: pay attention to, work with, and fund academic research in this space. As our present work shows, academic models run hand-in-hand with—and, indeed, by some metrics beat—commercially deployed systems, and it would be of great benefit to further encourage unrestricted growth in that space, and to fertilize that growth with cross-boundary communication of techniques that have been tried internally at for-profit firms. Specific to our setting, both the present work and previous works [e.g., 7, 18, 68] would benefit immensely from at least partial access to the internal workings of commercial systems, including dataset curation processes. Beyond simply measuring disparities, the natural next step is to hypothesize reasons for those disparities and then to, at least partially, mitigate them via new techniques. Indeed, as this paper shows, state-of-the-art academic models are arguably beating commercial models in some ways, so the value within this communication would flow both ways. Without a clear line of communication between academic and industrial researchers, this latter process is hampered.

- **To the public sector:** The public sector provides a great service in both impacting the evolution of, and creating as well as enforcing the present state of social and legal norms. For example, in the United States, for our specific setting, the National Institute of Standards and Technology (NIST) Face Recognition Vendor Test (FRVT) has measured and monitored progress in both commercial and academic facial analysis systems. It has been run for at least the last two decades, and has been updated numerous times. Indeed, in a recent FRVT Update, NISTIR 8280 (2019), NIST brought demographic concerns into the forefront. NIST’s venerable FRVT has a history of incorporating natural noise into its barrage of tests; we would ask NIST, and analogous non-regulatory and standards-settings bodies in other countries, to consider updating their tests (e.g., FRVT) to include the cross section of bias and forms of noise. Our work motivates the need for monitoring in this area.

To the regulatory side, we are encouraged by and seek further acceptance of results publicized by both academics and industrial researchers. Washington State aims to set an example here
with its recently enacted State Bill 6281, which states “if the results of ... independent testing identify material unfair performance differences across subpopulations ... then the processor must develop and implement a plan to address the identified performance differences” [59]. We believe that our work here meets this definition and hope the public sector has a robust enforcement mechanism for such legislation. We encourage other researchers to continue to audit existing commercial products, and believe our approach to compare commercial biases to academic biases enriches the scholarly and social discourse about facial recognition technology.

**Ethics Statement**

We believe that the main ethical challenge of this work centers on the use of the datasets. We acknowledge that the common academic datasets which we used to evaluate our research questions (Adience [22], MIAP [72], and UTKFace [90]) are all datasets of images scraped from the web without the informed consent of those whom are depicted. This ethical challenge is one that has plagued the research and computer vision community for the last decade [62, 63] and we are excited to see datasets being released which have fully informed consent of the subjects, such as the Casual Conversations Dataset [37]. Unfortunately, this dataset in particular has a rather restrictive license, much more restrictive than similar datasets, which prohibited its use in our study.

We also acknowledge that while our study is intended to be constructive in pointing out the ethical problems inherent in the use and deployment of facial recognition technologies, the specific ethical challenge we highlight is that of unequal or unfair treatment by the technologies. We note that our work could be taken as a litmus test which could lead to the further proliferation of facial recognition technology which could cause other harms. If a commercial company demonstrates their system is less biased on noise robustness tasks, this could be used as a reason for the further deployment of facial technologies and could further impinge upon unwitting individual’s freedoms and perpetuate other technological harms.

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A Replication Data

Information on replicating our study, results, and figures can be found here: https://dataverse.harvard.edu/privateurl.xhtml?token=013c2749-2268-46be-a330-61b98d0483f8.

B Statistical Tests on Precision

B.1 Precision – Service Comparison Claims

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for service on the Adience dataset can be found in Table 1.

|                | MogFace | TinaFace |
|----------------|---------|----------|
| TinaFace       | < 0.001 |          |
| YOLO5Face      | < 0.001 | < 0.001  |

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for service on the MIAP dataset can be found in Table 2.

|                | MogFace | TinaFace |
|----------------|---------|----------|
| TinaFace       | < 0.001 |          |
| YOLO5Face      | < 0.001 | < 0.001  |

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for service on the UTK dataset can be found in Table 3.

|                | MogFace | TinaFace |
|----------------|---------|----------|
| TinaFace       | < 0.001 |          |
| YOLO5Face      | < 0.001 | < 0.001  |

B.2 Precision — Corruption Comparison Claims

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for corruption on TinaFace and Adience can be found in Table 4.

|                | MogFace | TinaFace | impulse-noise | shot-noise | defocus-blur | motion-blur | snow | frost | fog | brightness | contrast | glass-blur | pixelate | log
|----------------|---------|----------|---------------|------------|--------------|-------------|------|-------|----|------------|----------|------------|----------|-----|
| TinaFace       | < 0.001 | < 0.001  | < 0.001       | < 0.001    | < 0.001     | < 0.001     | < 0.001| < 0.001|    |            |          | < 0.001    | < 0.001  | < 0.001|
| YOLO5Face      | < 0.001 | < 0.001  | < 0.001       | < 0.001    | < 0.001     | < 0.001     | < 0.001| < 0.001|    |            |          | < 0.001    | < 0.001  | < 0.001|

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for corruption on YOLO5Face and Adience can be found in Table 5.
Table 5: Precision. Pairwise Wilcoxon test with Bonferroni correction for corruption on YOLO5Face and Adience

| Short name | gaussian noise | impulsive noise | defocus-blur | glass-blue | motion-blur | noise | frost | fog | brightness | contrast | elastic-transform | p-value |
|------------|----------------|----------------|--------------|------------|-------------|-------|-------|----|------------|---------|-------------------|---------|
| precision  | 0.722          | 0.112          | < 0.001      | < 0.001    | < 0.001     | < 0.001| < 0.001| < 0.001| < 0.001    | < 0.001 | < 0.001          | < 0.001 |

Precision p-values for pairwise Wilcoxon test with Bonferroni correction for corruption on MogFace and Adience can be found in Table 6.

Table 6: Precision. Pairwise Wilcoxon test with Bonferroni correction for corruption on MogFace and Adience

| Short name | gaussian noise | impulsive noise | defocus-blur | glass-blue | motion-blur | noise | frost | fog | brightness | contrast | elastic-transform | p-value |
|------------|----------------|----------------|--------------|------------|-------------|-------|-------|----|------------|---------|-------------------|---------|
| precision  | < 0.001        | < 0.001        | < 0.001      | < 0.001    | < 0.001     | < 0.001| < 0.001| < 0.001| < 0.001    | < 0.001 | < 0.001          | < 0.001 |

Precision p-values for pairwise Wilcoxon test with Bonferroni correction for corruption on TinaFace and MIAP can be found in Table 7.

Table 7: Precision. Pairwise Wilcoxon test with Bonferroni correction for corruption on TinaFace and MIAP

| Short name | gaussian noise | impulsive noise | defocus-blur | glass-blue | motion-blur | noise | frost | fog | brightness | contrast | elastic-transform | p-value |
|------------|----------------|----------------|--------------|------------|-------------|-------|-------|----|------------|---------|-------------------|---------|
| precision  | < 0.001        | < 0.001        | < 0.001      | < 0.001    | < 0.001     | < 0.001| < 0.001| < 0.001| < 0.001    | < 0.001 | < 0.001          | < 0.001 |

Precision p-values for pairwise Wilcoxon test with Bonferroni correction for corruption on YOLO5Face and MIAP can be found in Table 8.

Table 8: Precision. Pairwise Wilcoxon test with Bonferroni correction for corruption on YOLO5Face and MIAP

| Short name | gaussian noise | impulsive noise | defocus-blur | glass-blue | motion-blur | noise | frost | fog | brightness | contrast | elastic-transform | p-value |
|------------|----------------|----------------|--------------|------------|-------------|-------|-------|----|------------|---------|-------------------|---------|
| precision  | 0.103          | 0.144          | < 0.001      | < 0.001    | < 0.001     | < 0.001| < 0.001| < 0.001| < 0.001    | < 0.001 | < 0.001          | < 0.001 |

Precision p-values for pairwise Wilcoxon test with Bonferroni correction for corruption on MogFace and MIAP can be found in Table 9.
Table 9: Precision. Pairwise Wilcoxon test with Bonferroni correction for corruption on MogFace and MIAI

| Corruption Type   | jpeg-compression | elastic-transform | defocus-blur | zoom-blur | snow | fog | brightness | contrast | elastic-transfrom | ground-truth |
|-------------------|------------------|------------------|--------------|----------|------|-----|------------|----------|-------------------|--------------|
| jpeg-compression   | 0.100            | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| elastic-transform  | 0.100            | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| defocus-blur       | 0.100            | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| zoom-blur          | 0.100            | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| snow               | 0.100            | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| fog                | 0.100            | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| brightness         | 0.100            | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| contrast           | 0.100            | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| elastic-transfrom  | 0.100            | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| ground-truth       | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     | < 0.001   | < 0.001  | < 0.001           | < 0.001      |

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for corruption on MogFace and UTK can be found in Table 10.

Table 10: Precision. Pairwise Wilcoxon test with Bonferroni correction for corruption on TinaFace and UTK

| Corruption Type   | jpeg-compression | elastic-transform | defocus-blur | zoom-blur | snow | fog | brightness | contrast | elastic-transfrom | ground-truth |
|-------------------|------------------|------------------|--------------|----------|------|-----|------------|----------|-------------------|--------------|
| jpeg-compression   | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| elastic-transform  | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| defocus-blur       | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| zoom-blur          | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| snow               | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| fog                | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| brightness         | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| contrast           | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| elastic-transfrom  | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| ground-truth       | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     | < 0.001   | < 0.001  | < 0.001           | < 0.001      |

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for corruption on YOLO5Face and UTK can be found in Table 11.

Table 11: Precision. Pairwise Wilcoxon test with Bonferroni correction for corruption on YOLO5Face and UTK

| Corruption Type   | jpeg-compression | elastic-transform | defocus-blur | zoom-blur | snow | fog | brightness | contrast | elastic-transfrom | ground-truth |
|-------------------|------------------|------------------|--------------|----------|------|-----|------------|----------|-------------------|--------------|
| jpeg-compression   | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| elastic-transform  | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| defocus-blur       | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| zoom-blur          | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| snow               | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| fog                | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| brightness         | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| contrast           | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| elastic-transfrom  | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| ground-truth       | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     | < 0.001   | < 0.001  | < 0.001           | < 0.001      |

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for corruption on MogFace and UTK can be found in Table 12.

Table 12: Precision. Pairwise Wilcoxon test with Bonferroni correction for corruption on MogFace and UTK

| Corruption Type   | jpeg-compression | elastic-transform | defocus-blur | zoom-blur | snow | fog | brightness | contrast | elastic-transfrom | ground-truth |
|-------------------|------------------|------------------|--------------|----------|------|-----|------------|----------|-------------------|--------------|
| jpeg-compression   | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| elastic-transform  | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| defocus-blur       | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| zoom-blur          | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| snow               | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| fog                | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| brightness         | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| contrast           | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| elastic-transfrom  | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     |            |          |                   |              |
| ground-truth       | < 0.001          | < 0.001          | < 0.001      | < 0.001  |      |     | < 0.001   | < 0.001  | < 0.001           | < 0.001      |

B.3 Precision — Age Comparison Claims

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for Age on TinaFace and Adience can be found in Table 13.
Table 13: Precision. Pairwise Wilcox test with Bonferroni correction for Age on TinaFace and Adience

| Age      | 0-2    | 3-7   | 8-14  | 15-24 | 25-35 | 36-45 | 46-59 |
|----------|--------|-------|-------|-------|-------|-------|-------|
| 3-7      | 0.015  |       |       |       |       |       |       |
| 8-14     | < 0.001| < 0.001|       |       |       |       |       |
| 15-24    | < 0.001| < 0.001| < 0.001|       |       |       |       |
| 25-35    | < 0.001| < 0.001| < 0.001| < 0.001|       |       |       |
| 36-45    | < 0.001| < 0.001| 0.001| < 0.001| < 0.001|       |       |
| 46-59    | < 0.001| < 0.001| 0.011| < 0.001| < 0.001| 0.912|       |
| 60+      | 0.017  | 0.00000| < 0.001| < 0.001| < 0.001| < 0.001| < 0.001|

Precision p-values for pairwise Wilcox test with Bonferroni correction for Age on YOLO5Face and Adience can be found in Table 14.

Table 14: Precision. Pairwise Wilcox test with Bonferroni correction for Age on YOLO5Face and Adience

| Age      | 0-2    | 3-7   | 8-14  | 15-24 | 25-35 | 36-45 | 46-59 |
|----------|--------|-------|-------|-------|-------|-------|-------|
| 3-7      | < 0.001|       |       |       |       |       |       |
| 8-14     | < 0.001| < 0.001|       |       |       |       |       |
| 15-24    | < 0.001| 0.005| < 0.001| < 0.001| < 0.001| < 0.001| < 0.001|
| 25-35    | < 0.001| 0.002| < 0.001| 0.835|       |       |       |
| 36-45    | < 0.001| < 0.001| 0.0003| < 0.001| < 0.001| < 0.001| < 0.001|
| 46-59    | < 0.001| < 0.001| 0.657| < 0.001| < 0.001| < 0.001| 0.029|
| 60+      | < 0.001| < 0.001| < 0.001| < 0.001| < 0.001| < 0.001| < 0.001|

Precision p-values for pairwise Wilcox test with Bonferroni correction for Age on MogFace and Adience can be found in Table 15.

Table 15: Precision. Pairwise Wilcox test with Bonferroni correction for Age on MogFace and Adience

| Age      | 0-2    | 3-7   | 8-14  | 15-24 | 25-35 | 36-45 | 46-59 |
|----------|--------|-------|-------|-------|-------|-------|-------|
| 3-7      | 0.0001 |       |       |       |       |       |       |
| 8-14     | 0.009  | 0.161|       |       |       |       |       |
| 15-24    | < 0.001| < 0.001| < 0.001|       |       |       |       |
| 25-35    | < 0.001| 0.00002| < 0.001| 0.003|       |       |       |
| 36-45    | 0.167  | 0.004| 0.142| < 0.001| < 0.001| < 0.001|       |
| 46-59    | 0.005  | 0.780| 0.418| 0.00000| 0.001| 0.055|       |
| 60+      | < 0.001| < 0.001| < 0.001| < 0.001| < 0.001| < 0.001| < 0.001|

Precision p-values for pairwise Wilcox test with Bonferroni correction for Age on TinaFace and MIAP can be found in Table 16.

Table 16: Precision. Pairwise Wilcox test with Bonferroni correction for Age on TinaFace and MIAP

| Age      | Young | Middle | Older |
|----------|-------|--------|-------|
| Unknown | 0.055 | 0.499  | < 0.001|

Precision p-values for pairwise Wilcox test with Bonferroni correction for Age on YOLO5Face and MIAP can be found in Table 17.
Table 17: Precision. Pairwise Wilcoxon test with Bonferroni correction for Age on YOLO5Face and MIAP

|                | Young | Middle | Older |
|----------------|-------|--------|-------|
| Middle         | < 0.001 |       |       |
| Older          | < 0.001 | < 0.001 |       |
| Unknown        | < 0.001 | < 0.001 | < 0.001 |

Precision p-values for pairwise Wilcoxon test with Bonferroni correction for Age on MogFace and MIAP can be found in Table 18.

Table 18: Precision. Pairwise Wilcoxon test with Bonferroni correction for Age on MogFace and MIAP

|                | Young | Middle | Older |
|----------------|-------|--------|-------|
| Middle         | < 0.001 |       |       |
| Older          | < 0.001 | < 0.001 |       |
| Unknown        | < 0.001 | < 0.001 | < 0.001 |

Precision p-values for pairwise Wilcoxon test with Bonferroni correction for Age on TinaFace and UTK can be found in Table 19.

Table 19: Precision. Pairwise Wilcoxon test with Bonferroni correction for Age on TinaFace and UTK

|                | 0-18 | 19-45 | 45-64 |
|----------------|------|-------|-------|
| 19-45          | < 0.001 |       |       |
| 45-64          | < 0.001 | < 0.001 |       |
| 65+            | < 0.001 | < 0.001 | < 0.001 |

Precision p-values for pairwise Wilcoxon test with Bonferroni correction for Age on YOLO5Face and UTK can be found in Table 20.

Table 20: Precision. Pairwise Wilcoxon test with Bonferroni correction for Age on YOLO5Face and UTK

|                | 0-18 | 19-45 | 45-64 |
|----------------|------|-------|-------|
| 19-45          | < 0.001 |       |       |
| 45-64          | < 0.001 | < 0.054 |       |
| 65+            | < 0.001 | < 0.001 | < 0.001 |

Precision p-values for pairwise Wilcoxon test with Bonferroni correction for Age on MogFace and UTK can be found in Table 21.

Table 21: Precision. Pairwise Wilcoxon test with Bonferroni correction for Age on MogFace and UTK

|                | 0-18 | 19-45 | 45-64 |
|----------------|------|-------|-------|
| 19-45          | < 0.001 |       |       |
| 45-64          | < 0.001 | < 0.001 |       |
| 65+            | < 0.001 | < 0.001 | < 0.001 |

B.4 Precision — Gender Comparison Claims

Precision p-values for pairwise Wilcoxon test with Bonferroni correction for Gender on TinaFace and Adience can be found in Table 22.
Table 22: Precision. Pairwise Wilcoxon test with Bonferroni correction for Gender on TinaFace and Adience

|       | Female | Male    |
|-------|--------|---------|
| Gender |        |         |
| Female | 0.00003|         |
| Male   | < 0.001|         |

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for Gender on YOLO5Face and Adience can be found in Table 23.

Table 23: Precision. Pairwise Wilcoxon test with Bonferroni correction for Gender on YOLO5Face and Adience

|       | Female | Male    |
|-------|--------|---------|
| Gender |        |         |
| Female | < 0.001|         |
| Male   | < 0.001|         |

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for Gender on MogFace and Adience can be found in Table 24.

Table 24: Precision. Pairwise Wilcoxon test with Bonferroni correction for Gender on MogFace and Adience

|       | Female | Male    |
|-------|--------|---------|
| Gender |        |         |
| Female | < 0.001|         |
| Male   | < 0.001|         |

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for Gender on TinaFace and MIAP can be found in Table 25.

Table 25: Precision. Pairwise Wilcoxon test with Bonferroni correction for Gender on TinaFace and MIAP

| Gender                  | Predominantly Feminine | Predominantly Masculine |
|-------------------------|------------------------|-------------------------|
| Predominantly Masculine | < 0.001                |                         |
| Unknown                 | < 0.001                | 0.00000                 |

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for Gender on YOLO5Face and MIAP can be found in Table 26.

Table 26: Precision. Pairwise Wilcoxon test with Bonferroni correction for Gender on YOLO5Face and MIAP

| Gender                  | Predominantly Feminine | Predominantly Masculine |
|-------------------------|------------------------|-------------------------|
| Predominantly Masculine | < 0.001                |                         |
| Unknown                 | < 0.001                | < 0.001                 |

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for Gender on MogFace and MIAP can be found in Table 27.

Table 27: Precision. Pairwise Wilcoxon test with Bonferroni correction for Gender on MogFace and MIAP

| Gender                  | Predominantly Feminine | Predominantly Masculine |
|-------------------------|------------------------|-------------------------|
| Predominantly Masculine | < 0.001                |                         |
| Unknown                 | < 0.001                | < 0.001                 |
Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for Gender on TinaFace and UTK can be found in Table 28.

Table 28: Precision. Pairwise Wilcoxon test with Bonferroni correction for Gender on TinaFace and UTK

|       | Female | Male   |
|-------|--------|--------|
| Female|        | < 0.001|

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for Gender on YOLO5Face and UTK can be found in Table 29.

Table 29: Precision. Pairwise Wilcoxon test with Bonferroni correction for Gender on YOLO5Face and UTK

|       | Female | Male   |
|-------|--------|--------|
| Female|        | < 0.001|

Precision $p$-values for pairwise Wilcoxon test with Bonferroni correction for Gender on MogFace and UTK can be found in Table 30.

Table 30: Precision. Pairwise Wilcoxon test with Bonferroni correction for Gender on MogFace and UTK

|       | Female | Male   |
|-------|--------|--------|
| Female|        | < 0.001|